Enhancing Wildfire Monitoring Through Remote Sensing With Sentinel-2 Imagery And Python Programming

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Abstract

Wildfires pose a significant global challenge, with the potential to cause extensive loss of life, property damage, and environmental degradation. These fires also pose health risks, have economic repercussions, and contribute to climate change. In regions like California, where wildfires are particularly prevalent, the need for effective monitoring solutions is acute. The August Complex wildfire of 2020, which consumed approximately 1,023,264 acres and destroyed nearly 18,000 structures—54% of which were homes—underscored this need. The economic impact in California alone was staggering, with capital losses nearing $28 billion, including extensive damage to homes and businesses. Given the limitations of ground and drone surveillance methods, which are time-consuming and often impractical on a large scale, satellite technology presents a more efficient alternative. This research leverages the capabilities of Sentinel-2 satellite imagery, known for its frequent revisits (approximately every five days) and the ability to capture the Short-Wave Infrared (SWIR) part of the spectrum, which is crucial for distinguishing wildfires from other phenomena. We have developed a comprehensive dataset based on the August Complex wildfire to enhance fire monitoring capabilities. This dataset was preprocessed and annotated using Python programming, providing a robust foundation for researchers aiming to develop deep learning models for wildfire detection. As a continuation of this work, we plan to develop a modified U-Net model specifically tailored for efficient and accurate wildfire detection from satellite imagery.

Objectives

1. Satellite Selection: Identify and utilize a publicly accessible satellite that offers high spatial and temporal resolution, optimizing the frequency and clarity of wildfire observations.

2. Spectral Band Selection: Pinpoint the key spectral bands that are closely correlated with temperature variations, ensuring the effective visualization and detection of wildfires. This involves prioritizing bands that can penetrate smoke and cloud cover to provide reliable data under varying conditions.

3. Data Preparation: Thoroughly preprocess and annotate the collected dataset to ensure it is optimized for use in advanced deep learning models. This step is critical to transforming raw satellite imagery into a structured format that facilitates effective training and validation of wildfire detection algorithms.

Methodology

1. Selection of Sentinel-2 for Enhanced Wildfire Monitoring

In our research, the choice of an appropriate satellite was pivotal, given the need for both high temporal and spatial resolution to monitor dynamic events such as wildfires effectively. After evaluating several candidates, including Landsat, MODIS, and others, we chose Sentinel-2 for its optimal balance of accessibility, revisit frequency, and spectral capabilities.

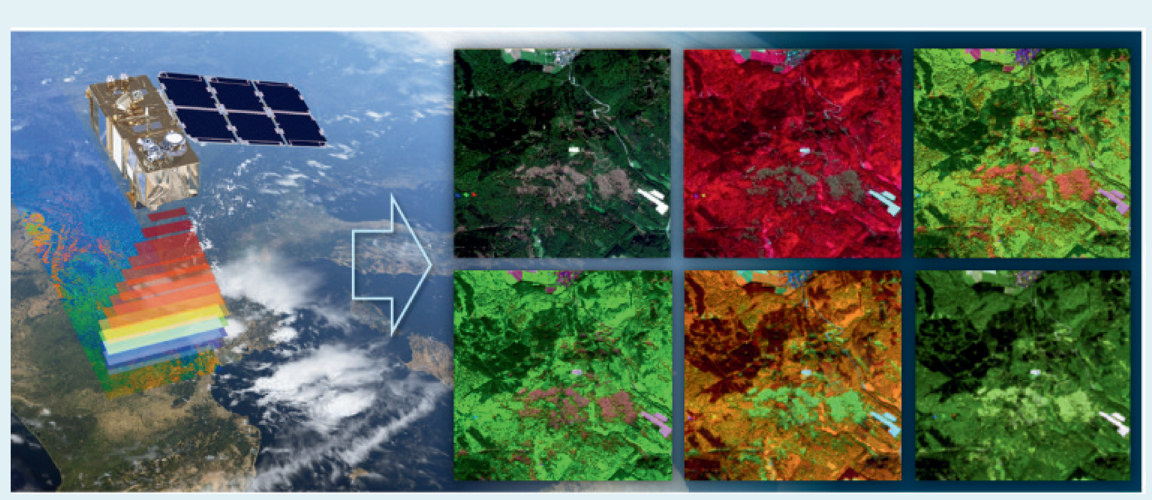

Figure 1. This image showcases the Sentinel-2 satellite, a key component of the European Space Agency's Copernicus program. Designed for high-resolution optical imaging, Sentinel-2 excels in capturing data across 13 spectral bands, making it invaluable for environmental monitoring, including the detailed observation of wildfire dynamics. Its capabilities are essential for the rapid detection and ongoing monitoring of wildfires, providing critical data to support firefighting and disaster management efforts [1].

