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AI-DRIVEN HAZARD MONITORING IN ALBANIA: COMBINING CLIP, IMAGE SEGMENTATION, AND WEB GIS FOR FLOODS, FIRES, AND DEFORESTATION

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Abstract

Albania is increasingly exposed to natural and anthropogenic hazards, including recurrent floods in the Shkodra basin, forest fires in mountainous protected areas, and ongoing deforestation linked to land-use change. Effective monitoring of these processes is challenged by fragmented datasets, delayed reporting, and the limited integration of advanced analytical methods into operational geoinformation systems. This article proposes a hybrid AI-GIS pipeline that combines semantic image classification with quantitative geospatial analysis to support hazard detection and management.

The approach integrates the Contrastive Language–Image Pretraining (CLIP) model for zero-shot classification of hazard-related imagery with pixel-level segmentation and spectral indices derived from remote sensing data. CLIP enables the automatic labeling of images and tiles according to natural language prompts such as "flooded farmland", "burned forest" or "deforested hillside" providing semantic context without the need for retraining. Segmentation methods and indices, including NDWI for floods, NDVI for vegetation loss, and dNBR for burn severity, are then applied to quantify the spatial extent of affected areas. The resulting outputs are structured in a PostGIS database, where hazard layers and attributes are stored and linked to spatial queries. A Web GIS environment built with Leaflet provides interactive visualization, dashboards, and temporal comparisons for end users.

Three scenarios are presented: flood extent mapping in Shkodra, wildfire impact in Lurë National Park, and deforestation monitoring in Tropoja. Results demonstrate that the integration of semantic classification and quantitative extraction enhances both the interpretability and accuracy of hazard assessments. The framework highlights the potential of combining AI and GIS technologies to create scalable, reproducible, and policy-relevant observatories for environmental risk monitoring in Albania.

Keywords: CLIP, Image Segmentation, Satellite Imagery, Environmental Hazards, Web GIS

MONITORING ZAGROŻEŃ W ALBANII PROWADZONY PRZY POMOCY SZTUCZNEJ INTELIGENCJI: POŁĄCZENIE METOD CLIP, SEGMENTACJI ZOBRAZOWAŃ ORAZ WEB GIS DLA POWODZI, POŻARÓW I DEFORESTACJI

Abstrakt

Albania staje się coraz bardziej narażona na katastrofy naturalne i antropogeniczne, takie jak powtarzające się powodzie w basenie Jeziora Szkoderskiego, pożary lasów na terenie obszarów chronionych w górach oraz trwająca deforestacja związana ze zmianami w użytkowaniu terenu. Skuteczny monitoring tych procesów napotyka liczne trudności, wynikające z rozproszenia zestawów danych, opóźnionego raportowania oraz ograniczonej integracji zaawansowanych metod analitycznych z systemami geoinformacyjnymi. W artykule przedstawiono propozycję hybrydowego ciągu AI-GIS, który łączy semantyczną klasyfikację zobrazowań z analizą ilościową, aby wspierać wykrywanie zagrożeń i zarządzanie kryzysowe.

Podejście to integruje model kontrastywnego języka-przedtreningu obrazu (ang. *Contrastive Language–Image Pretraining* – CLIP) do zerojedynkowej klasyfikacji zobrazowań związanych z zagrożeniem z segmentacją na poziomie piksela i wskaźnikami spektralnymi wyprowadzonymi z danych teledetekcyjnych. CLIP umożliwia automatyczne etykietowanie zobrazowań i warstw zgodnie z naturalnymi podpowiedziami językowymi, takimi jak "zalane grunty rolnicze", "spalony las" lub "wylesione zbocze", dostarczając kontekstu semantycznego bez potrzeby ponownego treningu. Metody segmentacji i wskaźniki, w tym NDWI dla powodzi, NDVI dla utraty roślinności i dNBR dla oceny szkód spowodowanych pożarem, są następnie stosowane do kwantyfikacji rozmiaru przestrzennego zmienionych obszarów. Otrzymane wyniki są włączane do bazy danych PostGIS, gdzie umieszczono warstwy zagrożenia i atrybuty, a także połączono je z wyszukiwaniami przestrzennymi. Utworzone za pomocą Leaflet środowisko Web GIS zapewnia użytkownikom końcowym interaktywną wizualizację, panele oraz porównania w czasie.

