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Towards Advanced Wildfire Analysis: A Siamese Network-Based Change Detection Approach through Self-Supervised Learning

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***Abstract*—Escalating wildfire incidents necessitate improved post-disaster management practices for more effective response and recovery. This study advances the integration of Earth Observation technologies into the wildfire damage assessment phase, contributing a novel approach to augment disaster recovery efforts. Multi-temporal satellite imaging is crucial for monitoring wildfire-affected areas, and the widespread availability of multispectral images with high revisit frequencies substantially improves the comprehensive study of these changes. This paper presents an examination of deep learning techniques for change detection, employing a Siamese convolutional neural network enhanced with an Atrous Spatial Pyramid Pooling block for efficient image data processing. The model is trained and validated on the "Sentinel-2 Wildfire Change Detection Dataset" (S2-WCD), a custom-made dataset aimed at change detection methodologies. By introducing this specialized dataset and applying advanced neural network techniques, the study fills crucial research gaps, offering improvements in wildfire disaster management, particularly in the critical recovery phase following wildfire events.**

***Keywords*—Wildfires, Change Detection, Earth Observation Technologies, Deep Learning, Convolutional Neural Networks, Self Supervised Learning, Siamese Networks, Sentinel-2 Images, Environmental Monitoring, Disaster Management.**

I. Introduction

Wildfires are an integral part of the Mediterranean ecosystems, playing a pivotal role in shaping plant communities and contributing to the diverse, mosaic-like patterns seen in Mediterranean landscapes today, characterized by varying levels of regeneration and degradation [2]. However, their occurrence, duration, and intensity have notably surged in recent decades. Specifically, in the Mediterranean basin, the climate regime characterized by prolonged dry and warm summer periods, flammable vegetation, complex topography, and human activities, all contribute to both the ignition and the spread of wildfires. Moreover, factors such as population growth and the expansion of wildland–urban interface (WUI) areas, compounded by the climate crisis, have heightened the frequency and severity of wildfires, causing devastating socio-economic and environmental impacts [3], [1]. The increasing challenges posed by wildfires underscore the critical need for effective emergency preparedness and response.

Disaster Management (DM) represents an evolving field of research focused on planning for and responding to emergencies, spanning all aspects of preparation and recovery for events such as floods, earthquakes, and wildfires [4]. This field is structured around the disaster management cycle, which includes mitigation, preparedness, response, and recovery phases [5]. Each phase is crucial for minimizing disaster impacts on communities and the environment. Integration of diverse information sources, including advancements in information and communication technology, significantly enhances the effectiveness of disaster management efforts.

As DM practices progress, there's a pressing need for more rapid advancements in Earth Observation (EO) technologies, given the urgency inherent in disaster response. Ensuring easier access to crucial data becomes paramount. The Copernicus programme, the EO component of the European Union's Space program, plays a vital role in facilitating this accessibility, serving as a cornerstone within the broader framework of disaster management. It provides accurate, timely, and easily accessible information to improve the management of the environment, understand and mitigate the effects of climate change, and ensure civil security. The data, freely available via the Copernicus Data Space Ecosystem, are an invaluable asset for environmental monitoring, offering a wealth of information for various applications including urban expansion, deforestation, and damage assessment. Central to the utility of the Copernicus programme for environmental monitoring is the Sentinel-2 satellite mission. It offers free, high-resolution optical imagery, contributing significantly to land monitoring, emergency response, and specifically to wildfire detection and post-event assessment [23]. With its frequent revisit time of five days at the equator with two satellites in operation and covering wide areas, Sentinel-2 provides updated and reliable data that is crucial for tracking changes in land cover and vegetation health over time. This frequent revisit capability ensures timely data collection, allowing for rapid assessment of wildfire events and facilitating the implementation of necessary management and recovery actions. Particularly for wildfire management, the European Forest Fire Information System (EFFIS) and the Copernicus Emergency Management Service (EMS) offer essential insights into the occurrence and spread of wildfires. EFFIS, administered by the European Commission's Joint Research Centre, combines data from satellites, meteorological inputs, and ground observations to provide a holistic perspective on forest fires across Europe. Concurrently, EMS stands as a vital resource during emergencies, offering real-time data and monitoring services, including rapid mapping derived from satellite imagery. These services, through their concerted efforts, empower stakeholders with the knowledge and tools necessary for effective fire detection, assessment, and response, safeguarding communities and ecosystems from the ravages of wildfires. EMS's provision of four product types—reference products, first estimate products, delineation products, and grading products—particularly emphasizes the system's capability to offer detailed information about the damage grade, its spatial distribution, and extent soon after an emergency event [22].

