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Advanced Baseline Imager (ABI) Algorithm Processing System for Early Forest Fire Detection: Theoretical Basis

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Abstract

Climate change has impacted a wide range of environmental phenomena, but perhaps forests were the most affected. Wildfires represent a global emergency, being one of the major contributors to global greenhouse gas emissions (GHG). They pose a serious threat to the environment and the planet, whether they are caused by natural forces or human activities. The nature of the planet cannot be controlled, but forest fire risk zones can be mapped to minimize the frequency of wildfires. This can be done through a combination of predictive modelling, early warning systems, and improved fire suppression techniques. Technology has brought us to a new age of monitoring and acting on changes more quickly, accurately, and efficiently. The importance of these technologies is more apparent than ever in fire zones, where a variety of challenges are present, such as degraded ecosystems, changing environments, increased greenhouse gases and respiratory illnesses affecting children and the elderly. This study aimed at developing a theoretical framework for incorporating early fire detection with an advanced baseline imager (ABI). Two stages can be distinguished in the proposed model: first, the collection and pre-processing of data and second, the identification of novel anomalies. Weather data from the National Oceanic and Atmospheric Administration (NOAA) have been used to track wildfire patterns. This paper may assist meteorologists in understanding fire behaviour and spread. It may also contribute to developing a processing system for incorporating early forest fire detection into advanced baseline imaging systems.

Keywords: Climate change, Early wildfires warning system, Remote sensing, Satellite imagery, Weather forecasting, Wildfires.

Nomenclature

I = Heat index
R = Daily average relative air humidity %
t = Daily average relative air temperature (°C)
NI = Nesterov index
w = The number of days since the last daily rainfall exceeding 3 mm
T_i = Air temperature (°C)
T_i^{dew} = Dew point temperature
ROS = Rate of spread (m/h)
Tg = Teragram

Subscript

dew = The temperature at which water vapour condenses into liquid water

Acronyms/Abbreviations

Advanced Baseline Imager (ABI), Advanced very-high-resolution radiometer (AVHRR), Artificial Intelligence (AI), Convolutional Neural Network (CNN), Earth Observation (EO), Early Warning Systems (EWS), Forest Fire Risk (FFR), Greenhouse gas (GHG), Geostationary Operational Environmental Satellite (GOES), Loop Heat Problems (LHP), Machine Learning (ML), Multispectral Scanner System (MSS), Moderate Resolution Imaging

Spectroradiometer (MODIS), National Oceanographic and Atmospheric Administration (NOAA), National Environmental Protection Agency (NEPA), Probability of Detection (POD), Remote Sensing (RS),Visible Infrared Imaging Radiometer (VIIR).

1. Introduction

Nearly 4 billion hectares of land are covered by forest, that's about 30% of the planet's surface.

With climate change left unaddressed, our planet's health continues to deteriorate. Wildfires of unprecedented magnitude and duration have successively been taken place in the past few years; and that is due to the increasing intensity and frequency of draught, strong winds, and lightening. Wildfires are predicted to increase in number by about 30% (at 4 °C warming in 2100) and in area by 35-50% (at 2 °C warming) as a result of climate change (UN Environment, 2022). By the end of this century, it is predicted that wildfires will significantly increase across 74% of the global landmass because of high greenhouse gas emissions (Sun et al. 2019). During 2019, wildfires ravaged Australia's southeast coast, covering nearly ten million hectares in less than three months, which resulted in a substantial affect in air quality and global climate, causing a long-lasting and adverse effects to human health due to certain chemicals composition and toxic pollutants of wildfire smoke. (Li et al. 2021).

1.1 Advanced Baseline Imager for geostationary operational environmental satellites

Being the primary instrument in the GOES-R Series, the Advanced Baseline Imager images Earth's weather, oceans, and environment. It has 16 different spectral bands, which cover a wide range of wavelengths, from visible to infrared and near-infrared channels to capture data from the Earth's surface. It can detect and measure temperatures, clouds, snow and ice cover, smoke plumes, and more ("ABI │ GOES-R Series," n.d.). The ABI has a resolution of 2 km at nadir and can capture images every 30 seconds. Diurnal ABI fire detection and characterization stands to revolutionize the way we detect, monitor, and understand wildfires and other earth events like volcanic eruptions and landslides (Szpakowski and Jensen, 2019).

