University of Nairobi

School of Engineering

APPLICATION OF FOREST FIRE DETECTION INDEX IN FOREST FIRES: A CASE STUDY OF ABERDARE FOREST

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DECLARATION

I, Japheth Omondi Aseko hereby declare that this project is my original work. To the best of my knowledge, the work presented here has not been presented for a degree in any other Institution of Higher Learning.

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JAPHETH OMONDI ASEKO Date

This project has been submitted for examination with our approval as university supervisor(s).

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DR. DAVID SIRIBA Date

DEDICATION

This work is dedicated to my late loving father Elly Aseko and my caring mother Siprose Aseko

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I would like to express my deep gratitude to Dr. Siriba, my research supervisor for the patient guidance, enthusiastic encouragement and useful critiques of this research work. I would also like to thank Professor C. Mito for his advice and assistance in keeping my progress on schedule.

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ABSTRACT

Forest fire detection is an important step in wildfire pre-suppression process. Many organizations involved in forest monitoring and surveillance strive to achieve efficient and faster methods to detect forest fires. This is due to colossal amount of money spent in forest restoration and rehabilitation after fire occurrences. Timely detection and efficient interpretation of the satellite and other terrestrial images allow fire personnel to contain the fire at its initial stage and this will reduce damages caused to both flora and fauna besides the suppression cost. It has been difficult to predict, detect and control forest fires in Kenya and in many cases different agencies are caught unawares in the instances of fires witnessed in the country. Forest fires spread faster due to the presence of dry vegetation covers especially during dry season and this requires a faster way of detection to avoid escalated damages as witnessed in the previous fire occurrences in our country; the latest being the one in Aberdare forest which formed the basis for this project. The motivation behind this project was to have a smooth means for forest fire detection through the use of a forest fire index that will help in detecting flames and smokes in the near-real time and to enable concerned parties to react quickly in case of forest fire. The method borrowed from the vegetation classification to detect distinct reflectance from both flame and smokes. Smoke has been difficult to detect because of the weak infrared radiations emitted at its production and this makes sensors not to detect it. In this project smokes was detected adaptively in the region of interest with the help of a variable factor. The project was carried out in phases; MODIS terra and aqua image acquisition from https://ladsweb.modaps.eosdis.nasa.gov/search/ and terrestrial image from drone on 30th March 2018, extraction of colour components, normalization of the colour components, using the forest fire detection index for smoke and flame detection and lastly and representing the output from colour analysis for smokes and flames in image forms. The method can be used in near-real time forest fire detection resulting in a more cost-effective outcome than the traditional systems involving water tanks and watch towers. This method is efficient in forest fire detection at the early stage when both satellite and drone images are made readily available.

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NOMENCLATURE

AVHRR	Advanced Very High Resolution Radiometer
BAER	Burned Area Emergency Response
dNBR	the difference in the NBR between pre-and post-fire images
FDI	Fire Detection Index
FFDI	Forest Fire Detection Index
GEO	Geostationary Orbit
KFS	Kenya Forest Services
LEO	Low Earth Orbit
LIDAR	Light detection and ranging systems
MODIS	Moderate Resolution Imaging Spectroradiometer
NBR	Normalized Burn Ratio
NDVI	Normalized Difference Vegetation Index
RCMRD	Regional Centre for Mapping of Resource for Development
RGB	Red, Green and Blue
ROI	Region of Interest

CHAPTER 1: INTRODUCTION

1.1 Background

Forests play an important role in our ecosystem. It is a source of many products and services which include; purification of air, provision of food, fuel, regulating services such as protection of watershed and carbon storage (Koziowski, 2002). Forest ecosystem services have proved to be of great economic value because they provide raw materials for industrial purposes like paper industry which has been a source of employment for many, source of shelter for wildlife making them a tourist attraction sites (Constanza etal., 1997). Despite the numerous benefits derived from the forest, it is unfortunate that forests throughout the world and especially in the tropics have been threatened by both natural and human-induced threats such as forest fire, logging, lightning and clearance of virgin lands for agricultural purposes due to the ever increasing population. Such threats have immensely reduced forest covers in Africa. One of the mostly felt threats in the world is forest fires. Forest fire is defined as a free propagation of uncontrolled fire in the forest ecosystem caused by accidental, natural and intentional causes (Chuvieco, 2009). Forest fires cause a lot of damages in the ecosystem; loss of forest vegetation cover, loss of lives to the animals and other organisms sheltered in the forests, increased carbon dioxide production which has an adverse effect in depletion of the ozone layer. The latter has led to climatic change whose effects include global warming, change in the sea levels, death of corals due to deprived oxygen supply and unpredictable weather pattern which has affected the agricultural population negatively.

The world has experienced numerous forest fire incidences resulting in more than 6 million ha of forest burnt from the estimated 220,000forest fires reported yearly (Gonzalez et al., 2005). Negative effects of the forest fires have attracted a lot studies and research striving to design best practices in the prediction, detection, monitoring, evaluation, mitigation and analysis of the effects of the forest fires. Countries like Russia, the United States of America and Canada have made steps in forest fire research (Sturtevant et al., 2009). Forest fire detection has received a lot of attention because of the remote location of many forests making the fire to be detected after some minutes, hours and days. Forest fire suppression and monitoring have never been easy because of the remote location of forests, dangers of the wild animals and poisonous plants in the forest making human interaction with the forest greatly reduced. Countries have made steps towards monitoring of forest by developing forest management system and forest fire risk forecast systems in time and space. Kenyan government formed Kenya Forest Services (KFS) to help in recording all fire incidences and stocking every station with fire extinguishing equipment. Adoption of such measures has been low due to the funds involved in their purchases and expertise in their operation.

Kenya is faced with high instances of forest fire outbreaks due to her tropical climatic condition and uncontrolled human activities. Different methods have been put in place to reduce human to forest contacts by having some by-laws that declare forest as a government asset and this has reduced encroachment of forested areas for human settlement. In spite of reduced human settlement in the gazetted forest areas, there are still many forest fire incidences reported. This therefore calls for an efficient way of detecting forest fires to enable its suppression at the earliest stage possible. Early detection reduces extinction time, requires fewer executors and fire fighting equipment hence increasing efficiency and reducing the damages to the lowest level possible. The project was designed to address early detection challenge in order to ease the suppression. This was achieved by combining already established algorithms to detect smoke and flames from both satellites and terrestrial images. Commonly used method for fire detection is based on human surveillance and transmission of the information to the authorities is always untimely and unreliable.

The justification and necessity to apply this method is due to the fact that there is high number of fire incidences which are always accompanied by huge loss of the forest covers and lives in the forests; fauna. Fire departments in various agencies therefore need this model to help in detection of fire at the nascent stage of smoke emission.

The latest forest fire recorded in Kenya is the Aberdare forest fire which consumed hectares of the forest cover (Mugo, 2018). The Aberdare forest was affected just three after another inferno destroyed 300 hectares of Mt. Kenya forest. This formed the basis of the study as the forest is under constant surveillance by the Regional Centre for Mapping of Resources for Development (RCMRD). Figure 1.1 below is an aerial view of Aberdare forest taken before fire breakout and it shows an ample forest cover made of trees and grass.

Figure 1.1 Aberdare Forest before fire

Figure1.2. Aerial view of a section of the Aberdare Forest that was on fire on February 25, 2018.

Figure 1.2 above is an aerial view of the forest cover taken during the fire outbreak; a huge plume of smoke is clearly seen blowing westward with fresh fire scars left behind in the moorland. It may not be easy to see an active fire in the forest but certainly it can be seen using an in-depth analysis of the image using an algorithm; forest fire detection index algorithm.

Forest fire is uncontrolled fire in the forest which causes damage to nature and human and impacts aquatic, terrestrial and atmospheric systems in the world. Over the years, forest fires have received remarkable attention because of the wide range of ecological, political, economic and social values at stake. Its impact on both spatial and temporal scale has prompted stakeholders to strive to understand the relationship between, patterns, process and the restoration measures. The fire can stimulate soil microbial processes and promote seed germination and sprouting. This will burn vegetation, ultimately altering the structure and composition of both soil and vegetation (McHugh and Kolb 2003). The fire may also affect the quantity and quality of the water yield; accelerate erosion and sedimentation having a detrimental impact on the aquatic systems (Gresswell 1999; Vieira et al.2004). Forest fire effects are felt globally in large scale when gaseous pollutants are emitted into the atmosphere since they have direct impact on the atmospheric biochemical cycles and the earth's radiative budget (Andrea and Merlet 2001; Smith et al.2005a).

Forest fires can be divided into three categories;

a) **Ground fires**: Found beneath litters of composed material on the forest floor and produce intense heat but practically no flame. They are relatively rare and most difficult to detect because they are undetectable until they blaze up. They cause a lot of damages to the lives of animals that live underground because by the time they blaze up, under growths have already been reduced to ashes.
b) **Surface fires**: They are the most prevalent fire in our forests and their spread is regular and depends on the wind speed. It is detectable. They are found the ground covers and scrubs.
c) **Crown fires**: Normally found in the low level coniferous tress and are the most dangerous fires for the forest since they spread rapidly.

Kenya has five main forest areas which include; Mt Kenya, the Aberdare ranges, the Mau complex, Mt Elgon, and Cherangani Hills. The forest covers have degenerated over the past years due to population pressure and forest fires due to biomass usage. Forest fires have been the major cause of this degradation and its effect has been felt across the country due to destruction on the major water towers; Mt Kenya and Aberdare ranges. The problem of fire outbreak has become more severe than in the previous years due to increased human encroachment. Main concern has been on the detection of the fire at the initial stage and this has not been fully achieved due to the methods deployed currently; the use of watch towers and forest guards survey by the KFS. The methods were too mechanical and suffer from low accuracy resulting from the operator fatigue, time of the day and the geographic location.