Sentinel-2, part of the European Space Agency's Copernicus program, is freely available and designed to provide detailed optical images at high spatial resolution. Crucially for wildfire monitoring, Sentinel-2 has a revisit time of five days at the equator, facilitated by its twin satellites, Sentinel-2A and Sentinel-2B, which significantly enhances our ability to monitor changes in wildfire-prone areas like California rapidly. The satellite's payload includes a MultiSpectral Instrument (MSI) that captures data in 13 spectral bands ranging from the visible (VNIR) to the shortwave infrared (SWIR). This range includes bands specifically sensitive to vegetation health and stress, crucial for monitoring wildfires. The spatial resolution varies by spectral band, with the key bands for vegetation and fire monitoring (B2, B3, B4, and B8) providing a resolution of 10 meters, and the SWIR bands (B11 and B12), which are vital for temperature differentiation, offering 20 meters resolution. These specifications make Sentinel-2 exceptionally suitable for continuous observation and detailed analysis, critical for the early detection and monitoring of wildfires, and subsequent damage assessment and recovery planning.

2. Sentinel-2 Band Selection

Sentinel-2 is equipped with 13 spectral bands that capture data ranging from the visible to the shortwave infrared (SWIR) part of the spectrum. These bands are crucial for differentiating various earth surface conditions and phenomena, including wildfire detection. figure 2 displays the center wavelengths and bandwidths of each Sentinel-2 spectral band, illustrating the range of detection capabilities from visible light to the SWIR spectrum.

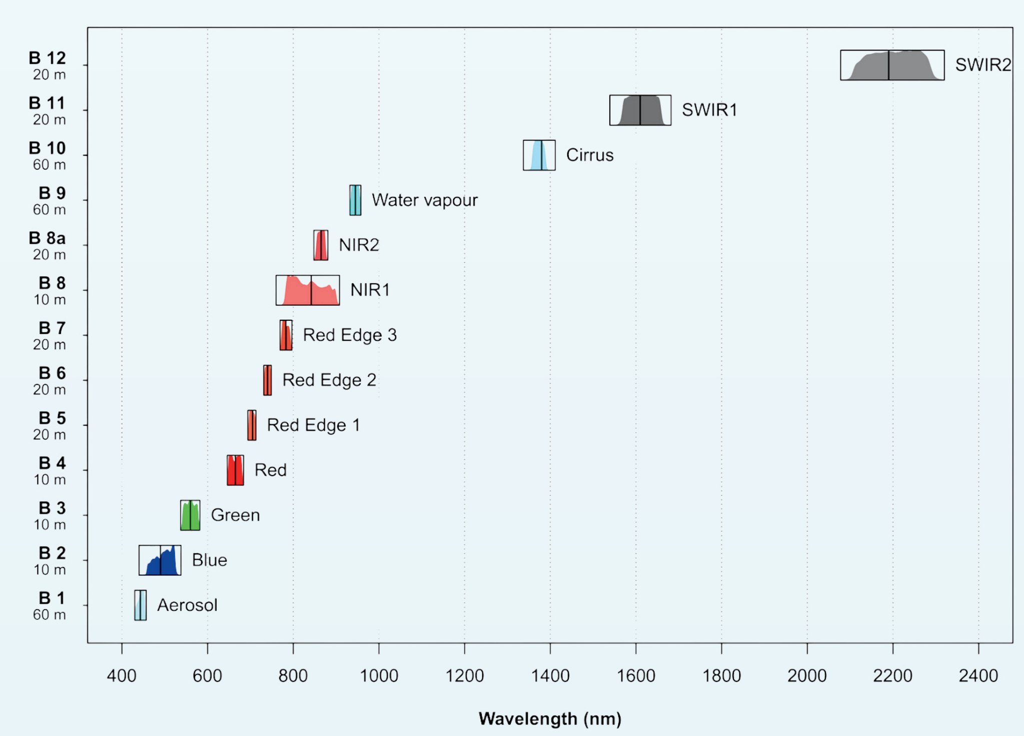

Figure 2: Sentinel-2 Spectral Bandwidths and Center Wavelengths [2].