W artykule przedstawiono trzy scenariusze: mapowanie rozprzestrzeniania się pożarów w rejonie Szkodry, skutki pożaru w Parku Narodowym Lurë oraz monitoring deforestacji w rejonie Tropoi. Wyniki pokazują, że integracja klasyfikacji semantycznej z ekstrakcją ilościową zwiększa zarówno łatwość interpretacji, jak i dokładność oceny zagrożeń. Ramy te ukazują możliwości połączenia technologii AI i GIS w celu stworzenia w Albanii punktów monitoringu ryzyka środowiskowego, dostarczających danych, które są skalowalne, powtarzalne i istotne dla polityką zarządzania ryzykiem.

Słowa kluczowe: CLIP, segmentacja zobrazowań, zobrazowania satelitarne, ryzyko środowiskowe, Web GIS

1. INTRODUCTION

Albania is experiencing increasing environmental pressures from natural and human-driven hazards, including recurrent flooding in the Shkodra basin, frequent forest fires in mountain ecosystems, and deforestation linked to land-use change and logging activities. These processes not only threaten ecosystems and biodiversity but also pose serious socio-economic risks to communities. Traditional approaches to monitoring such hazards rely on fragmented datasets, delayed reporting, and static cartographic products, which often fail to capture the full dynamics of environmental change in near-real time.

Recent advances in artificial intelligence (AI) and geospatial technologies provide new opportunities for enhancing hazard detection, quantification, and visualization. In particular, image segmentation applied to satellite imagery enables the retrieval of detailed spatial information, such as flood extent, burned areas, and deforested patches. For instance, segmentation combined with spectral indices can detect a 3–5 % increase in burned area in fire-affected regions, while automated delineation of flood pixels has shown strong correspondence with field reports. In the case of deforestation, integrating NDVI trends with AI-based interpretation can highlight bare soil patches and forest degradation patterns.

Complementing pixel-level analysis, the Contrastive Language–Image Pretraining (CLIP) model offers the ability to perform zero-shot classification of hazard-related images. This allows images to be categorized according to relevance or impact, based on natural language prompts such as “flooded farmland”, “burned forest” or “deforested hillside.” Such semantic classification provides contextual meaning to the imagery without the need for additional training.

By combining segmentation for quantitative measurement with CLIP for semantic categorization, hazard-related information can be structured into a PostGIS database, where layers are stored together with attributes such as hazard type, date, severity, and estimated area. Finally, this information can be served through a Web GIS platform (e.g., Leaflet/QGIS Web), enabling interactive dashboards, temporal comparisons, and spatial queries. This integrated pipeline creates a scalable and reproducible framework for environmental risk monitoring in Albania, bridging the gap between raw imagery and actionable geospatial intelligence.

2. LITERATURE REVIEW

The application of geospatial technologies to environmental hazard monitoring has gained increasing attention in recent decades [1, 2]. Remote sensing has been particularly important for detecting and quantifying landscape changes caused by floods, wildfires, and deforestation. Traditional methods often rely on spectral indices, such as the Normalized Difference Vegetation Index (NDVI) for monitoring vegetation health and forest cover [3, 4], the Normalized Difference Water Index (NDWI) for mapping flood extent [5, 6], and the Normalized Burn Ratio (NBR) and its derivative dNBR for assessing wildfire damage [7, 8]. These

indices have been widely used to support disaster assessment and ecological monitoring at both regional and global scales [9, 10].

Beyond index-based approaches, advances in computer vision have expanded the toolkit for image interpretation. Segmentation algorithms such as U-Net [11], DeepLab [12], and more recently the Segment Anything Model (SAM; [13]) enable pixel-level classification of satellite or aerial imagery [14]. These methods provide finer delineation of hazard-affected areas compared to manual interpretation or threshold-based techniques. Several studies have shown the utility of deep learning segmentation in fire severity mapping, flood extent detection, and land-use change analysis [15], highlighting their potential for automated monitoring. Benchmark datasets such as ADE20K [16] have further supported the training and evaluation of semantic segmentation models across diverse scenes.