Forest fires bring a lot of changes in the vegetation spectral signatures measured by various satellite sensors. There is a drastic reduction in the visible to near-infrared surface reflectance as a result of the charring and removal of vegetation (Eva and Lambin 1998a; Trigg and Flasse 2000). The project focused on the detection of changes in the spectral signatures by analysing the colour composition and the colour changes in the vegetation and its surrounding. This was an important step in detection of the flames and smoke where the latter has not been easily detected due to its weak radiations emitted. Smoke is the first phenomenon to be witnessed before the actual fire and so its detection is the surest way to suppress the forest fire incidences. Spectral changes due to burning have led to invent of various spectral indices; Normalized Burn Ratio (NBR), the difference in the NBR between pre-and post-fire images (dNBR), and the Normalized Difference Vegetation Index (NDVI). NBR and dNBR are used to infer fire severity from remotely sensed data (Key and Benson 2002; Cock et al. 2005; Roy et al. 2006) and are used to produce maps for Burned Area Emergency Response (BAER) teams (Parsons 2003). Forest Fire Detection Index has an edge over the rest because it combines flames, smokes and vegetation elements in the detection process. This makes it to be more efficient, precise and accurate in its results. The index can be used in both satellite and terrestrial images from drones which are used to show the changes in the forests as a result of fire. Satellite images re majorly from MODIS which has been pivotal in forest monitoring. The project used the forest fire detection index on both MODIS and drone images for near- real time smoke and fire detection for easy suppression.

1.2 Problem Statement

Principle of early detection combined with quick initial attack while the fire is small is the most effective approach to controlling forest fires. Effective daily detection planning requires proper understanding of the forest fire behaviour over time. Forest fires undergo various phases which can progress unnoticed without proper detection. The first phase is the ignition where man or lightning starts the fire. This process occurs in a very short time interval ranging from a few milliseconds with lighting to a few minutes with human sources such as cigarettes. Moisture and fuel density condition may not sustain such combustions thus it is not guaranteed that having an ignition source may make the fire detection possible. Of all lightning fire reported, about 20% have no physical evidence of lightning (Kourtz 1967), the assumption is derived from the fact they are in remote locations. The second phase of the forest fire is the smouldering phase where a fire ignited in the latter part of the day smoulders into the next burning period if is to become detectable. Visual detection of fire at the smouldering phase using air patrol is difficult though not impossible. The third phase is characterised by sufficient energy build up to sustain the flame spread. Many of the detections are made during this stage. Large proportions of Kenyan forest fires are detected while burning at low and moderate energy states. With few exceptions smoke emissions are sufficient for the visual detection of forest fires.

Kenyan forests are managed by the Kenya Forest Services (KFS) a government entity which relies on government funding for smooth running of their day to day operations. This has resulted in limited investment in the early detection of the forest fires thus leading to great losses in the forest covers. In 2017 alone over 7000ha of the forest covers was consumed by the raging fire as reported by the Daily Nation on Feb 25, 2018 for both Aberdares and Mt. Kenya forests between January and March. This followed the March 12, 2012 loss of bamboo forest in Chogoria and Chuka whose value was estimated to be USD80.8 million. The study focuses on Aberdare forest due to its latest fire outbreak on February 25, 2018 which consumed its tens of thousands of acreage despite being under constant surveillance by the Regional Centre for Mapping of Resources for Development (RCMRD) using MODIS fire information systems. The study therefore uses forest fire detection index on the MODIS data and terrestrial image collected to test their accuracies in fire detection with the hope of avoiding such loses in future.

1.3 Objectives

The main aim of the project was to detect forest fire using a forest fire detection index on Aberdare forest.

Specific objectives

- To extract and normalize RGB colour component from MODIS data and terrestrial image.
- To calculate the detection indices for flames, smoke and vegetation and defining their regions.

1.4 Justification for the Study

Forests play a crucial role in nature. They help to purify water, maintain ecological balance, provide habitat for wildlife and act as water towers. Economically, forests sustain forest product industries which provide direct jobs to the youths through established processing and manufacturing plants which altogether generate revenue for the country's GDP growth.

Unfortunately, every year forest areas are consumed by wildfires which result from both human and natural causes. Wildfires help in development of new forest but their encroachment into sensitive areas which may threaten the ecological balance or human infrastructure and lives may be difficult to control (Hirschand Fuglem 2006). Forest fires have become a serious natural danger (Mandallaz and Ye 1997; Kolaric et al.2008); therefore its detection is considered to be an important step in protection and preservation of natural resources.

Early detection and suppression of the forest fire are important in preventing massive loss due to their rapid convection propagation and long combustion cycle (Lin et al.2014). Many measures have been put in place in monitoring, detection and fighting forest fires to prevent their negative impacts in our niche. Traditional methods of forest fire monitoring and detection involved mechanical devices and human interventions. These methods are outweighed by the emergence of computer software and systems that can efficiently detect emergence of forest fires.

The study employs the use of detection index that operate on vegetation background colours as a result of the fire effect. This method is considered superior as it works on both terrestrial and satellite acquired imageries to detect both flames and smokes automatically through an algorithm. The latter; smoke has been difficult to detect by sensors due to their weak infrared emissions.

Scope of work

The project aims at real time forest fire detection by using forest fire detection index algorithm. The algorithm was then used on MODIS satellite imageries acquired from RCMRD on Aberdare forest and later on the terrestrial image from the drones. The algorithm was varied using a weighting factor α. which helped in detecting both flames and smokes by varying the RGB colour components. The effect of the weighting factor was then shown by varying it and its effect shown on the images. The detection process was shown in a systematic manner until the fire fronts and smoke propagation resulted.

CHAPTER 2: LITERATURE REVIEW

2.0. Introduction

Forest is an important natural resource that is widely considered as the protector of the earth's ecological balance. Many at times forests have suffered from wildfires which unfortunately are only discovered after they have widely spread due to inept mechanisms put in place for the forest fire monitoring. Forest fires have adverse effects on both flora and fauna. Long term effects of the forest fires are drastic changes in the weather patterns and global warming and extinction of flora and fauna lives. Such effects are irreparable and quick interventions have to be taken to avoid forest fire outbreaks. Major hurdles faced with forest fires is that forests are remote or unmanned areas and made of trees, dry and parched woods and leaves which act as fuel during fire outbreaks. These materials act as catalysts during the initial ignition fire stage and later during the spread as they are highly combustible. Wildfires may erupt as a result of careless smoking, bonfires by party revellers and natural causes like rise in temperatures during dry spell or broken glasses which may act as lenses converging sun rays to a spot for a long time resulting into fire ignition. Forest fires are categorised as ground fire, surface fire and the crown fire which is the most dangerous of all due to its faster spread depending on the weather condition and the terrain.

Tens of thousands of hectares of forest are destroyed by the wildfires and this call for immediate methods for monitoring and early detection to avoid such losses and to reduce the cost of fire fighting. A simple thumb rule applies in the forest fire fighting; 1 minute-1 cup of water, 2 minutes-100 litres of water and 10 minutes-1000 litres of water. This presents an urgent need to detect the forest fire at its early stage, its localization and to alert the fire units in time to significantly reduce the reaction time. Such measures will enhance or ensure that the fire is put out at an early stage or before it causes a significant damage. There are a number of monitoring systems employed by fire fighting units ranging from the patrols, watch towers, aerial and satellites systems and recent monitoring systems based on optical camera sensors.

This section gives a review of various methods used in detection and monitoring of forest fires, experience in their usage and ratings in terms of efficiency, versatility, accuracy and other attributes.

2.1. Traditional Fire suppression and detection techniques

Many organizations and forest management service providers employ various techniques in the detection and suppression of forest fires. These methods include; control burning, watch towers, education and awareness through fire watch for house owners and water tanks. The latest technology used includes the use of mobile/ smart phone calls for early detection. Canada uses aerial water tankers and in some cases the fire is left to burn to completion so long as it does not affect human lives. These suppression techniques are expensive and require huge budgetary allocation by the ministry concerned. It all depends on the probability of the human observation and this may raise a question of the reliability and accuracy especially on the localisation of fire. Considering the Australia case where fire is left to burn and engulf the entire forest until it stops as long as it does not affect human life is disadvantageous because forest harbour flora and fauna lives. The method is not accurate and timely thus cannot be used for real time monitoring and detection.

2.2. Satellite systems

Satellites and air-floating devices have been employed to detect fires. Advanced Very High Resolution Radiometer (AVHRR) launched in 1998 and Moderate Resolution Imaging Spectroradiometer (MODIS) launched in 1999 have been used for the fire detection. The two satellites produce images with low resolution making identification of the flame and more so smoke difficult due to the difficulties experienced in detection weak smoke radiations by satellite sensors. Besides the time frame constraint due to the high revisit time, quality of the satellites can also be affected by the weather condition. Direct observation of forest fires from geostationary (GEO) or Low Earth Orbit (LEO) may not provide full forest coverage. The two satellites GEO and LEO are located on the orbit over 22,800 miles limiting detections of the feeble intensity of infrared and optical radiations emitted by flames in early stages. Radiation intensity decreases as the inverse square of the distance. Not all satellites are equipped with transponders, antennas, amplification reception, regeneration and downlink transmission suited for detection of forest fires.

In some case, the satellite may lack appropriate frequency and bandwidth for the detection purpose. It is very rare for a country to launch satellite into space for forest fire detection due to the expenses involved in the whole process. Satellite operation is also bounded by national and international treaties and agreements and this complicates its operation in a small area like forest covers. The images produced by these satellites may not bring out the flames and smoke location and this can be solved by the use of the forest fire detection index.