In the era of advancing EO technologies, Change Detection (CD) emerges as a critical field, pivotal for assessing the impacts of natural disasters, including wildfires [24], [7]. CD involves identifying variations in the condition of an object or phenomenon through observations made at distinct time intervals. The primary aim is to analyze satellite images and assign binary labels—change or no change—to each pixel, providing a clear demarcation of affected areas. This process, however, is not without its challenges. Temporal EO data inherently contain noise due to environmental factors like weather conditions, shadows, and cloud cover, making it difficult to discern actual changes from natural variability. Algorithms, therefore, must adeptly generalize from this data to produce meaningful predictions. The advent of deep neural networks (DNNs) has marked a significant leap forward in this domain. Coupled with sophisticated unsupervised or supervised learning algorithms, the field of CD has seen remarkable advancements, notably enhancing the accuracy and efficiency of detecting changes across varied landscapes [17] [25] [26] [27]. Linking CD to the DM cycle, particularly within the recovery phase, underscores its indispensable role. Accurate and timely CD is crucial for the effective allocation of resources and planning of recovery efforts following wildfire incidents. By providing a precise assessment of damage, CD enables decision-makers to prioritize areas in need and implement targeted rehabilitation measures, thus facilitating a more efficient and impactful recovery process. For instance, through CD techniques applied to Sentinel-2 imagery, which offers a spatial resolution of up to 10 meters, decision-makers can calculate the size of affected areas, such as determining the hectares of land impacted by wildfires, enabling the focused allocation of recovery resources and efforts.

The exploration of CD in the context of EO has demonstrated the critical need for advanced analytical capabilities. The introduction of DNNs has been a game-changer, offering a significant leap in processing complex, high-dimensional data inherent in satellite imagery [6], [7], [27]. DNNs, through their layered architecture, excel at identifying intricate patterns in data, pivotal when discerning subtle changes in the landscape affected by natural disasters such as wildfires. In the realm of machine learning, the distinction between supervised and unsupervised learning methodologies outlines the broad spectrum of approaches for training models. Supervised learning, reliant on labeled datasets, contrasts with unsupervised learning, which uncovers hidden patterns without pre-defined labels [8]. Bridging the gap between these methodologies, SSL emerges as a powerful strategy [29], [17], [9]. SSL, by generating its own supervisory signals from the data, enables the effective utilization of vast amounts of unlabeled data, significantly enhancing model robustness and reducing the dependency on extensive labeled datasets. Central to this work is the adoption of Siamese Convolutional Networks (SiamConv), which have shown exceptional promise in the field of CD [29], [17], [9]. These networks leverage the strength of CNNs in extracting spatial hierarchies of features, while Siamese architectures are uniquely suited for comparison tasks—essential for identifying changes over time in paired satellite images. Further enhancing our CD framework is the integration of the Atrous Spatial Pyramid Pooling (ASPP) module [11]. ASPP facilitates precise segmentation tasks by capturing multi-scale contextual information without losing resolution, a critical feature when pinpointing areas affected by wildfires. By combining these advanced techniques—SSL for leveraging unlabeled data, SiamConvs for effective change detection, and ASPP for detailed segmentation—this work presents a comprehensive approach to CD in wildfires. Last but not least, the aforementioned CD techniques were trained on a custom-made dataset, called S2-WCD, that will be publicly available.