For our study, we focused on the August Complex wildfire, selecting the epicenter of the fire on the start date to analyze spectral reflectance. Our findings indicated that the SWIR bands, specifically bands 12 (SWIR at 2190 nm) and 11 (SWIR at 1610 nm), exhibited high reflectance values in fire-affected pixels, correlating closely with temperature changes due to the fire. These bands are particularly effective in distinguishing between burning material and its surrounding environment due to their sensitivity to heat. To create a false color composite that would highlight fire intensity and spread, we selected bands 12, 11, and 4 (Red at 665 nm). This combination enhances the visibility of fire-affected areas, making it easier to monitor and analyze wildfire progression. figure 3 presents the digital number outputs across all Sentinel-2 bands for a selected pixel within the fire zone, highlighting the elevated reflectance values in the SWIR bands, which are critical for detecting and monitoring wildfire activity.

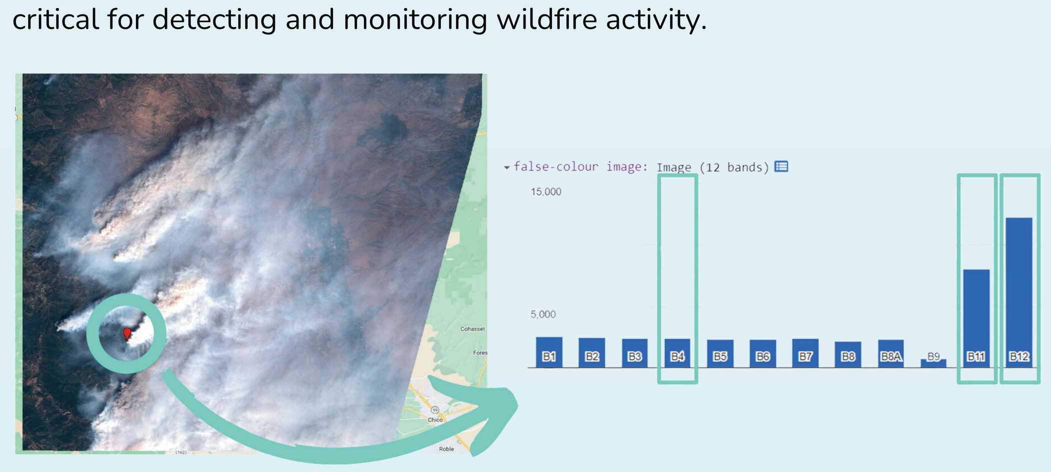

Figure 3: Spectral Reflectance of Fire-Affected Pixels

3. Data Preparation

For our study on the August Complex Wildfire, we initially selected 100 locations during the fire's inception and resolution phases. Using data augmentation techniques like zooming, rotating, and flipping, we expanded our dataset fivefold to 500 images. We resized all images to 128x128 pixels using clipping and padding. Using Label Studio, we meticulously labeled fire-affected pixels to ensure precise data for training our deep learning models. This preparation is crucial for our wildfire detection analysis.

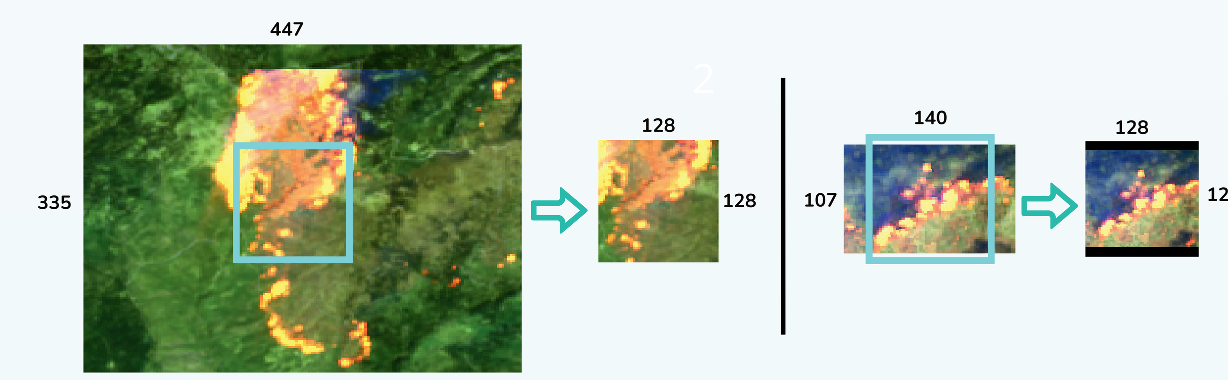

Figure 4. This figure illustrates the process of identifying the center and crop images to 128x128 pixels.