2.3. Sensors and Digital cameras

System of optical sensors and digital cameras have helped in automatic forest fire detection and monitoring. Two commonly used sensor networks used for fire detections are; camera surveillance and sensor network. The system has Video-camera sensitive to visible spectrum of smoke recognizable during the day and fire recognizable at night, Infrared (IR) spectrometer for identifying the spectral characteristics of the smoke and Light detection and ranging systems-LIDAR that measure laser rays reflected from the smoke particles. The sensors work based on the algorithms designed by their producers and this may lead to false alarms thus, inaccurate information relayed. The cameras are expensive to acquire and therefore their operations depend on financial resources available. The camera may not take the topography of the land and this result in localisation error due to variation in the atmospheric conditions. A lot of modifications have to be done to improve the performance of the optical sensors in order to yield maximum result devoid of false fire alarms as a result of reflections, human activities and wind-tossed trees.

Camera surveillance also proved to be ineffective due to the need for manual installations an in line of sight of the image and this may results into false alarms generated due to;

i. Moving clouds,
ii. Daily motion of the sun,
iii. Variation in the atmospheric extinction,
iv. Vegetation

Optical sensors and digital cameras are expensive and therefore uneconomical to buy and install in remote areas besides the inefficiencies and false fire generated.

2.4 Wireless Sensor Networks

These are conglomeration of sensors capable of sensing their environment and computing data. They are capable of sensing physical parameters such as temperatures, humidity, pressure as well as chemical parameters such as carbon monoxide, carbon dioxide, and nitrogen dioxide. One of the advantages of this system over the others discussed above is that the sensors operate in a self-healing and self-organising wireless networking environment. Wireless sensor network follow an efficient algorithm interfaced with other technologies or networks for forest fire detection. It has a potential to be applied everywhere. In Spain, *Lloret and others* deployed a mesh network of sensors with an internet protocol to detect fire at the beginning and send alarm signals to the sink. *Yu and others* presented a real- time forest fire detection using a neural sensor network system which relied on a clustering algorithm as a routing technique to collect physical and chemical parameters from clustered sensors for analysis. The resultant outputs are great resource to The United States national Fire Danger Rating System. Wireless sensor networks rely on a complicated technology and its result is greatly determined by atmospheric conditions which have diverse effects on the radiation transfers. Further to that, image processing must be done afterwards using Markov model thus; achieving the real forest fire detection can be a toll order.

2.5 Unmanned Aerial Vehicle (UAV)

This is a new area of study attracting several research works on its feasibility, efficiency and accuracy in forest fire detection. There are numerous advantages of this method over others in terms of the aerial coverage, active sensors in place and precise fire location. The system can also be used in areas which are not accessible by the forest guards due to the dangers posed by the harboured animals in the forest. This new method of forest fire detection suffers a major blow due to the expenses involved in purchasing a drone and its operation costs compared to the forest revenue. There has been a challenge in getting the operation license in many countries due to data security concerns.

2.6. Forest Fire Detection Index

The method is based on the vegetation classification and is the one used in this project. Forest fire detection index can be adapted to detect tonalities of both flames, smoke and heat; parameters which have been of interest to many researchers in the forest detection. The project uses the index in the region of interest (ROI) with the help of variable factors to detect both smoke and flame in the near real time. Multiple tests were carried on the MODIS images and terrestrial images from the drones downloaded and the highest detection precision was achieved and the forest fire hotspots could be seen clearly. The method can be used to augment both satellite and drone technology by helping in separating the smoke region from the flames. The algorithm can also be embedded in detection systems like Unmanned Aerial Vehicles and mobile phones for faster and accurate fire locations. This method would result in more cost-effective outcomes than any other conventional systems implemented in satellites or UAV. Various smoke detection techniques have been used before and they were based purely on temperature sampling, particle sampling and air transparency testing. During such tests, an alarm was not raised until smoke particles reach the sensors and activate them. This is the reason why smoke detection by satellite sensors has been difficult. The automatic image processing technology using systems such as ERDAS made fire detection based on image processing using the FDI more feasible than any other traditional methods such as watch towers, sensors and satellites. FDI method is based on image processing and can monitor and detect the forest fires for 24 hour-real time because it can work well on both satellite and terrestrial images from drones effectively. This will generate alarms at an early stage of fire due because of the smoke detection thus making preparation for the suppression possible and minimising the losses witnessed before. The image processing technique is also less costly so long as the image has been acquired.

Compared to the traditional methods, the fire detection techniques that are based on image processing can monitor the forest for 24 hour real-time. It is capable of generating alarms at the very early stages of the fire. Moreover the image processing techniques costs as the algorithm is used ion cheap computation. The methods detects fire by distinguishing the colour of the forest (green) and the fire (red) and smoke (grey or white) and uses the difference between the sequential images to detect the rapid formation of smoke.

The colour spaced used in this method is the RGB which has the ability to distinguish luminance from chrominance. Fire is normally yellowish-red in colour and therefore with the RGB rule $R > G > B$. The same rule applies to the smoke and vegetation where green dominates the colour index.

Summary of literature review

Forest fire detection has been achieved by using various methods ranging from the traditional use of watch towers to the computational techniques which employs computer algorithm for automatic detection. Traditional methods suffered major blows because of the remote location of the forests leading to untimely detection and this made them unreliable in their usage. They depended so much on the operator's accuracy and in many cases were achieved after great losses. The use of cameras and optical sensors for surveillance and detection also proved inefficient and expensive because of huge funds required in the camera installations and maintenance. Cameras could also not take all the fire and smoke location due to the topographical differences and this may lead to false alarms. Another milestone in the detection was achieved when satellites and drones were deployed to take forest images which can be analysed to show areas of both smoke and fire fronts. Satellite operations are expensive and the resultant images have low resolutions which must be taken through rigorous computations to detect the areas of interests. Raw satellite images require step by step processing to give meaning and this may take time therefore hampering the detection time and this affect the suppression process negatively. The project uses FDI algorithm on the images obtained from both drones and satellite images to ease their interpretations within the shortest time. The method uses vegetation classification which takes into account the colour differences between vegetation, flame and smokes. It was easy to detect fires from vegetation and smokes from vegetation because it is based on the three primary colours RGB which encompasses the vegetation, flame and smokes. Once an image has been obtained from the satellite or drones, it is subjected to the algorithm which separates vegetation from fires and smoke.

CHAPTER 3: MATERIALS AND METHODS

3.1: Area of study

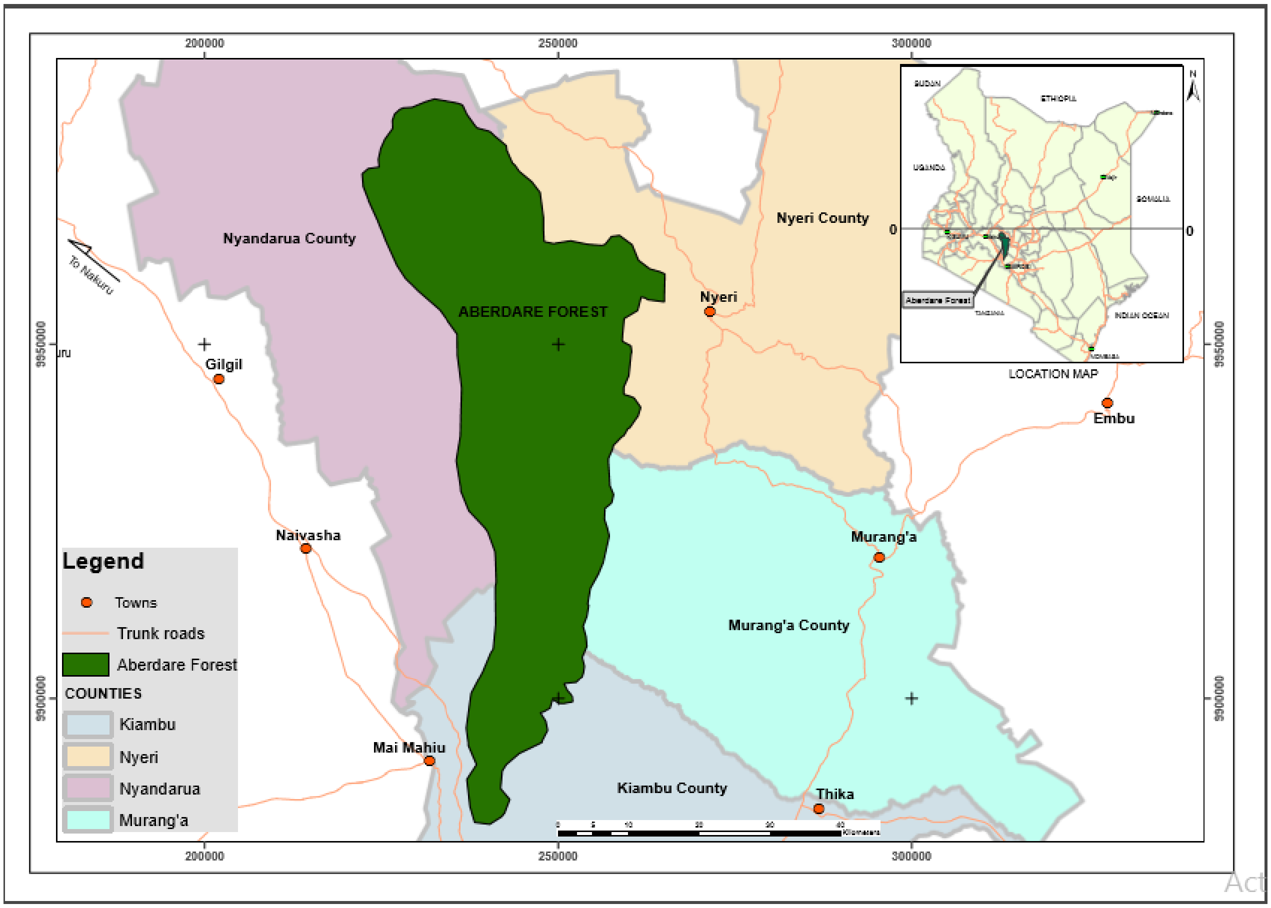


Figure 3.1 Aberdare forest topographic maps.