The following sections of this paper are organized as follows: In Section 2 the proposed architecture is presented. Section 3 introduces the training and implementation details of the proposed network. The results of the study are demonstrated in Section 4, while the conclusion is included in Section 5.

II. Proposed architecture

This work introduces an evolution of the SiamConv network, initially proposed by Oikonomidis et al. [9], by integrating an advanced ASPP module (CD-ASPP) tailored for multispectral imagery analysis. Termed SiamConvASPP, this enhanced model adheres to the encoder-decoder architectural paradigm, as illustrated in Fig. 1.

A. Siamese Configuration

The encoder segment of this neural network operates on a Siamese structure with two parallel CNNs designed to process a pair of multispectral images (T1 and T2) representing different temporal stages. Each convolutional layer in the branches utilizes 32, 3x3 filters. These layers are reinforced with L2 regularization to help the model avoid overfitting. To accomplish quicker learning and ensure consistency in the learning process, batch normalization was applied after each convolutional layer, bringing the layer's inputs to a common scale. Following the normalization, the ReLU activation function is used to give the network the ability to unravel nonlinear patterns in the data. In order to build resilience in the network's feature interpretation, a dropout rate of 0.1 was used. Additionally, no pooling methods applied to ensure that the feature map resolutions will remain the same throughout the depth of the network.

The outcomes from the two branches of the network are merged together through a layer which calculates their absolute difference. This fused feature contains spatial and temporal information from the satellite input images, providing a single encoder output.

B. Change Detection Atrous Spatial Pyramid Pooling Block (CD-ASPP)

In the next stage, the resulting fused feature from the encoder is received by the Change Detection Atrous Spatial Pyramid Pooling (CD-ASPP) block. This module maintains the foundational use of atrous (dilated) convolutions for multi-scale feature analysis, while introducing several improvements.

As presented in the diagram in Fig. 2, the first improvement of the proposed module is the addition of a 1x1 convolution layer, a compact but powerful tool for shaping the depth of feature maps without losing spatial details perfect for managing the rich data from EO imagery. This layer is followed by batch normalization, which evens out the data to help the model learn faster and more effectively. The ReLU activation function introduces non-linearity to help the model detect complex patterns indicating changes in the region.

Following the initial 1x1 convolution in the proposed module, atrous convolutions were employed with two dilation rates, 6 and 12. The rates were chosen after extensive testing to expand the model's perception of the input, without increasing the complexity. Each atrous convolution has a kernel size of 3x3 and it is designed to extend its reach across the feature map, capturing both subtle and broad changes essential for detailed change detection. The number of filters is equal to 32, allowing to pick up a diverse range of features which are the key for identifying changes in the landscape. The next enhancement is that the features are passed through batch normalization layer with the utilization of the ReLU activation function. The same approach was followed for both dilation rates.

In the final step, the feature maps, from each atrous convolution, were concatenated with the initial 1x1 convolutional layer. This stage is crucial for integrating insights from multiple