Results

1. Cloud Coverage Assessment

To ensure the quality and usability of satellite images for monitoring the August Complex Wildfire, we implemented a cloud coverage assessment using Python programming and the GEEMap package integrated with Google Earth Engine. We executed queries spanning the duration of the wildfire to identify and download images. Our criteria were stringent, only selecting images with less than 10 percent cloud cover. This approach significantly improved the clarity and reliability of the imagery used in our analysis.

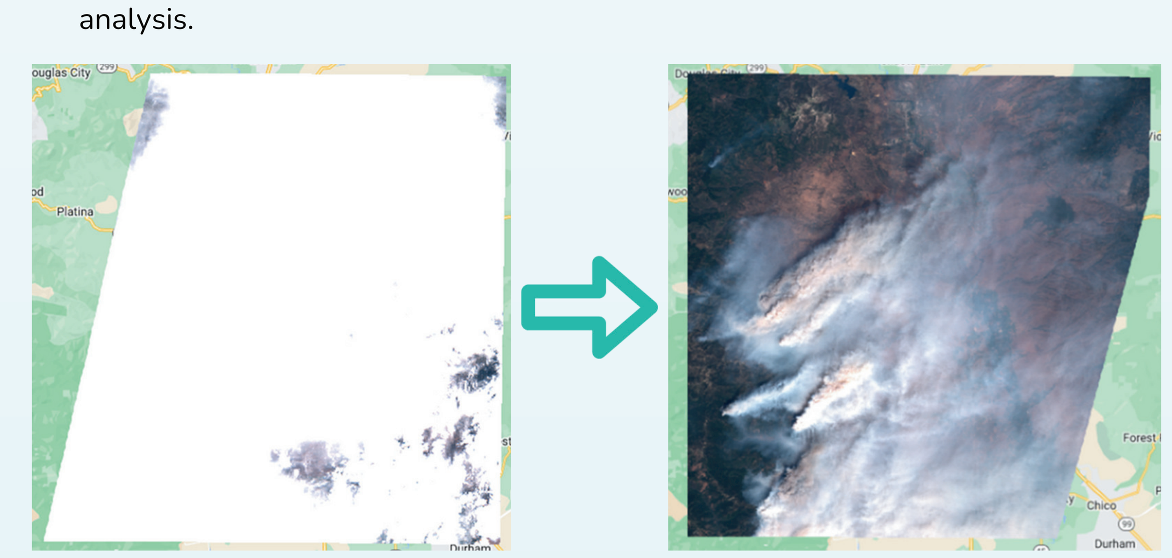

Figure 5. This figure illustrates a sample output from our cloud masking process, showcasing an image that met our criteria by having minimal cloud interference, which is essential for accurate wildfire monitoring and analysis.

2. Enhanced Fire Visualization

Following the acquisition of satellite imagery with minimal cloud interference, we focused on enhancing fire visibility. We utilized SWIR2, SWIR1, and Red bands (Band 12, 11, and 4) for visualization. This specific combination penetrates smoke—which can often be confused with clouds in both deep learning models and human analysis—allowing for direct observation of fires. These bands are particularly sensitive to temperature changes, making them ideal for detecting active fire zones.