The project focuses on Aberdare forest which is one of the water towers in Kenya. This forest has suffered major destruction caused by the forest fires the latest being on February 25, 2018 which destroyed its 7000ha of coverage.

This section provides the technical details of the pilot project aimed for Aberdare forest which not only integrates a spectrum of preventive measures for forest fire prevention but also on the real time detection of the fire. The method employed in this project will go a long way in both pre and post fire approaches for the frequently experienced forest fires in Aberdare forest. Aberdare forest is highly exposed to forest fire risk mainly during dry season due to the numerous trees with high number of dry leaves and that the forest location is on an expansive highly populated area.

The project will be carried out in the following phases;

3.1 Data preparation

MODIS image was downloaded from MODIS web http://ladsweb.modmaps.eosdis.nasa.gov where its coordinates latitude of -0.4894 and longitude of 36.6414 and the date specified to be on the 2/20/2017 which was available. The images with low cloud interference were selected and used for the project. More details of the image used can be found on Appendix A4. Layer stacking of the images was done with respect to the primary colours RGB in bands 3, 2, 1 respectively using ERDAS. Colour clustering was then done and the region of interest where the fire was reported taken into consideration; South Laikipia and Bellevue bloc.

Figure 3.2. MODIS image of Aberdare forest downloaded in 2/20/2017

Figure 3.3 .Terrestrial image of Aberdare forest taken from Drone taken on 2018:03:30; Appendix A5

3.2. Generation of fire detection indices

This chapter describe the procedure to follow in creation of the general Fire Detection index (FDI) and a specific Forest Fire Detection Index (FFDI) for the fire detection in the environment of green colours. The project borrows a lot from the aspect of vegetation index which is used to identify excess green colours which is later used in the development of the FFDI

The success of Vegetation index (VI) has been seen in many projects to identify specific crops, plants or weeds in agricultural remote sensing tasks. These indices are grayscale images obtained by arithmetic operations on the three colour components Red, Green and Blue; RGB used to enhance certain colours while attenuating other unwanted ones. Excess Green colour, ExG stood out in this project as it helps vegetation to be extracted from the background. It gives green component of the RGB more value and so the resultant image will have more green than red and blue; vegetation colour is therefore enhanced by a factor of two.

$$ExG = 2g - r - b \qquad (1)$$

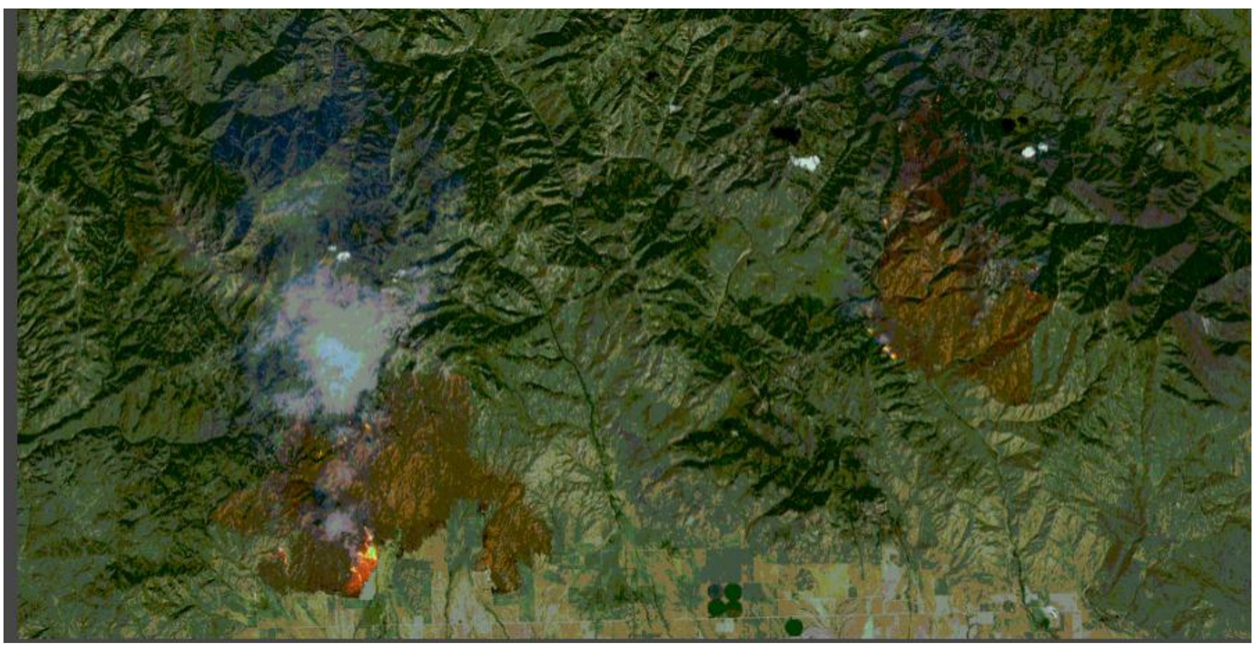


Figure 3.4 Excess green colour algorithm used on MODIS image

When the same algorithm was applied on the terrestrial image the resultant excess green colour obtained was as shown below in figure 3.5.

Figure 3.5. Excess Green colour on Terrestrial image from Drone.

The project borrowed a concept of the excess vegetation green and instead concentrated on the flame and smoke colour (red and grey to white colours). This was achieved by enhancing the red colours against both blue and green colours which were attenuated as shown in the subsequent sections

The process involved normalisation of the red, green and the blue component of the RGB followed by arithmetic operations resulting to different indices.

3.2.1. Normalisation

This is done to achieve a better robustness against different conditions. The components are normalised by their maximum values (255) and then by the sum of the RGB leading to;

$$r = \frac{R}{R+G+B}, \qquad g = \frac{G}{R+G+B}, b = \frac{B}{R+G+B} \qquad (2$$

This process is automated by the system.

3.2.2. Relation between colour components

In this part component of the region of interest was analysed where those with stronger influence are enhanced and others attenuated. In equation (1) of the ExG=2g-r-b the green colour is reinforced by duplication while red and blue are subtracted. Those colours which are composed of more green than red and blue appear brighter while those containing red and blue appear darker in the resultant image. The resultant image is an excess green colour denoted by ExG.

The main aim of the project is to detect areas of fire which include flames and smoke and probably steams. Colour range to be detected therefore will have yellow, red and orange tones for flames and white and greyish parts of smoke. Analysis was done on an images obtained from MODIS on Aberdare forest during the February 22, 2017 forest fire and terrestrial image obtained from the done on March 30, 2018 of the same forest. All pixels in the ROI were subjected to the algorithm and resultant images produced to give distinct areas of smokes, flames and vegetation.

Histogram distribution of the three components (RGB) was then analysed to show the colour intensities of the component in the ROI; where horizontal -axis denotes the pixel values ranging from 0 to 255 while the vertical -axis shows the number of pixels found for each value. All the mean values were then averaged over the MODIS aqua and terra images giving a relation below.

$$r > g \text{ and } r > b \qquad (3)$$

3.2.3. Fire Detection Index

The fire detection index is obtained based on the fact that the red component is predominant in the flame and it is our main interest thus both green and blue components will be subtracted from red components then the result added to form the FDI.