At the same time, recent progress in foundation models for vision–language tasks has opened new opportunities for semantic image understanding. The Contrastive Language–Image Pretraining (CLIP) model [17] has been applied in zero-shot classification of remote sensing and hazard-related imagery, while open-source variants such as OpenCLIP [18] have facilitated broader adoption in scientific workflows. CLIP enables images to be categorized based on natural language prompts without requiring additional training, supporting applications in disaster assessment, urban monitoring, and environmental change detection [19]. While CLIP does not provide pixel-level segmentation, it complements quantitative methods by offering contextual classification and automated tagging of hazard imagery.

The integration of these AI methods with geospatial databases and visualization platforms further strengthens their practical utility. PostGIS provides advanced spatial data management and query functions that enable the storage of hazard layers with attributes such as type, severity, and temporal extent [20]. Coupled with Web GIS frameworks such as Leaflet or QGIS Web, the results of AI-driven analyses can be disseminated to decision-makers, practitioners, and the public through interactive dashboards and spatial queries [21, 22]. Previous work has also shown the importance of integrating citizen and volunteered geographic information into hazard monitoring [23–25], while studies have highlighted accuracy and privacy concerns in free geocoding and mapping services [26].

Recent research has considerably expanded the application of artificial intelligence and vision–language models in environmental monitoring. Study [27] provides a comprehensive overview of AI innovations in environmental assessment, outlining advancements and challenges in achieving real-time hazard detection. Building on these developments [28] demonstrates the effectiveness of contrastive vision–language supervision for zero-shot classification in remote sensing imagery. Complementary approaches have emerged in hazard-specific contexts, as shown by [29] in flood susceptibility mapping using multi-temporal Sentinel-1 data and deep learning, and by [30], which introduced a novel multi-spectral index for burned area detection. Study [31] enhances land-use classification accuracy from Sentinel-2 data through ground-level prompting, while [32] discusses recent advances in geospatial artificial intelligence for flood extent mapping, emphasizing the integration of satellite-based analysis with Web GIS platforms. Collectively, these works highlight the rapid evolution of AI-driven approaches for hazard monitoring and remote sensing, reinforcing the methodological foundation of the present research [33].

In summary, the literature highlights three complementary research streams: (1) spectral indices for quantitative hazard detection, (2) deep learning segmentation for detailed spatial delineation, and (3) vision–language models like CLIP for semantic classification. However, few studies have combined these approaches into a unified pipeline integrated with PostGIS and Web GIS for policy-relevant hazard monitoring. This gap motivates the present study, which develops and applies such a framework to case studies of floods, fires, and deforestation in Albania.

3. METHODOLOGY

The workflow begins with the acquisition of satellite images representing the main hazards of interest in Albania, namely floods, forest fires, and deforestation. These images constitute the raw data input, capturing both the spatial extent and the temporal evolution of environmental changes.

An illustrative dataset was compiled from publicly available online sources to represent the three main hazard categories. Approximately seven images depicting flood events, five showing wildfire-affected areas, and five illustrating deforestation processes were collected