1.2 The advanced baseline Imager (ABI) performance and cooling system issues

The GOES-17 cooling system issue is an anomaly with the spacecraft's loop heat pipe (LHP), which affects the cooling of the satellite's instruments. This cooling issue can cause imagery from the ABI to become saturated. The loop heat pipe anomaly on GOES-17, degraded imagery may occur in the ABI when the external temperatures are high, and the satellite is in eclipse. The loop heat pipe acts as a heat transfer device, which helps to remove heat from the ABI instruments to the exterior of the satellite. As the satellite moves in and out of eclipse, the external temperatures can change drastically, causing the satellite to enter a "thermal runaway" state. When this occurs, the loop heat pipe is not able to effectively cool the ABI instruments, which can lead to the imagery becoming saturated. Additionally, although the ABI algorithm can detect fires in both clear and cloudy conditions, it is more likely to fail in the presence of opaque clouds. In the ABI fire algorithm, which was originally developed by Matson and Dozier (1981) for NOAA Advanced Very High-Resolution Radiometer (AVHRR) data, a multispectral thresholding contextual process is used for detecting anomalies using band 7, which is capable of detecting anomalies in subpixels caused by high temperatures more easily than band 14. For better fire monitoring, the algorithm was specially tuned for AVHRR data to maximize the accuracy of pinpointing hot spot anomalies.

1.3 forthcoming modifications in advanced baseline imager (ABI)

The theoretical basis of this technology is to use advanced imaging techniques to detect and monitor remote sensing and forest fire activity. This can be done by using a variety of sensors and cameras to capture and analyse data in real time. Advanced imaging techniques allow for the visualization of remote sensing and forest fire activity in a way that has not previously been possible.

Satellite imagery with higher resolution and more spectral bands can capture more detailed information about the Earth's surface. This allows for a better understanding of the location and extent of fires, as well as their effect on the environment. This information can be used to develop more reliable mapping of burned areas (Kurbanov et al., 2022).

2. Materials and methods

Understanding spatial patterns of wildfire and the identification of areas susceptible to and affected by forest fires was found to be crucial in this study. To better identify areas at risk of future fires, temporal and spatial dynamics of past incidents were analysed. This was done based on the availability of thermal hotspot data and past fire activity records.

2.1 Data search

Meteorological data from the National Oceanic and Atmospheric Administration (NOAA) have been used to track and understand spatial patterns of wildfires. NOAA's data have been critical in providing insights into the cause and effects of forest fires. These insights can be combined with supervised and unsupervised approaches for early forest fire anomalies.

2.2 Data analysis

Temperature can have a significant impact on forest fires. As vegetation becomes drier at higher temperatures, forest fires are more likely to occur (Thapa et al., 2021). The GOES-R ABI fire products can capture small fire events at peak burning even with a spatial resolution of 2 km, providing a complete picture of burning areas across the Western Hemisphere than those derived from higher spatial resolution polar orbiting satellites. The GOES-R ABI fire products represent a major advancement in the ability to detect and monitor fires, as they allow for the capture of even small fire events in near real-time with unprecedented resolution.

3. Forest Fires Across the Globe

Wildfires in tropical areas damage the planet's ability to absorb carbon dioxide and regulate its temperature as a result of forest loss (Center for Climate and Energy Solutions, 2018). Many endangered species in the region are threatened by forest fires, which destroy their habitats and biodiversity. The destruction of these landscapes causes a wide range of environmental effects. These effects include not only reducing the number of animal habitats, but also polluting water supplies for humans and animals alike. Aside from causing burns and deaths, wildfire smoke also has long- and short-term adverse effects on human health due to its hazardous chemical composition (Gao et al. 2023). It is especially damaging to the environment when forest fires are uncontrolled. By reducing vegetation, consuming oxygen, and emitting hazardous gases into the air, they leave charred remains of once-thriving ecosystems. Changes in climate can affect the frequency and intensity of forest fires, which can in turn have a direct impact on the amount of carbon released into the atmosphere. Understanding the relationship between climate and fire regimes can help prevent or reduce the amount of damage caused by forest fires. The intensity, spread, and behaviour of fires are affected by air temperature, humidity, and wind levels (Carmel et al. 2009). Knowing how these factors influence the fire behaviour can help to predict the likelihood of a fire starting and its potential intensity, as well as to determine the area's most prone to fire risk. This information can be used to create more effective management plans and help protect forests and communities.