$$A = r - b, B = r - g$$

$$A + B = FDI = 2r - g - b$$

Thus,

$$FDI = 2r - g - b \qquad (4)$$

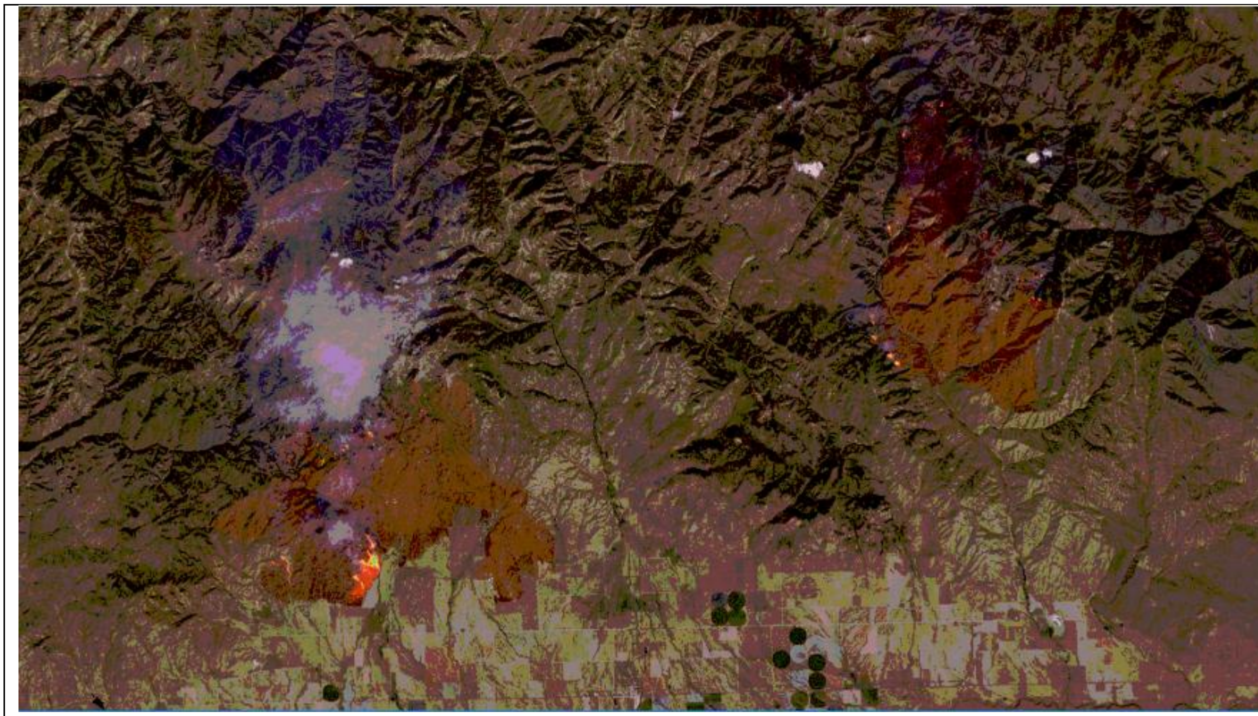


Figure 3.5 Fire Detection index applied on the MODIS image

In the resultant image, red is predominant and enhanced by a factor of two. The MODIS image can then clearly show the area under fire and smoke. The red and grey component which shows an area of smoke and flame appear brighter than the green areas denoting vegetation. From the equation, red component is enhanced while green and blue attenuated by subtraction.

3.2.4. Forest Fire Detection Index (FFDI)

This is a more specific index formed by extending the FDI to cope with the vegetation background. FFDI helps in detecting the smoke area as well as discriminating the green tones from the background vegetation. Smoke area is made more salient via the FDI and the vegetation through ExG. By subtracting the indices; ExG is negated and this further enhances FDI against green components. A scalar component alpha α is then added to enhance the colour components of both smokes and flames as shown below on the FDI resulting in the FFDI.

Thus;

$$FFDI = \alpha * (FDI) - ExG \qquad (5)$$

$$FFDI = \alpha(2r - g - b) - (2g - r - b) = r(2\alpha + 1) - g(\alpha + 2) + b(1 - \alpha) \qquad (6)$$

From equation 6, lowering the value of α enhances colours with high amount of red components compared to both green and blue components. Bigger values of α between 0 and1 ($0 < \alpha \leq 1$) cause an enhancement of yellow and brown tonalities and blue channel completely cancels out. If α=1, the blue channel in equation 6 cancels out while green and blue channels are equally weighted and subtracted leading to;

$$FFDI = 3r - 3g \qquad (7)$$

Equation (7) implies that equal amount of red and green components will counter each other making their effects be negligible.

Further increase of α to a higher value of 2 will cause red component to be higher and weighted positively while the green component will be weighted negatively leading to;

$$FFDI = 5r - 4g - b \qquad (8)$$

When the algorithm was applied on the terrestrial image, the resultant image was as shown in figure 3.6.

Figure 3.6. Forest fire detection index used when α=2 on terrestrial image

In this image, the red component which denotes the flame is enhanced by a factor of 5 and is more visible than the surrounding vegetation areas. The smoke region is still visible when such a factor of 2 is used. The green component is attenuated by a factor of 4 and is subtracted from the red component.

CHAPTER 4: RESULTS AND DISCUSSIONS

4.1 Results

Forest fire detection index is a specific detection index used to establish regions of smoke and flames from the entire forest coverage. It borrows its principle from the vegetation classification index where it uses different spectral signatures and tonalities of the primary colours RGB to establish flames and smoke zones. In most cases the normalised red colour is enhanced through the attenuation of both blue and green component of the RGB as shown below.

From figure 3.4, when blue component of the RGB is attenuated and red component will be brighter as shown below in figure 4.1.

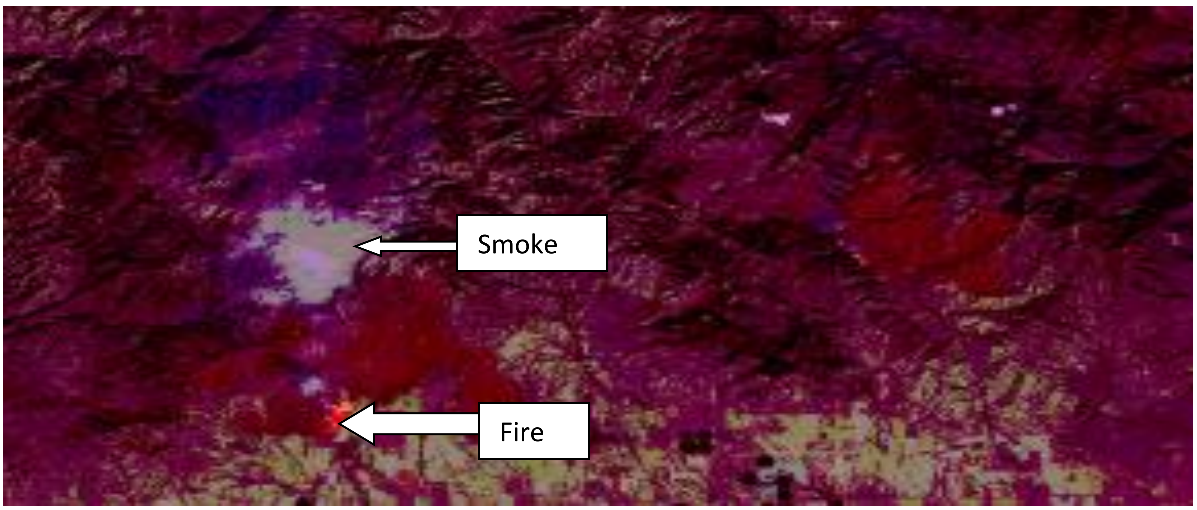


Figure 4.1. Smoke and flame zones detected clearly in r- b

When the green component was attenuated against the red component, the resultant image was as shown below in figure 4.2.

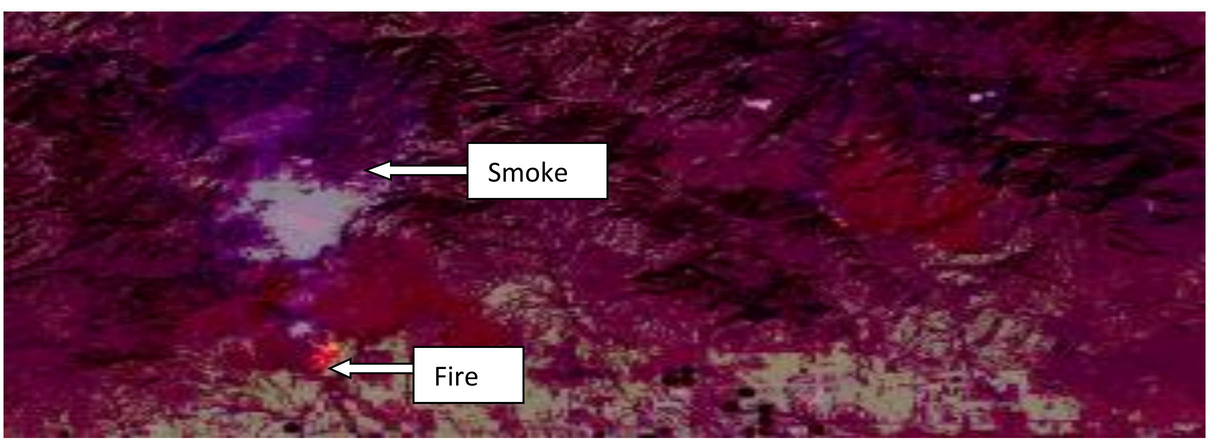


Figure 4.2. Smoke and flame zones detected r- g.

The equations $r - g$ and $r - b$ were added resulting into fire detection index $2r - g - b$ image whose image is shown in the figure 4.3 below.

Figure 4.3. Resultant image when $2r - g - b$ is used on the MODIS image.

The resultant image has clarity on the smoke and fire spots, some of which could not have been seen when only one colour component was attenuated against red component. It can also show the vegetation cover; the affected and the green vegetation.

Terrestrial image from the drone was clearer than that of MODIS because of resolution differences. It was therefore chosen in the discussion of the result and this can also be applied to any image both from satellites and optical sensors.

Terrestrial image from the drone was also used to attest the effectiveness FFDI on forest fire detection.

Figure 4.4. Original image of ROI, RGB components are at their original states

On application of the FDI algorithm, the resultant image had a clear distinct boundaries between flame, smoke and vegetation as shown in figure 4.4 below.

Figure 4.5. Resultant image on application of FDI on terrestrial image

In figure 4.4, the FDI confirmed the fire location and its direction from the smoke fronts. This would help in designing effective suppression mechanisms.