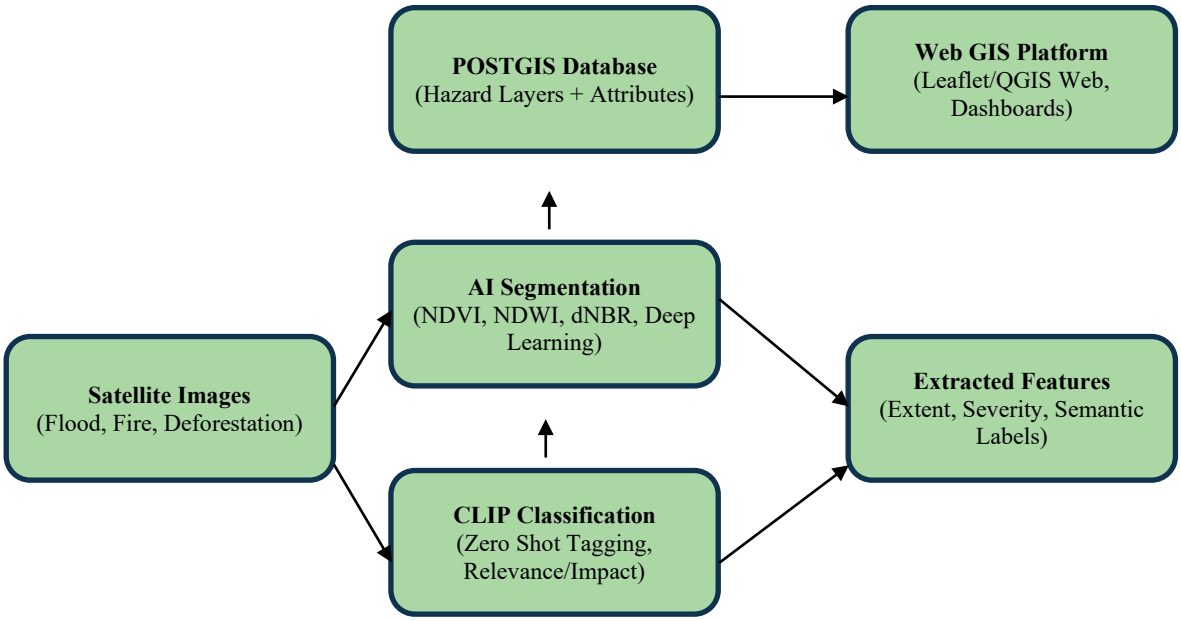

Fig. 1. Workflow integrating AI segmentation and CLIP classification for hazard monitoring
Ryc. 1. Schemat integrujący segmentację AI i klasyfikację CLIP w monitoring zagrożeń

from web-based repositories such as the DLR SAFER portal, ASIG geospatial archives, and open satellite imagery platforms (e.g., CNES/Airbus DS and Google Earth). These images were selected for their clarity and relevance to the study objectives. From the collected material, three representative results one for each hazard type were selected and presented in this paper to demonstrate the workflow and visualization approach.

Once collected, the imagery follows two parallel analytical paths. The first involves AI Segmentation, which applies spectral indices such as NDVI for vegetation monitoring, NDWI for flood mapping, and dNBR for fire severity, combined with advanced deep learning segmentation models. This process allows the precise delineation of hazard-affected zones, generating spatial masks that capture the extent and severity of the impacted areas.

In parallel, the same satellite images are processed using CLIP Classification, a vision–language model capable of zero-shot tagging. Here, images or tiles are matched against natural language prompts such as "flooded farmland", "burned forest" or "deforested hillside". Unlike segmentation, which focuses on quantitative spatial measurement, CLIP provides semantic categorization, assigning contextual meaning and impact relevance to the imagery without requiring prior training on hazard-specific datasets.

The results from these two AI components converge into the Extracted Features stage. This intermediate block consolidates both the quantitative information produced by segmentation (area, severity, boundaries) and the qualitative insights derived from CLIP (semantic labels and relevance categories). Together, they form a comprehensive description of the hazards under analysis.

These extracted features are then structured and stored within a PostGIS Database, where they are managed as hazard layers enriched with attributes such as type, date, severity, and semantic category. The database enables spatial queries, cross-referencing with administrative boundaries, and integration with additional environmental datasets.

Finally, the information is made accessible through a Web GIS Platform (e.g., Leaflet or QGIS Web), where end-users such as researchers, planners, and decision-makers can visualize hazard layers interactively. The platform supports dashboards, temporal comparisons, and spatial filtering, turning raw satellite data into actionable geospatial intelligence.

To demonstrate the applicability of the proposed workflow, representative satellite images of different hazard scenarios (Fig. 2, 3, 4) are included. These examples cover fire-affected regions, flooded areas, and