3.1 Forest Fires Mapping and Monitoring

Due in part to the extreme megafires that have taken place recently in correlation with the extreme droughts that have been hitting the northwest, fire's potential interaction with climate change has received an increasing amount of attention across the globe. Satellite maps show that peak megafire season occurs in the spring and summer. It can cause significant damage to forest areas, threaten residential areas, kill animals, and seriously pollute the air. Summer 2022 was an exceptional wildfire season, both in terms of the number of fires observed, and the area burned (figure 3.1), as well as in terms of smoke emissions. Fires increased in Europe between mid-June and mid-August 2022, according to EFFIS (European Forest Fire Information System). The current value exceeds the long-term average from 2006-2021 and the previous peak. Fire events were followed by successive ones till September. Compared to previous years, summer 2022 was a particularly active wildfire season, though it had the highest number of fires that lasted for a three-month period (June to September).

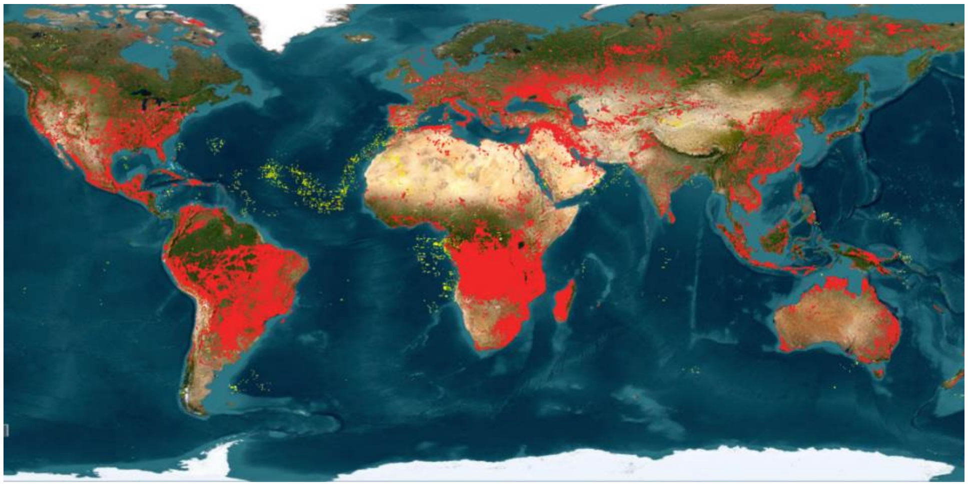

Figure 3.1 Active fires detected by MODIS worldwide in July 2022. Adapted from NASA

Figure 3.1 Active fires detected by MODIS worldwide in July 2022. *Adapted from* NASA

Forest fires can cause immense destruction to the environment, especially when they are uncontrolled. They reduce the amount of vegetation, consume oxygen, and emit dangerous gasses into the air, leaving charred remains of what was once a thriving ecosystem (Volkova et al. 2019).

Furthermore, forest fires can spread quickly in areas with dry and dense vegetation. This is because the heat generated by a fire can create its own wind, which helps to carry the fire to distant locations. Additionally, fuel in the form of dry leaves and sticks can easily ignite in such areas, making it difficult to contain the fire (Park et al. 2022)

3.2 Forest Fire Risk Indices

To assess fire risks, the Swedish Angstrom index is commonly used (Willis et al. 2001). The index is calculated by analysing the statistical relationships between the number of reported fire events and antecedent weather-related information (Lukic et al. 2017). Since all inputs are obtained from point measurements at a weather station, weather-based indexes can only predict fire risk for an area-averaged area (Onderka, 2009). The Angstrom index indicate how likely it is that there will be fires on a particular day based on air temperature and relative humidity.