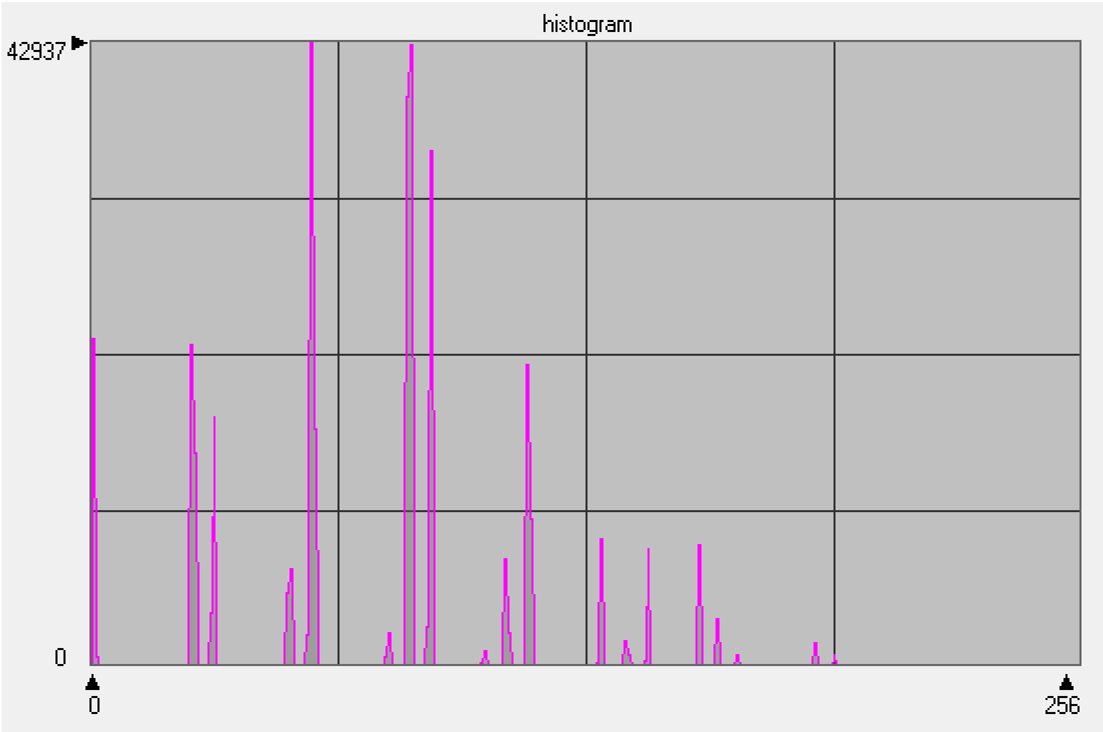


Figure 4.6. Histogram representing $FDI = 2r - g - b$

Figure 4.6 shows the attenuation of both green and blue colours and enhanced red colour in the RGB component.

Excess green vegetation algorithm was also applied on the image to show the effect of fire on the vegetation, this algorithm is helpful to estimate the damages caused by fire. It separates vegetation severely affected from those which are moderately affected. This is an important step to plan for vegetation recovery through resource allocation in reforestation. The resultant image of ExG on terrestrial image is as shown in figure 4.5 below.

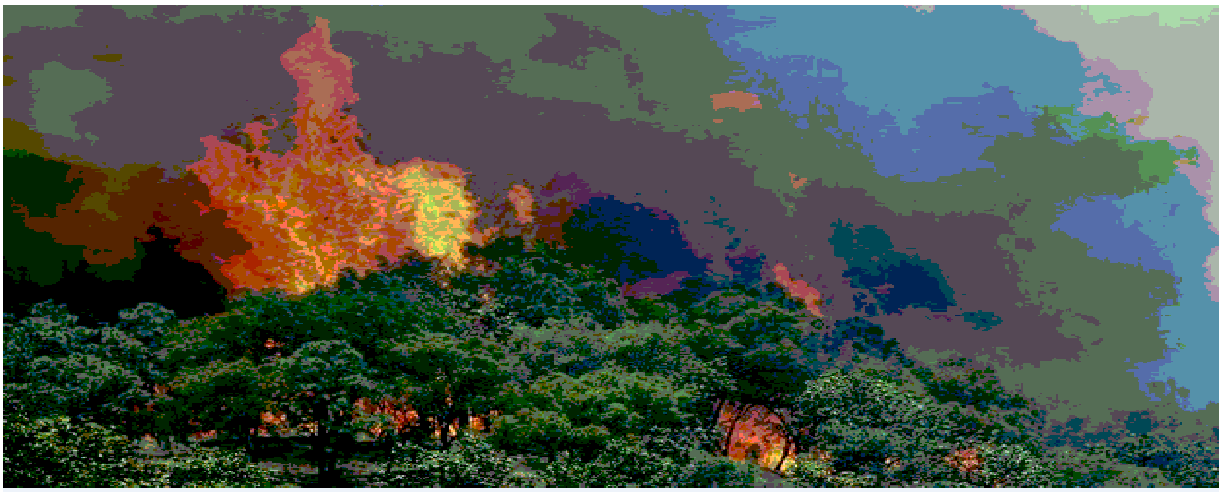


Figure 4.7. Resultant image on application of $ExG, 2g - r - b$.

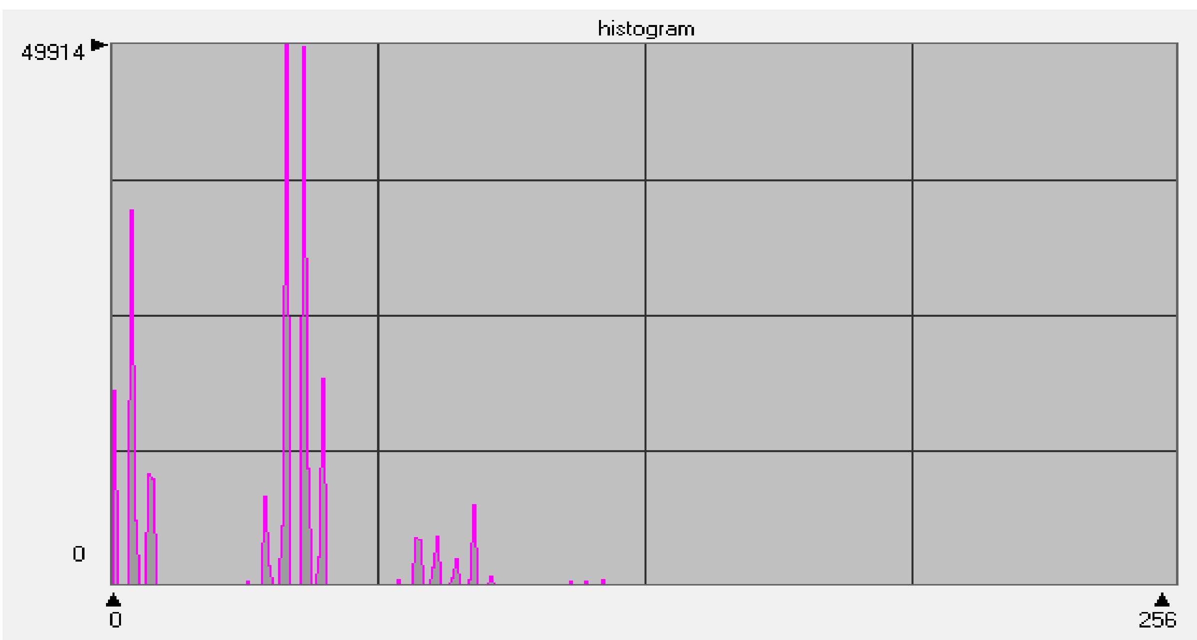


Figure 4.8. Histogram representing $ExG = 2g - r - b$

Figure 4.6 shows various weighting of each colour channel in ExG with green being predominant.

FFDI is made effective and adaptive to various conditions by a factor α, as in equation 6 where;

$$\boldsymbol{FFDI = \alpha\,(2r - g - b) - (2g - r - b) = r\,(2\alpha + 1) - g\,(\alpha + 2) + b\,(1 - \alpha).}$$

Various values of α were used ranging from 0.1 to 2 resulting into the images shown below.

When $\boldsymbol{\alpha = 0.1}$;

$$\boldsymbol{FFDI = 1.2r - 2.1g + 0.9b}$$

Figure 4.9. Effect of the factor α when it is 0.1

When $\boldsymbol{\alpha = 0.5}$

$$\boldsymbol{FFDI = 2r - 2.5g + 0.5b}$$

Figure 4.10. Effect of the factor α when it is 0.5

When $\boldsymbol{\alpha = 2}$

$$\boldsymbol{FFDI = 5r - 4g - b}$$

Figure 4.11. Effect of the factor α when it is 2

From figures 4.8, 4.9 and 4.10, influence of factor α on the weighting of each colour channel in the FFDI was tested resulting in a correlation that helped in determination of the smoke and flame detected areas. It was then clear that a lower value of α enhances colours with high amount of red compared to other channels. Increasing the value of α enhances colours with yellow and brown tones as it reaches a point when blue channel cancels out; when $\alpha = 1$.

4.2. Discussion

The entire detection process was done following the steps below.

i. MODIS Image acquisition from https://ladsweb.modaps.eosdis.nasa.gov/search/ and terrestrial image from the drone.
ii. Extraction of colour components Red, Green and Blue.
iii. Normalization of colour components the red, green and blue components of the RGB
iv. Calculation of detection indices; forest fire detection indices; Excess green (ExG), Fire detection Index (FDI) and Forest Fire Detection Index ($FFDI$)

FFDI is formulated with the help of a factor α which helps in varying the strength of FDI against ExG to separate the quantity of smoke area surrounding the flame against the vegetative background. This factor is important as it helps in augmenting the algorithms in various applications.

From equation (5); where $FFDI = \alpha * FDI - ExG$ we can analyse the effect of the weighting factor ranging from $0 < \alpha < 1$ and see its effect on the image.

When α= 0, the equation reduces to $FFDI = -ExG$ which implies an exclusive application of negative ExG and so it does not apply. Both red and blue are not altered; only green is reduced twice making the equation to change as follows, $FFDI = r - 2g + b$.