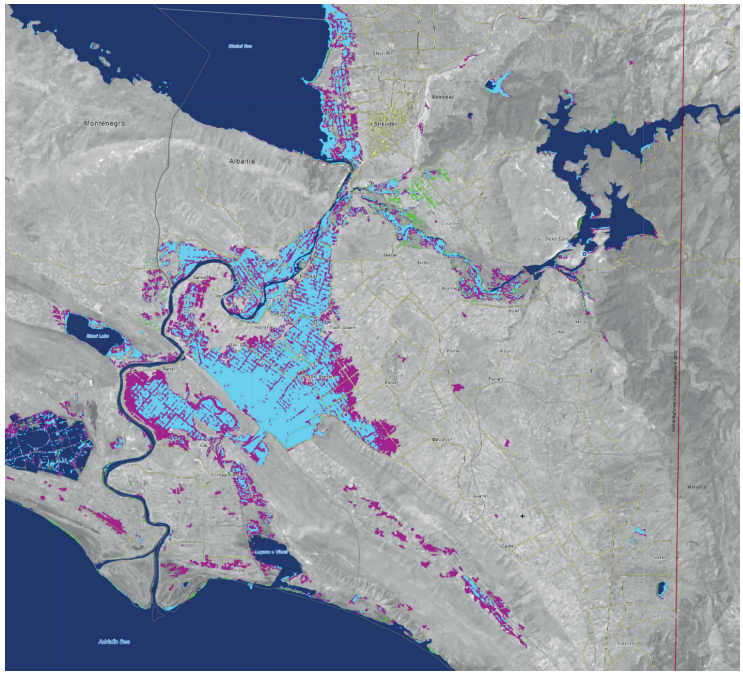

Fig. 2. Map of the January 2010 floods in northern Albania derived from RADARSAT satellite imagery. Source: German Aerospace Center (DLR) / GMES Emergency Management Service (SAFER). Albania Floods, RADARSAT Change Detection, 12 January 2010. DLR Activations Portal

Ryc. 2. Mapa powodzi, które nawiedziły północną Albanię w styczniu 2010 r., opracowana na podstawie zobrazowań satelitarnych RADARSAT. Źródło: Niemieckie Centrum Lotnicze (DLR) / GMES Serwis Zarządzania Kryzysowego (SAFER). Powodzie w Albanii, RADARSAT Wykrywanie Zmian, 12 stycznia 2010 r. Portal Aktywacji DLR

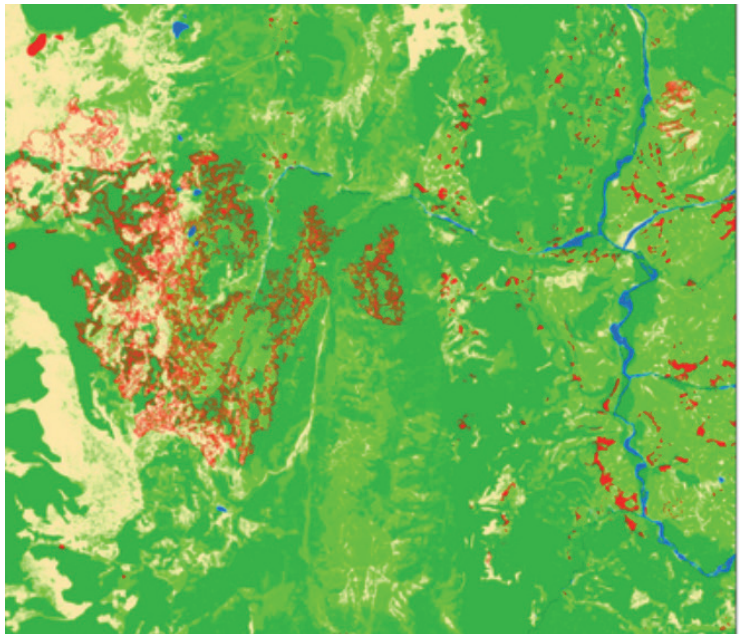

Fig. 3. Satellite images showing fire-affected areas in Lurë and Boga, Albania (August 2025). Source: CNA / ASIG

Ryc. 3. Zobrazowania satelitarne pokazujące obszary doświadczone przez pożary w rejonach Lurë i Boga, Albania (sierpień 2025 r.). Źródło: CNA / ASIG

Fig. 4. Satellite comparison showing deforestation in Southeast Bulqizë, Albania, between 2017 and 2024. Source: Imagery © 2017–2024 CNES / Airbus DS / Earth Genome

Ryc. 4. Porównanie zobrazowań satelitarnych pokazujące deforestację w południowo-wschodnim rejonie Bulqizë, Albania, pomiędzy rokiem 2017 i 2024. Źródło: Imagery © 2017–2024 CNES / Airbus DS / Earth Genome

deforested landscapes in Albania. Such imagery provides the visual basis for both segmentation and zero-shot CLIP classification, allowing the pipeline to extract meaningful features (e.g., burned surfaces, inundated pixels, or bare soil patches) that are subsequently integrated into the PostGIS database.