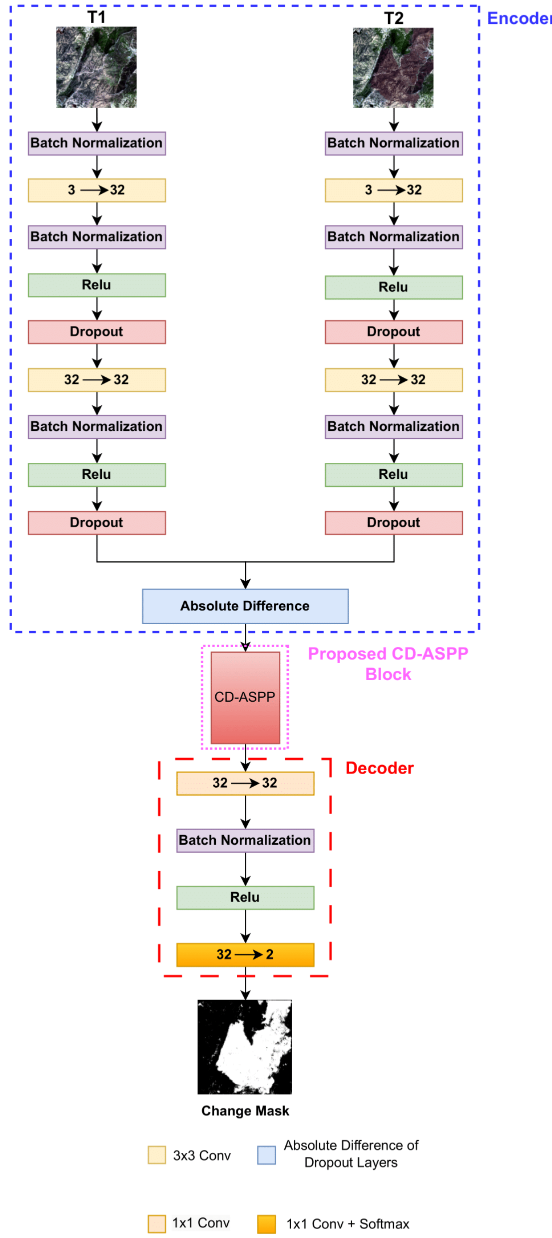

Fig. 1. Model structure diagram of the proposed Siamese Convolutional ASPP Neural Network. The Backbone model is marked with blue dashes and the advancements are marked with red.

scales derived from initial layers, providing a holistic representation of the data. Afterwards, the dimension of the outcome has to be reset, in order to be the same as the initial input. To achieve dimensionality reduction, a 1x1 convolution is used. By maintaining the spatial integrity of the concatenated feature maps, the model remains computationally efficient. The reduced feature map undergoes batch normalization, a process that standardizes the features to accelerate and stabilize learning across the network. Thereafter, a ReLU activation function is applied. Summarizing, the CD-ASPP block prepares the features for the subsequent decoding phase.

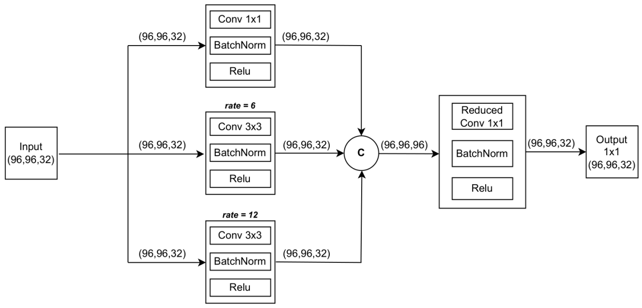

Fig. 2. Change Detection Atrous Spatial Pyramid Pooling Block

C. Convolutional Classifier

In the proposed framework, the decoder is a convolutional classifier. As its name indicates, convolutional layers with 1x1 filters are used for the generation of change prediction masks. In this method also known as "Networks in Networks" [10], the 1x1 filters are capable of identifying patterns across the depth of the image. Consequently, the filters not only serve as a mechanism for dimensionality reduction but also enhance the network's learning capability by introducing a layer of depth-wise feature analysis. The proposed convolutional classifier incorporates a hierarchical structure of two convolutional layers and descends the number of filters from 32 down to 2. Finally, the output employs a Softmax activation function to yield a 1x2 vector that indicates the likelihood of each pixel being categorized as 'change' or 'no change'.

III. Training and Implementation

All models were implemented on a NVDIA RTX3060 12GB GPU.

This section outlines the custom wildfire dataset and training configurations. The introduction of this new dataset facilitates the development of innovative methods for detecting changes caused by wildfires, providing access to data that was previously unavailable.

Afterwards, a detailed explanation of the specific problems for each task is presented, followed by a comprehensive description of the training process, including insights of the utilized datasets and the configuration of parameters for both tasks. The final segment presents a discussion about the metrics employed for evaluating the performance of the downstream and pretext tasks.