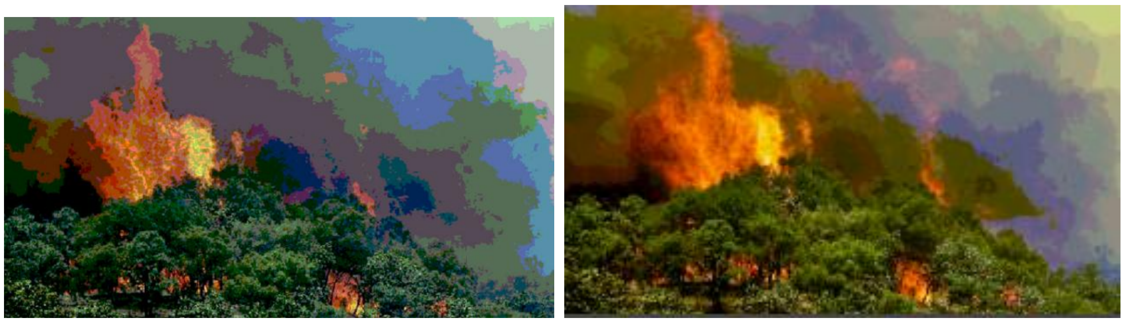
When α= 1, the blue channel is completely cancelled out while red and green value are equally weighted in that those with equal values counter each other. This results in an $FFDI = 3r - 3g$.

Further increase of the value α increases the value of the red component while reducing the blue and green component with the green reducing tremendously. This can be seen when $\alpha = 2$,

$$FFDI = 5r - 4g - b.$$

Figure 4.10 shows how an increase in the value of α from α= 0.1 to α= 2 increases the detection areas of both smoke and flames. When α= 0.1 only flame was clearly visible while when the value of α was increased to 1.5 and 2, full flame and smoke areas were detected as shown in figures 4.9 and 4.10.

α=0.1 α= 0.5 α=0.75 α= 1 α=1.25



α = 0 α = 2

Figure 4.12.Effects of the weighting factor α in detection of flames and surrounding smoke

4.2.1 Early Detection of Forest Fires

Forest fire detection quality and rate depend on the prevailing weather condition. This adversely affects the fire spread and smoke distribution. A smoke is normally seen first before flame and its accurate location may not be observed during windy condition. Smoke can be seen from a distance as compared to flames which can only be observed from a distance closer to the fire front. Flame therefore gives more accurate information on the fire since its colour can easily be detected. Using the detection indices therefore present an accurate result since it detects flame and smokes as well as heat aspect which can raise an alarm on the potential fire hazard.

The factor α helps in adjusting FFDI to adapt to different conditions hence there is room for further research on the use of the index in efficient detection of smokes around the flame environment. An increase in the value of α increased the area of detection for both smokes and flame and this is an important factor to compliment both satellite and drone in accurate location of both smokes and flames. The method therefore a recipe for accurate detection of forest fires at an early stage where smokes are emitted. Processing the image and using the weighting factor takes less than one minute and therefore giving an instant result which can be analysed and the information used to deter further spread of the fire. Near-real time detection of the forest fire can therefore be achieved through this method.

FFDI is therefore the best method as it provides an affordable method of near real-time forest fire detection and a faster result transmission due to the least time required in processing the image. The method is also efficient and precise in detection as compared to other traditional method like the use of watch towers and is not affected by various environmental conditions since the weighting factor can be adjusted to suit any condition.

CHAPTER 5: CONCLUSIONS AND RECOMMENDATIONS

5.1. Conclusions

The application of forest fire detection index was successfully applied on both terrestrial and satellite images. Through FFDI, it was possible to show both flames and smoke against vegetation background and that was its major success over other traditional methods used by different agencies in fire detection and suppression departments. Satellite images may not show smoke areas because smokes emit weak infrared radiations which cannot be detected by satellite sensors and this makes the detection index helpful since satellite images are freely available from the internet. The detection index can therefore be used to compliment both satellites and drones in their operations to detect smokes and flames in the near-real time.

The factor α made the index to be efficient and adaptive to various environmental conditions making the whole process's result not to depend on any condition, and this can help in reducing false fire alarm generation. Processing of an image took less than one minute to show fire and smoke areas when the algorithm was applied making the method to be timely which is an important factor to be considered in the forest fire suppression process.

During the detection process, smoke direction was evident and that can form the basis for the determination of the fire front hence easy way to design a suppression method. It was also possible to estimate the level of destruction caused on the vegetation since the index also encompasses the green component which is used to show vegetation spectral signatures.

In post fire analysis, the method can be used in estimation of the area burnt and this can be used to estimate the number of trees to be planted and their costs during reforestation process. During forest regeneration it can also detect bare grounds against vegetated areas.

The method also gives more information on the size of the burnt area which can easily be calculated from the height information and image size or resolution. Pixel colours can be used to classify combustion because different materials yield different colours during combustion process.

Image sequence comparison can also be used to show the direction and speed of the fire propagation and this can prompt forest workers in designing the best suppression method and also in resource allocation.

5.2. Recommendations

Results from the application of the algorithm shows an efficient use of FFDI in detection of both smokes and fire. Fire product qualities from FFDI need some improvements to meet the needs of user communities. The quality of the product may vary due to inconsistent technological limitations ranging from poor spatial resolution, sensor saturations and low frequencies from satellite overpass and drones used. More research and development studies need to be done in order to improve the quality of fire product from this algorithm and these may include; identification of algorithm limitations, improvement on the algorithm parameters and innovations that will enable the algorithm to be used on various platforms. The limitations on the algorithm can be identified through an intensive verification of the results against the ground-truth information during fire occurrences. More efforts need to be exerted in the collection of ground-truth data sets especially using satellites with high temporal resolutions such Sentinels. More research should be considered to take into account the multi-sensor capabilities in the future satellite observations. Thresholds should also be set on the land cover, land use to predict its emissivity and this can further be enhanced by using physical models for easy result productions. Time series utility of the images should be studied and researched on with emphasis on how the algorithm can adapt to it. This will help in giving the correct fire and smoke area estimations and the rate of fire spread which can efficiently guide on the suppression process. An efficient FFDI algorithm should always be robust, accurate and automatic with low rate of commission and omission errors in both satellites and drone images analysis.

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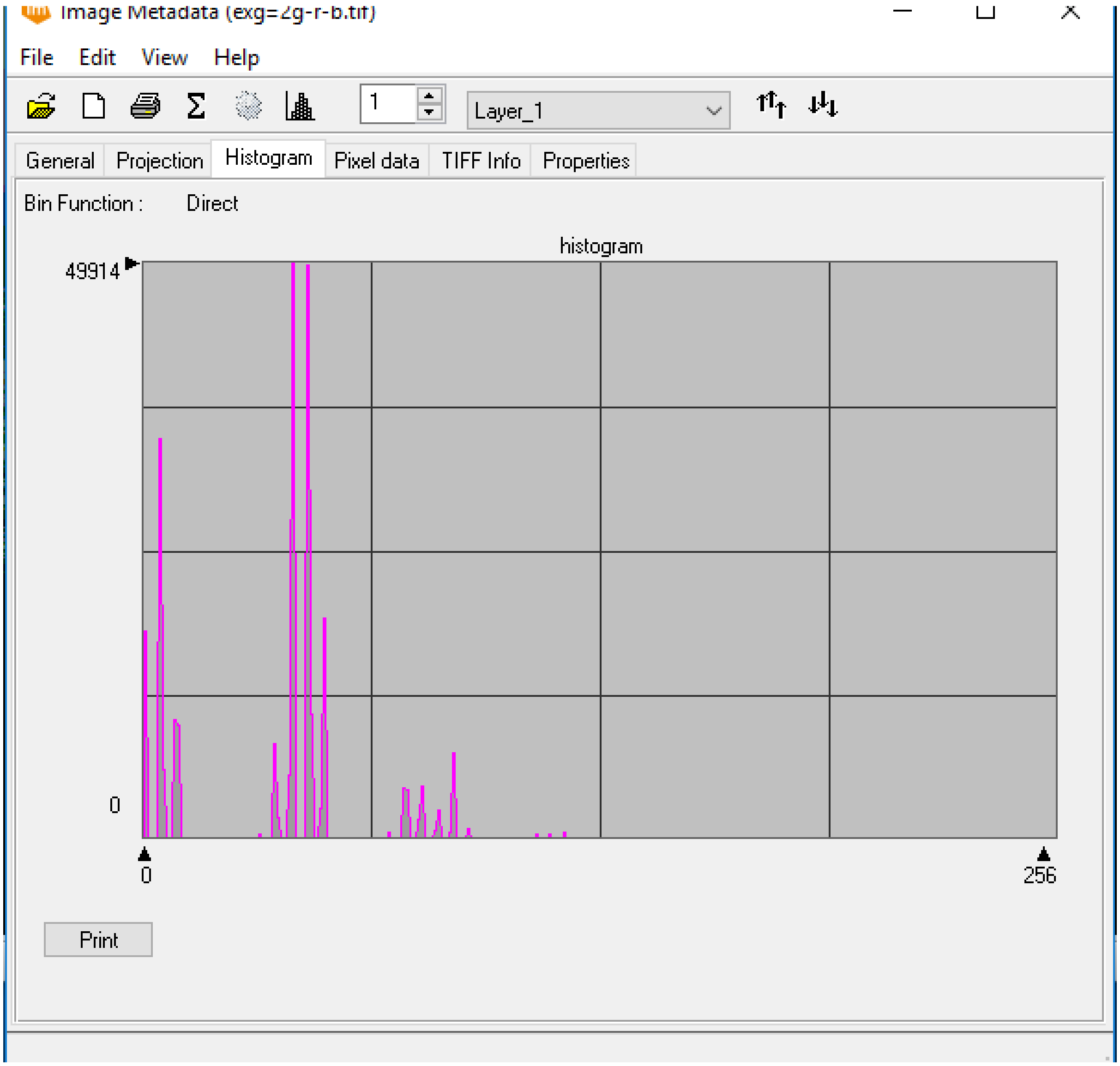
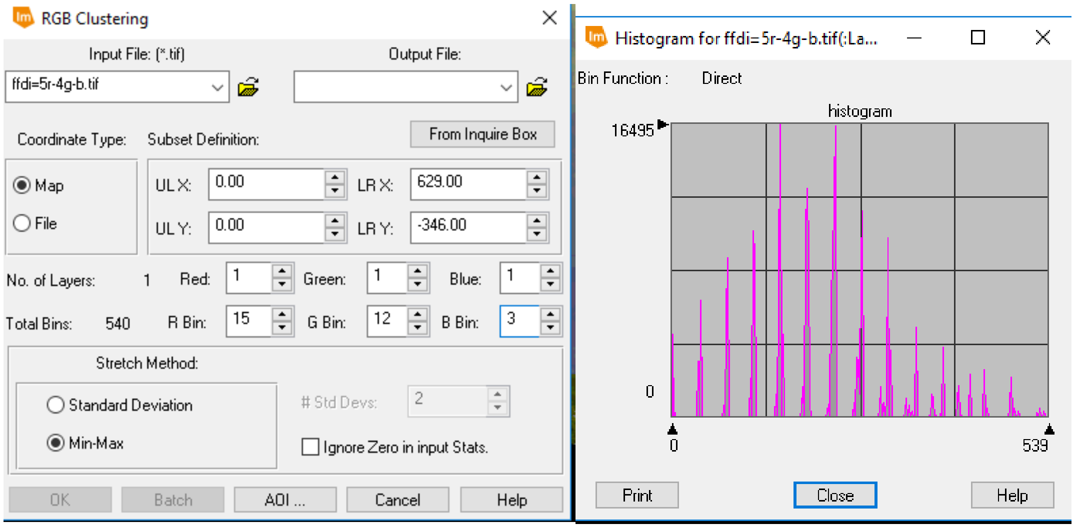
APPENDICES