The index, *I*, is calculated as follows (Skvarenina et al. 2003)

$$I = \frac{R}{20} + \left(\frac{27-t}{10}\right) \tag{1}$$

Where t represents the daily average temperature (°C), and *R* represents the daily average relative humidity (%). From equation (3), it can be seen that the index, *I*, decrease as the relative humidity increases and increases as the temperature decreases. There is a heightened risk of fire in an area with a reduced index. An explanation of how the index is used to categorize risks is given in Table 1.

A categorical scale for assessing and rating fire risk was first proposed by Nesterov (Shetinsky 1994).

The Nesterov Index is calculated as follows:

$$NI = \sum_{i=1}^{w}\left(T_i - T_i^{dew}\right)T_i \tag{2}$$

Where, NI stands for the Nesterov index, w stands for the number of days since the last rainfall exceeded three mm per day, T stands for the daily temperature in degrees Celsius, and T dew stands for the dew point temperature in degrees Celsius. Nesterov index is intrinsically designed to reset to "zero" whenever daily rainfall exceeds 3mm per day (Shetinsky 1994). Table 1 illustrates Nesterov's original risk levels.

Table 3.2 The output values of Nesterov index (NI) classified into fire risk probability (Shetinsky 1994).

Index values	Interpretation	Probability of fire
NI < 300	Fire occurrence unlikely	No risk
301 < NI < 1000	Fire occurrence unfavourable	Low risk
1001 < NI < 4000	Fire conditions favourable	Medium risk
4001 < NI < 10000	Fire conditions more favourable	High risk
NI > 10000	Fire occurrence very likely	Extremely high risk

The risk levels of forest fires can range from low to extreme, depending on the area and severity of the fire. This table can help decision makers determine the risk level of an area, and prioritize forest management activities accordingly.To ensure effective fire prevention, fire risk rankings for each district should be considered when preparing for controlling and mitigating any fires. This data can be used to allocate resources and efforts in a way that yields the maximum benefit in terms of risk reduction.

The chart below shows how the temperature of the focal plane in the ABI changes throughout the course of the year. The differences between Northern Hemisphere Vernal and Autumnal Equinoxes occur because the Earth is closer to the Sun at the Northern Hemisphere Vernal Equinox. The chart also shows the effects of 'Eclipse' — when the satellite moves through the Earth's shadow. When the ABI is in the Earth's shadow, it is not being heated by the Sun (and that's why the GOES-R Series carries batteries to power the satellite at that time). The reduced heating occurs between 26 February and 14 April in the Spring, and between 30 August and 16 October in the Fall.

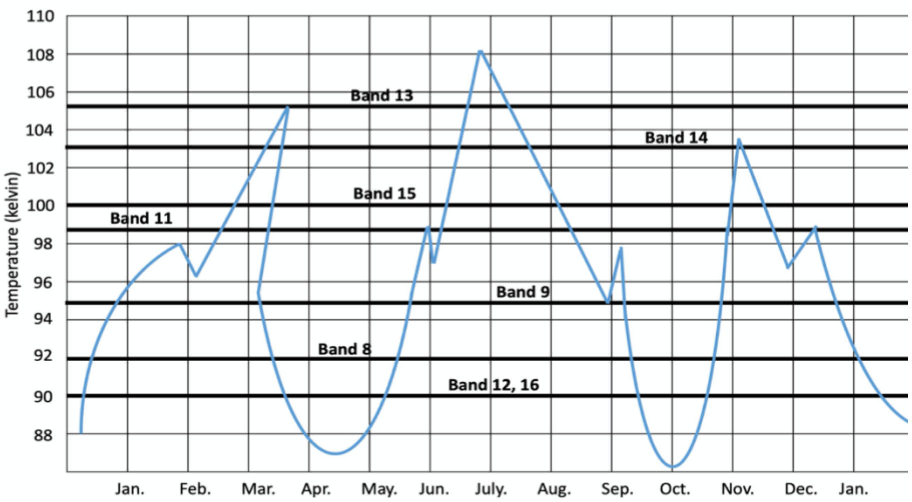

Figure 2. Sunlight penetration to ABI system. Source ABI-18-518, Rev-D, 2019-01,11

The chart also contains for the longwave infrared bands the temperature at which the heat from the satellite increases the likelihood of inaccurate data. At these times, the ABI does not receive any direct sunlight, so its batteries need to provide power for the satellite to continue working. The long-wave infrared bands are susceptible to heat from the satellite itself. Therefore, the temperatures reflect the threshold at which the heat from the satellite can start to interfere with the data and the accuracy of the readings. Marginal saturation may be observed when temperatures rise above the black lines for each band. As temperature curves exceed the black line, the imagery provided becomes unusable.