A. Dataset

In this work, two main EO datasets were utilized which contain 13 spectral bands with various resolutions between 10m and 60m. The Sentinel-2 Multitemporal Cities Pairs dataset (S2MTCP [17]) was used for the pretext task. This dataset is comprises of 1,520 Sentinel-2 Level 1C (L1C) [18] image pairs. The images, approximately 600x600 pixels in size, incorporate the complete range of bands of the Sentinel-2 product, all resampled to a 10-meter resolution. It is worth mentioning that images with over one percent cloud cover were removed from the data.

The Sentinel-2 Wildfire Change Detection (S2-WCD) custom-made dataset was used for the downstream task (CD). It was shaped with Sentinel-2 L1C products and contains multispectral images with pixel-level change ground truth masks for each pair, from different areas in Europe and Oceania. The total amount of images were obtained from the Copernicus Dataspace Ecosystem, capturing scenes from time periods before and after the event occurred.

The dataset includes 41 image pairs with an image resolution of 1066x1066 pixels. Diverse wildfire events from various countries, including Australia, France, Greece, Italy, Portugal, and Spain, are examined in this paper. The reference period spans from January, 2021, to September, 2023, during which a total of 25 events were selected. Open access datasets through EFFIS and EMS were exploited to obtain the spatial extent of the burned areas. The EFFIS database was consulted to identify fires that caused significant destruction in forested and shrubland areas. Subsequently, burned area delineation data were extracted from EMS, leveraging its high accuracy. The images of every pair were shaped based on the aforementioned data with the utilization of a related shapefile. This file is comprised of various vector layers, outlines the burn areas within each Area of Interest (AoI). Afterwards, it is used to precisely crop the Sentinel-2 L1C products to the extents of the wildfire damage. They were also used to created the ground truth masks for the S2-WCD data. They consists of 0 and 1 values, where the 0 indicates an unchanged pixel while the 1 stands for changed pixel. The final train and test sets are consisted of the red, blue and green band.

B. Training

In order to expand both S2MTCP and S2-WCD, 96x96 pixel patches were extracted from each image. In addition, each patch underwent random rotations and both vertical and horizontal flips as part of the pre-processing stage. During the training phase, the model undergoes two distinct assignments, the pretext task and the downstream task. The weights learned through the pretext task are transferred to the downstream task for initialization. Through this process, the model is capable of identifying changes using minimal amounts of labeled data.

During the pretext task, the model tries, and specifically its encoder, with the use of the S2MTCP, to detect similarities between non-overlapping and overlapping patches. Considering the non-overlapping patches, a label of 1 is assigned, while overlapping patches receive a label of 0. Ten patch pairs, overlapping or non-overlapping, were randomly selected from each image pair, creating 15,200 pairs. The model was initialized with a dropout rate of 0.1 and a decay factor of 0.0001. The Adam optimizer was chosen for this task.

During the downstream task, or CD, the full model (Encoder, CD-ASPP and Decoder) was trained using the S2-WCD dataset. For the training, 31 image pairs were used and each image contributed 100 patches, leading to a total of 3,100 paired patches. The rest 10 pairs were utilized producing 1,000 paired patches for testing. Specifically the encoder weights were initialized through the pretext task. For the training, a learning rate of 0.001 was selected and the final model was trained for 55 epochs, balancing the need for thorough exposure to the data against the risk of overfitting. A batch size of 5 was selected for enhancing the model's performance and accuracy. Adam optimizer with a learning rate of 0.001 was selected once more, for its adaptability and efficiency in handling sparse gradients on noisy problems. The network was compiled using a customized Weighted Categorical Cross Entropy loss function 1, with weights set to (0.1, 0.2) to address class imbalance.

$$Loss = -\sum_{i=1}^{N}(y_i \cdot \log(\hat{y}_i) \cdot weights) \tag{1}$$

where:

- N represents the total number of samples in the dataset.
- y_i denotes the actual label for the i^{th} observation, which attains values of either 0 or 1.
- $\hat{y}_i$ indicates the predicted probability for the i^{th} observation being classified as 1.
- 'weights' are applied during the loss calculation to prioritize a certain class, addressing the issue of class imbalance effectively.

