From Fire to Data: Capturing Wildfire Dynamics with Semantic Segmentation & Spatiotemporal Reconstruction

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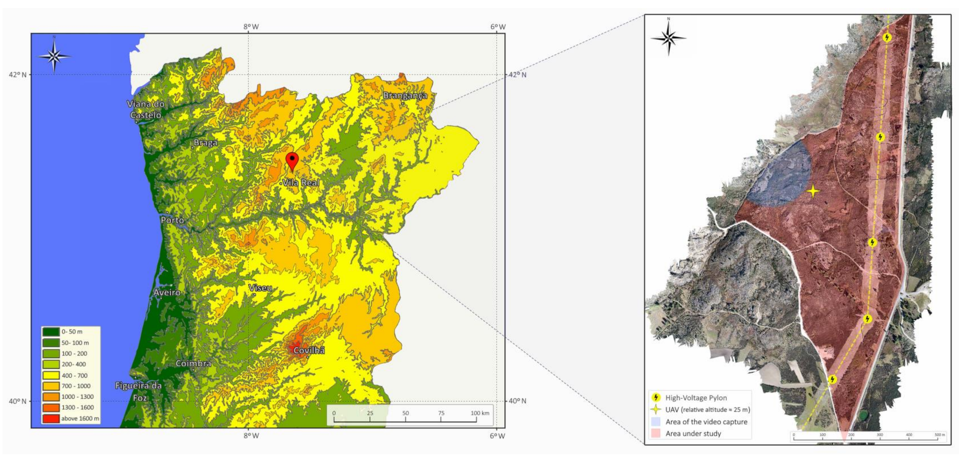
Introduction and Motivation

Wildfires have far-reaching consequences, threatening lives, economies, and the environment. Understanding their dynamics and environmental impacts is crucial, especially in high-incidence regions. Recently, machine learning-based models have emerged as promising solutions for comprehending the dynamics of wildfires.
In that vein, this research proposes three different elements:

I. We introduce a wildfire dataset for semantic segmentation of burned area
II. Provide tools to benchmark testing and validating semantic segmentation models in the context of wildfires
III. Present an autoencoder-based continuous spatiotemporal interpolation models to represent real-world phenomena such as wildfire burned area evolution.

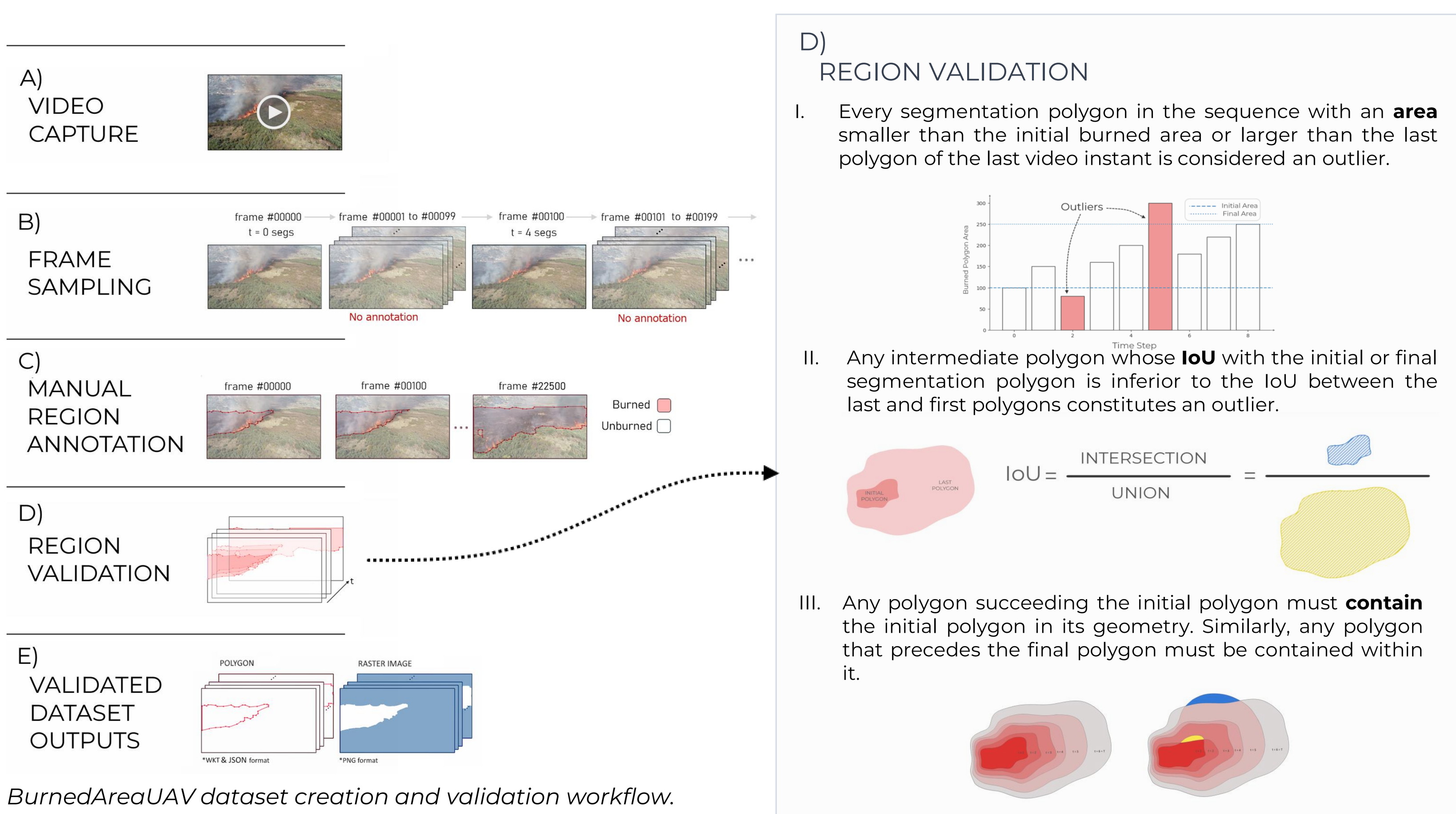
I. A novel burned area dataset: construction and validation