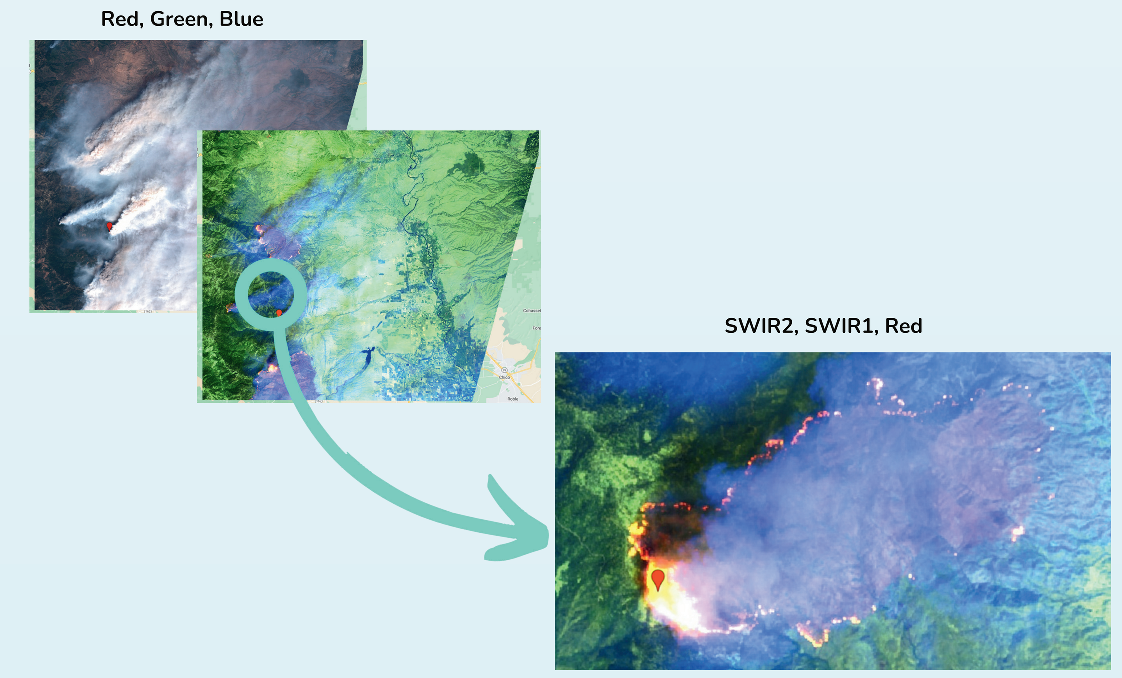

Figure 6: SWIR and Red Band Visualization - This figure displays a transformed RGB image using SWIR2, SWIR1, and Red bands, specifically tailored to enhance the visibility of fire. This visualization technique highlights active fire areas, distinguishing them clearly from smoke and cloud cover.

3. Dataset Annotation for Fire Detection

After conducting a thorough cloud coverage assessment and identifying the optimal spectral bands for detecting wildfires, we annotated all 500 images using Label Studio. This process has produced a comprehensive dataset that enables researchers to utilize Sentinel-2 imagery effectively. By extracting crucial bands and utilizing our annotated images, researchers can perform detailed fire segmentation, facilitating timely reporting and action.

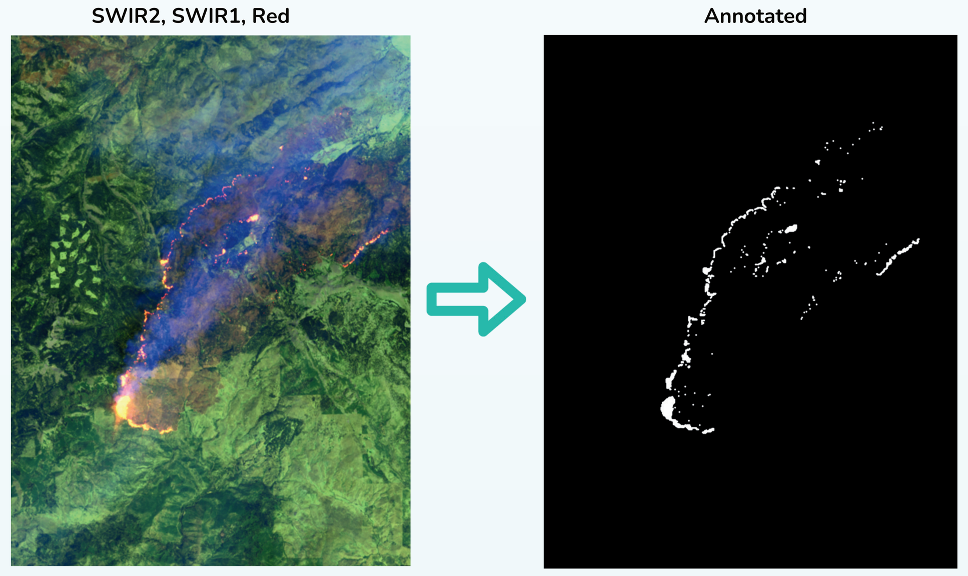

Figure 7: Comparison of Raw and Annotated Images - This figure presents a side-by-side comparison of an original input image (left), using SWIR2, SWIR1, and Red bands, against its annotated counterpart (right). This illustrates the enhancements made to highlight fire zones, providing a clear visual tool for researchers studying wildfire detection and management.