Prior to analysis, the satellite images undergo basic pre-processing steps to ensure data quality. These include atmospheric correction to reduce haze and illumination effects, cloud masking to remove irrelevant areas, and tiling to standardize image size and resolution. Such steps guarantee that both the segmentation workflow and CLIP classification receive consistent and reliable input data, which is crucial for accurate hazard detection.

The outputs of the segmentation and CLIP classification (Fig. 5) processes are validated against independent reference sources. For flood events, delineated water extents are compared with official ASIG reports and, where available, in-situ measurements. Fire detection maps are assessed against national burned area statistics and local field observations, while deforestation outputs are cross-checked with NDVI change detection. CLIP-generated labels are further evaluated through expert review to ensure semantic consistency with the observed scene. This validation framework provides confidence in the reliability of the automated workflow.

All processed results are stored in a PostGIS database, which allows integration with external spatial datasets such as administrative boundaries, land cover maps, and population density layers. This integration supports multi-criteria risk analysis and decision-making in hazard management. Moreover, the proposed workflow is designed to be modular and scalable: additional hazard types or new AI models can be integrated with minimal adjustment, ensuring the methodology remains adaptable to evolving environmental challenges in Albania and beyond.

The system takes as input predefined textual labels (Burned Forest, Smoke Plume, Healthy Vegetation, Bare Soil) and a satellite image of a fire event. The

pretrained CLIP model encodes both text and image, computes similarity scores, and produces an output ranking of labels, which highlights the most relevant classes (e.g., Burned Forest) for the observed scene.

4. RESULTS

The proposed workflow was applied to selected hazard scenarios in Albania, focusing on wildfire events, flood occurrences, and deforestation processes. Zero-shot CLIP classification successfully identified burned forest regions with the highest similarity score (62 %), followed by smoke plumes (18 %), while areas of healthy vegetation and bare soil received lower relevance scores. Segmentation further refined the outputs, delineating burned surfaces consistent with ground observations.

Automated segmentation of water pixels provided accurate delineation of flooded areas. CLIP classification distinguished between flooded farmland (55 %) and urban flood zones (22 %), offering semantic context to the segmented extents. The results aligned closely with available hydrological reports. NDVI differencing revealed patches of vegetation loss, which were corroborated by CLIP classification identifying bare soil or cleared areas. The combination of spectral and semantic information provided by the workflow allowed for enhanced discrimination of human-driven forest change. All outputs were systematically stored in the PostGIS database as spatial layers, including flood masks, fire burn areas, and deforestation patches. Each layer was enriched with CLIP-derived semantic labels, enabling advanced querying and spatial analysis.

The processed results were published through a WebGIS platform, allowing interactive access to hazard layers. Users can toggle between different scenarios, visualize affected areas, and query associated attributes directly from the PostGIS backend.

5. DISCUSSION

The integration of segmentation and zero-shot CLIP classification demonstrated promising results in extracting hazard-related features from satellite imagery. In the fire scenario, CLIP was able to identify burned areas with high confidence while also capturing contextual elements such as smoke plumes, which traditional pixel-based methods often overlook. This illustrates the added semantic value of CLIP in complementing spectral indices and segmentation-based approaches. Similarly, in flood mapping, the workflow provided both delineated inundation extents and a semantic distinction