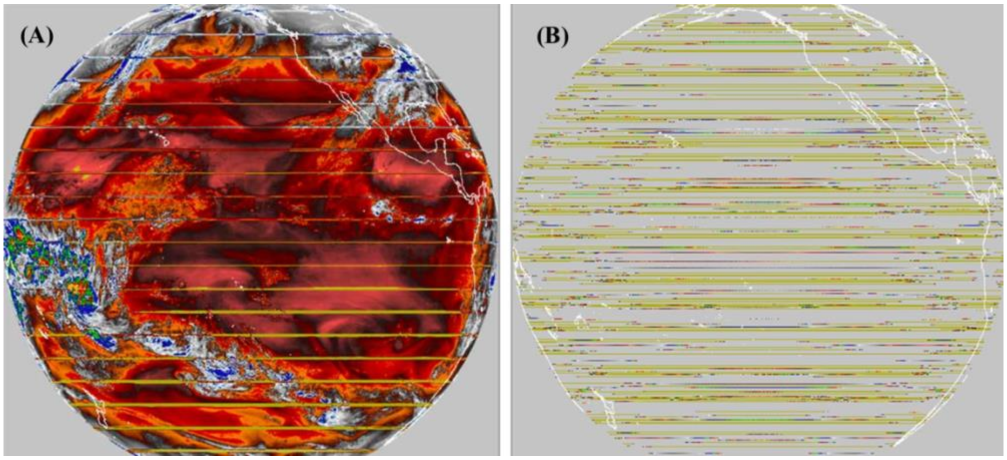

Figure 3. Images provided by GOES-17, marginal data (A) and unusable data (B). Source GOES-R

The image above illustrates what degraded imagery looks like (figure 3). As a result of the penetration of sunlight into the ABI system, high noise is introduced into the imagery. This makes interpretation of the data much more challenging, and sometimes even impossible. As data quality is a major factor in the effectiveness of any space mission, it is imperative that any disturbances, including but not limited to extreme heat, noise interference, and instrument problems, are prevented in order to preserve data quality and prevent the instrument from malfunctioning and producing poor imagery.To prevent this, it is necessary to take measures such as using advanced shielding materials, incorporating instrument redundancy, and enacting proper calibration. This will minimize any undesirable side effects on the data.

A total of five modules make up the system (figure 4). They are based on historical anomaly detection methods as well as on an array of advanced models. These models, together, give the system the ability to accurately detect subtle anomalies in GOES image sequences and estimate expected temperatures for landscapes that do not burn. It is designed to provide an advanced early fire detection system that locates anomalous heat sources in GOES image sequences with high accuracy.

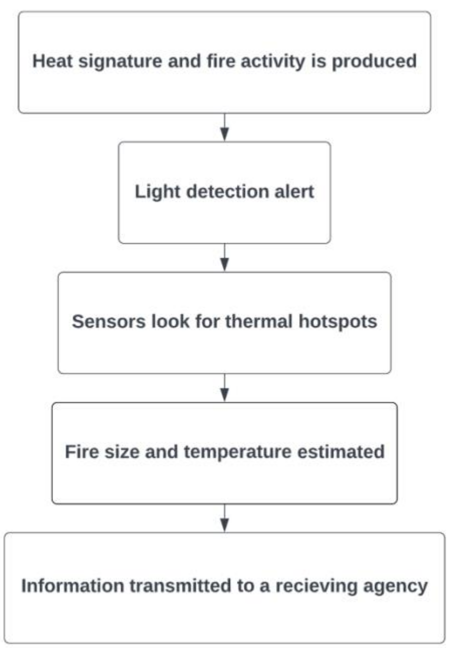

Figure 4. Overview of the workflow proposed for advanced early fire detection

Wildfires can be predicted beforehand with the system. By detecting and analyzing changes in temperatures, humidity, wind speed, and other environmental conditions, the workflow provides an early wildfire detection system that is reliable and advanced. The presence of these changes may be indicative of a wildfire. Using the system, personnel will be alerted to potential fire hazards and heat maps will be generated of areas affected by the fire.