The loss function evaluates the performance of the classification model, which produces a probabilistic outcome between 0 and 1.

C. Evaluation metrics

Regarding the pretext task, the loss and accurracy metrics were used. For the downstream task, the performance of the proposed and the backbone model was evaluated with the use of the Sensitivity [21], Specificity [21], Precision [20], F1 Score [19], Accuracy [21].

These metrics offer valuable insights into different aspects of model performance, such as accuracy, label prediction, and the ability to handle imbalanced datasets. The Sensitivity/Recall often referred to as the true positive rate, measures the proportion of actual positives that are correctly identified by the model. The Specificity also known as the true negative rate, quantifies the proportion of true negatives that are accurately recognized by a classification model. The Precision also called positive predictive value, calculates the proportion of correctly identified positives out of all the instances labeled as positive by the model. The F1 score, a harmonic mean of precision and recall, serves as a robust performance indicator for binary classification scenarios, valued between 0 and 1, where it reaches its maximum in the absence of false negatives and false positives, highlighting a model's balanced accuracy without considering true negatives. Finally, the Accuracy quantifies the overall proportion of correct predictions made by a model, encompassing both true positives and true negatives, out of the total number of cases evaluated.

IV. Results

A. Quantitative Evaluation

The Table I presents the outcomes of the change detection task by utilizing the pre-trained weights of the pretext task. All the experiments were conducted by using the blue, green and red (2, 3, 4) spectral bands. Moreover, the performance of the proposed architecture is compared with the SiamConv network, which is the core model of this study as mentioned before. Both SiamConv and SiamConvASPP were trained and evaluated on the S2-WCD dataset. The Sensitivity improved by 0.65%, Specificity increased by 1.20%, Precision rose by 1.72%, the F1 Score saw an enhancement of 1.22%, and Accuracy improved by 0.99%. This overall improvement suggests that the integration of the CD-ASPP into the network's architecture contributes positively to the performance of the model, indicating a refined ability to discern relevant features for wildfires change detection for the proposed dataset.

Furthermore, Table II displays the evaluation results for the pretext task.

TABLE I
Quantitative Evaluation of Downstream Task

S2-WCD Dataset	**Results**	
	SiamConv	***SiamConvASPP***
Sensitivity	93.51	94.16
Specificity	91.81	93.01
Precision	87.26	88.98
F1 Score	90.28	91.5
Accuracy	92.45	93.44

TABLE II
Quantitative Evaluation of Pretext Task

S2MTCP Dataset	**Results**	
	Validation Set	***Test Set***
Loss	0.0790	0.0478
Accuracy	98.27	98.65

B. Qualitative Evaluation

The Fig. 3 displays pre-event and post-event satellite images, illustrating the landscape of three different regions, Los Guajares, Rhodes, and Cohilva, before and after a wildfire. Additionally, the figure shows the prediction masks generated by the networks alongside the corresponding ground truth masks.

The SiamConvASPP model exhibits superior performance compared to the SiamConv model. The results demonstrate that the SiamConvASPP model is more sensitive to changes in the landscape after a wildfire event, as evidenced by the more precise and contiguous areas identified in the prediction masks. This enhanced detection capability is also notable in complex terrains, where the differentiation between burned and unburned areas is less distinct as seen from (A) & (B) in Fig. 3. The SiamConvASPP produces better prediction masks in comparison with SiamConv, demonstrating superior performance, even though the quantitative improvement is minor.