Future Work

Having developed a dataset of 500 images annotated for fire pixels across all spectral bands of Sentinel-2, our next objective is to advance the application of deep learning models for fire segmentation. We plan to implement the U-net architecture, renowned for its effectiveness in segmentation tasks, to assess our dataset. Initially, we will utilize the U-net model as adapted by Pereira et al., 2021, for wildfire detection on Landsat 8 data. This will serve as a benchmark for our analysis. Subsequently, we aim to optimize the model's hyperparameters to better suit our Sentinel-2 based dataset and to eventually develop a tailored deep learning model for enhanced wildfire detection accuracy.

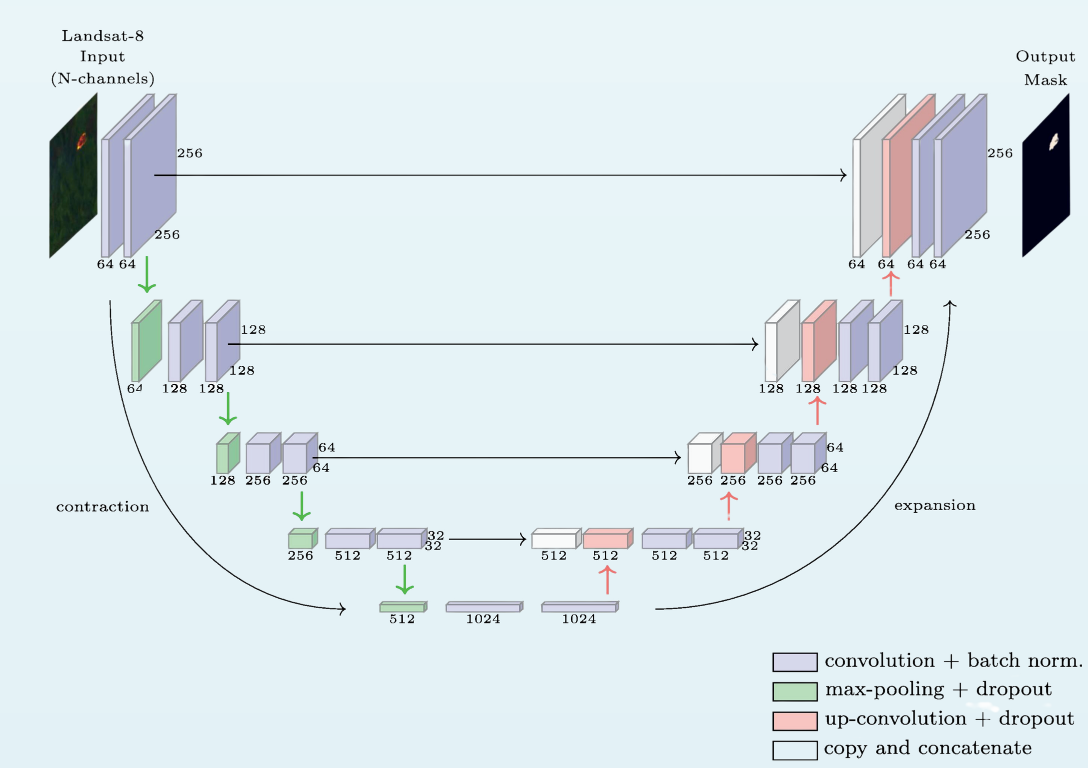

Figure 8: U-net Model Overview - This figure illustrates the U-net model architecture as used by Pereira et al., 2021. It highlights the model's structure, which is critical for understanding how it processes spatial data for effective segmentation, particularly in the context of wildfire detection [3].

References

1. OpenGeoEdu. (n.d.). Sentinel-2 Teil 1. Retrieved from: https://learn.opengeoedu.de/en/fernerkundung/vorlesung/copernicus/Sentinel-2-Teil-1
2. UP42. (n.d.). Enhancing Sentinel-2 Images to Superresolution. Retrieved from: https://up42.com/blog/sentinel-2-superresolution
3. de Almeida Pereira, G. H., Fusioka, A. M., Nassu, B. T., & Minetto, R. (2021). Active fire detection in Landsat-8 imagery: A large-scale dataset and a deep-learning study. ISPRS Journal of Photogrammetry and Remote Sensing, 178, 171-186.