Climate change is causing temperatures to rise in many parts of the world, which leads to drier conditions that can help fuel more intense wildfires. The countries listed in the table below already had a history of wildfires, so they will be particularly at risk of more frequent and more intense fires due to the changing climate (table 2). Additionally, regions that were previously not in danger of wildfires may become increasingly vulnerable due to the deteriorating climate.

Table 2. Countries with most burned land by wildfires (2022) Source Statista

Country	Hectares
Ukraine	453,972
Spain	299,669
Romania	149,440
Portugal	104,450
Bosnia and Herzegovina	71,867
France	65,660
Italy	58,273

Wildfires are increasing while countries outside the Mediterranean high zone are experiencing extreme suffering, causing drastic changes in the local climate, air quality, and water availability, leading to respiratory issues, heat-related illnesses, and water shortages. They can also reduce biodiversity, leave toxic residues in the soil, and increase the risk of soil erosion.

4. Results

As remote-sensing technology in EO satellites continues to improve, satellite sensors can monitor the Earth's surface with higher resolution and accuracy than traditional methods. They can provide a more nuanced view of various environmental changes, including those associated with forest fires (Wooster et al., 2021). By the end of this century, it is predicted that wildfires will significantly increase across 74% of the global landmass as a result of high greenhouse gas emissions (Sun et al., 2019b).

4.1 Climate applications

Researchers have used EO data and RS techniques to map and monitor forest areas, which is essential for a successful forest management strategy. Researchers have also been able to identify small-scale changes in forest health by analyzing high-resolution satellite imagery (Matin et al. 2017). Additionally, (MODIS) sensors can detect and monitor forest fires very accurately because of their high temporal resolution. This enables them to capture pictures of the same area over a short timeframe. For active forest fire detection, these sensors can capture changes in the landscape in real-time.

5. Discussion

Recent advancements in earth science makes it possible to anticipate, model, and prepare for natural disasters and thereby reducing the number of fire fatalities. This study found that the technological advances in remote sensing sensors and software, such as the Advanced Weather Interactive Processing System (AWIPS) and high-resolution satellite imagers facilitate the availability of fine-grained earth observation data. These technologies allow scientists to observe and track minute changes on the Earth's surface, such as changes in vegetation, soil moisture, and air temperature. This data can be used to better understand and predict changes in global climate and weather patterns.

This is enabling a revolution in the way we monitor, map, and analyse our world, with the potential to improve natural resource management, disaster response, and climate change adaptation. Such data reveal the vegetation canopy in high spatial detail. Efficient methods are needed to fully harness this unprecedented source of information for vegetation mapping. Machine learning (ML) and Deep learning (DL) algorithms such as Convolutional Neural Networks (CNN) are currently paving brand-new avenues in the field of image analysis and computer vision. Minimizing damage to global environmental disasters caused by wildfires by ensuring accuracy and speed in Early wildfire detection.

5.1 Key findings

The initial data and existing literature suggested that satellite viewing angles are limited to 80° when processing fire data. For optimal accuracy, fire processing should focus on data within 65° of the satellite viewing angle, avoiding certain biomes and sun-glint regions. Moreover, the ABI algorithm is more likely to fail when there are opaque clouds present, even though it can detect fires in both clear and cloudy conditions. As a result, to further enhance the accuracy of the identification of areas at risk, the combination of thermal hotspot data and past fire activity records can be used to create predictive models and identify future fire-prone area

6. Conclusions

This paper has taken the first steps in gathering the necessary data to employ a theoretical framework for early forest fire detection in geostationary operational environmental satellites (GOES). The potential impact of these advancements on the field of Earth Sciences is profound and stands to revolutionize the way we observe and understand our planet. The findings of this paper propose imperative climate implications, including the capability of early wildfire detection in remote sensing and earth observatory satellites. Unless addressed, the impact of forest fires on the planet's health will continue to be a challenge as climate change contributes to the increase in frequency and magnitude of wildfires around the world.

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