V. Conclusions

This paper focused on the importance of damage assessment in environmental disasters, i.e. wildfires, with the utilization of

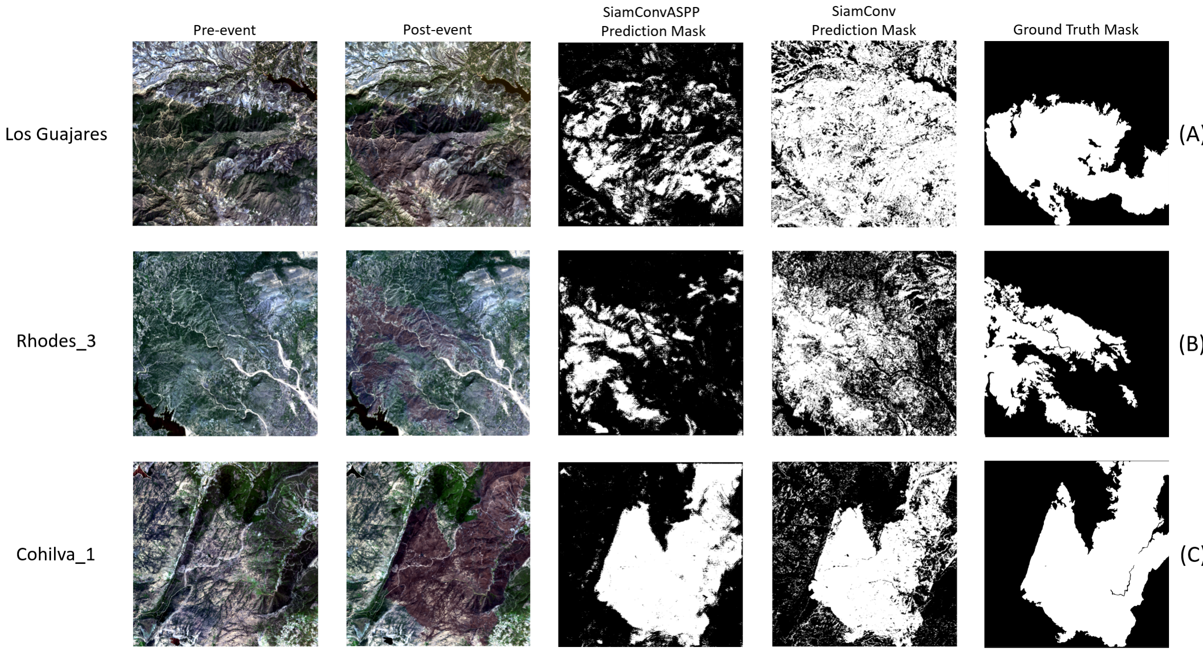

Fig. 3. Comparative visualization of change detection results in three distinct regions (Los Guajares, Rhodes and Cohilva), presenting pre-event and post-event satellite images with corresponding ground truth masks and prediction masks.

a custom wildfire change detection dataset (S2-WCD) and the enhancement of a previously proposed model in combination with a novel atrous convolution block.

SSL enables the exploitation of unlabeled EO datasets, such as S2MTCP, to expand the capabilities of detection models. The acquired knowledge from the pretext task is later transferred in the downstream task for expanding the network's performance, resulting in notable outcomes.

The new CD-ASPP module is based on the atrous principals and it is tailored on the architecture of a SiamConv model. By utilizing this approach, the now SiamConvASPP network is capable of identifing and classifing changes resulting from wildfires with decent accuracy and detail. Consequently, the ASPP's integration empowers the model to maintain high performance even in complex scenes, where changes might be subtle or obscured by various factors such as shadow, cloud cover, or the inherent variability of natural landscapes. This multi-scale feature extraction capability, therefore, stands as a major advantage, ensuring that the model remains robust and versatile across diverse change detection scenarios.

The proposed approach produced improved results in all evaluation metrics as well as predicted change masks. Furthermore, the outcomes of this study contribute to bridging the existing gap in change detection methods for wildfire incidents. The introduction of the novel S2-WCD dataset facilitates the exploration and application of advanced change detection techniques in wildfire settings, as demonstrated in this research. In the future, this work will be extended for different change detection datasets. Additionally, another avenue is the exploration of more sophisticated machine learning techniques, such as integrating more advanced versions of the CD-ASPP block or exploring novel neural network architectures like transformers for spatial analysis. These approaches could be a useful tool for the disaster management cycle to minimize the cost of the calamity aftermath.

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