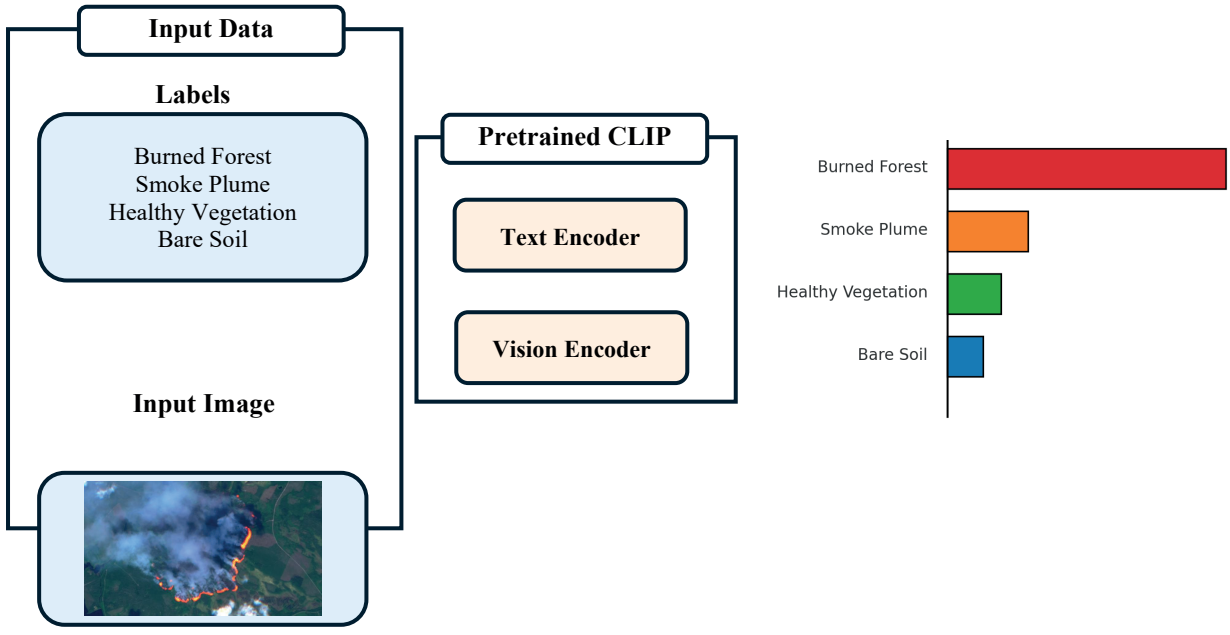

Fig. 5. Zero-shot classification workflow with CLIP applied to fire imagery
Ryc. 5. Schemat klasyfikacji zerojedynkowej przy pomocy CLIP zastosowany do zobrazowań pożarów

between flooded farmland and urban areas, which is essential for assessing socioeconomic impacts.

Compared with conventional remote sensing workflows relying exclusively on indices such as NDVI or water ratio indices, the proposed methodology offers a dual advantage: pixel-level precision from segmentation and human-interpretable classification from CLIP. This duality allows for more nuanced insights, especially in complex environments where spectral signals alone may be ambiguous. However, it also highlights a dependency on the quality and representativeness of textual prompts, which can influence the classification outcomes.

Another important dimension is the integration into PostGIS, which ensures that results are not only stored as static layers but also remain queryable and interoperable within existing geospatial infrastructures. By linking hazard layers to administrative boundaries and demographic data, the workflow supports applications ranging from emergency response planning to long-term land-use management. Nevertheless, validation remains a critical step. While preliminary comparisons with reports and field observations were encouraging, further accuracy assessments with high-resolution reference datasets are needed to establish robustness across different hazard types.

Finally, the scalability of the workflow is worth noting. The modular design allows for adaptation to additional hazards such as landslides or coastal erosion, and the WebGIS publication ensures that results can be communicated effectively to stakeholders beyond the scientific community. Yet, challenges such as computational cost, prompt engineering, and potential biases in AI models must be acknowledged and addressed in future research.

6. CONCLUSION

This study demonstrates how the integration of AI-based image analysis, zero-shot CLIP classification, and geospatial databases can enhance the monitoring of natural hazards in Albania. By combining pixel-based segmentation with semantic classification, the workflow was able to identify and categorize hazard-specific features such as burned forest areas, flooded farmland, and deforested patches. The use of PostGIS as a central repository ensured structured storage of both spatial layers and semantic labels, while the WebGIS interface provided intuitive access for visualization and decision support.

The results highlight that AI-driven approaches not only complement traditional remote sensing methods but also offer scalable and adaptable tools for multi-hazard assessment. Although validation with ground truth data remains essential, the methodology is flexible enough to be extended to additional hazard types and geographic contexts. Future work will focus on refining accuracy, integrating higher-resolution imagery, and expanding the WebGIS platform for real-time monitoring applications.

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