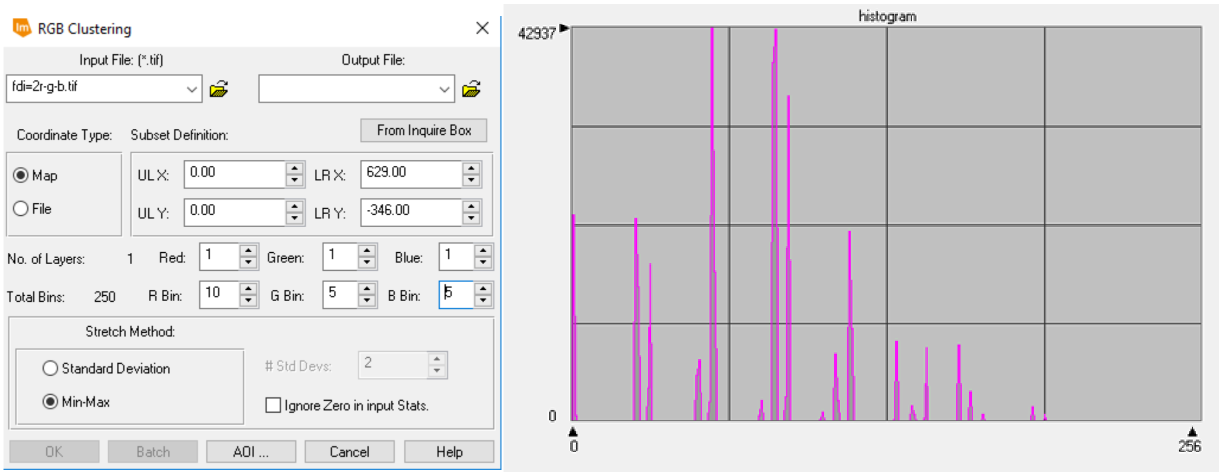
Appendix A1: Image Metadata $ExG = 2g - r - b$



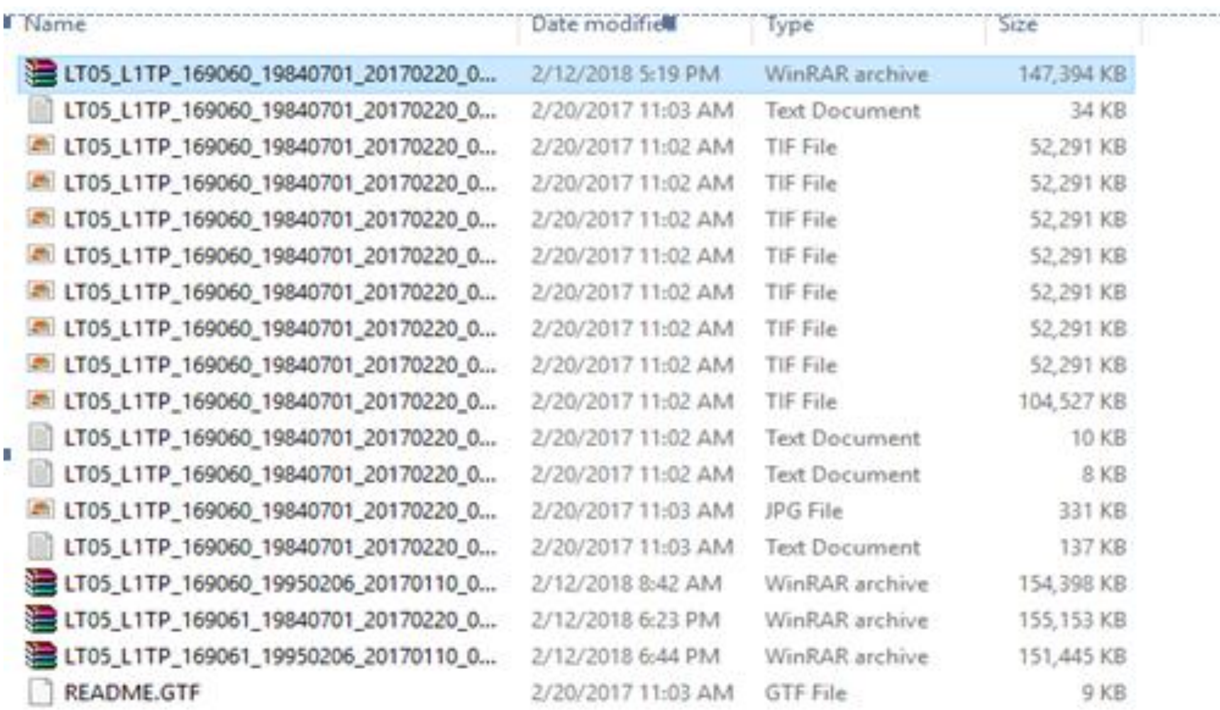
Appendix A2: Image Metadata $FFDI = 5r - 4g - b$



Appendix A3: Image Metadata $FDI = 2r - g - b$



Appendix A4. MODIS DATA



Appendix A5. Terrestrial Image properties.

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FILE.FileDateTime: 1522539638
FILE.FileSize: 3604057
FILE.FileType: 2
FILE.MimeType: image/jpeg
FILE.SectionsFound: ANY_TAG, IFD0, THUMBNAIL, EXIF, GPS, INTEROP, WINXP
COMPUTED.html: width="4000" height="2250"
COMPUTED.Height: 2250
COMPUTED.Width: 4000
COMPUTED.IsColor: 1
COMPUTED.ByteOrderMotorola: 0
COMPUTED.ApertureFNumber: f/2.2
COMPUTED.Thumbnail.FileType: 2
COMPUTED.Thumbnail.MimeType: image/jpeg
IFD0.ImageDescription: DCIM\100MEDIA\DJI_0015.JPG
IFD0.Make: DJI
IFD0.Model: FC220
IFD0.Orientation: 1
IFD0.XResolution: 72/1
IFD0.YResolution: 72/1
IFD0.ResolutionUnit: 2
IFD0.Software: v02.06.5666
IFD0.DateTime: 2018:03:30 12:27:09
IFD0.YCbCrPositioning: 1
IFD0.Exif_IFD_Pointer: 182
IFD0.GPS_IFD_Pointer: 686
IFD0.Comments: 0.9.143
IFD0.Keywords: N
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THUMBNAIL.XResolution: 72/1
THUMBNAIL.YResolution: 72/1
THUMBNAIL.ResolutionUnit: 2
THUMBNAIL.JPEGInterchangeFormat: 41972
THUMBNAIL.JPEGInterchangeFormatLength: 6729
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EXIF.FNumber: 220/100
EXIF.ExposureProgram: 2
EXIF.ISOSpeedRatings: 100
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EXIF.ApertureValue: 227/100
EXIF.ExposureBiasValue: -21/32
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EXIF.Flash: 32
EXIF.FocalLength: 470/100
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EXIF.FlashPixVersion: 0010
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EXIF.WhiteBalance: 0
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EXIF.SceneCaptureType: 0
EXIF.GainControl: 0
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EXIF.Sharpness: 0
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GPS.GPSLatitudeRef: N
GPS.GPSLatitude: Array
GPS.GPSLongitudeRef: W
GPS.GPSLongitude: Array
GPS.GPSAltitudeRef:
GPS.GPSAltitude: 1748335/1000
INTEROP.InterOperabilityIndex: R98
INTEROP.InterOperabilityVersion: 0100
WINXP.Comments: 0.9.143
WINXP.Keywords: N