Datasets play a crucial role in training and validating ML models. However, collecting UAV videos in harsh conditions of high temperatures and toxicity further complicates data collection. Furthermore, segmenting burned areas presents unique challenges due to frequent occlusion by fire and flames and the and the amorphous nature of the burned area. Recognizing the scarcity of datasets with these specific characteristics and the ongoing challenges in semantic segmentation of burned areas, we propose a new dataset.



Hypsometric map indicating the relative position of the video capture (left) and orthophoto highlighting the region where the prescribed fire were conducted (right).

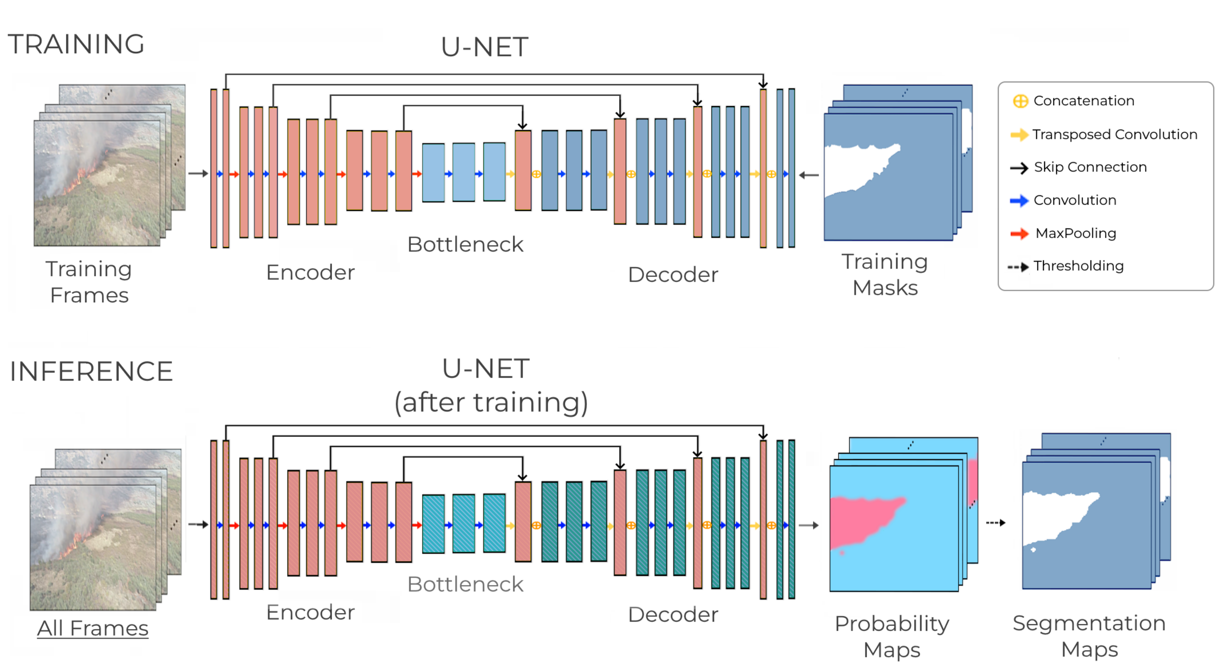
This novel dataset is based on a UAV-captured video of a prescribed fire at Torre de Pinhão in northern Portugal. Below, we present the workflow of creation of semantic segmentation dataset.



BurnedAreaUAV dataset creation and validation workflow.

II. U-Net as a baseline to capture frame-wise burned area

We employ the U-Net, a fully convolutional deep learning architecture widely utilized for semantic image segmentation tasks, to perform the semantic segmentation of the burned area.



Employed U-Net Architecture: Training and Segmentation Maps generation (U-Net Samples).

We evaluate three U-Net variants: U-Net Base, U-Net RED, and U-Net 3D. We train the models in the *BurnedAreaUAV* dataset and perform semantic segmentation for the entirety of the video.

Results

Model	IoU [%]	Recall [%]	Precision [%]	F1-Score [%]
U-Net Base	**95,31**	**98,30**	**96,92**	**97,61**
U-Net RED	92,74	95,34	97,15	96,24
U-Net 3D	94,01	98,21	95,67	96,92

U-Net classification metrics for BurnedAreaUAV testing set.

Model	Temp. Inconsistency
U-Net Base	**4,40E-03**
U-Net RED	9,11E-03
U-Net 3D	2,64E-02

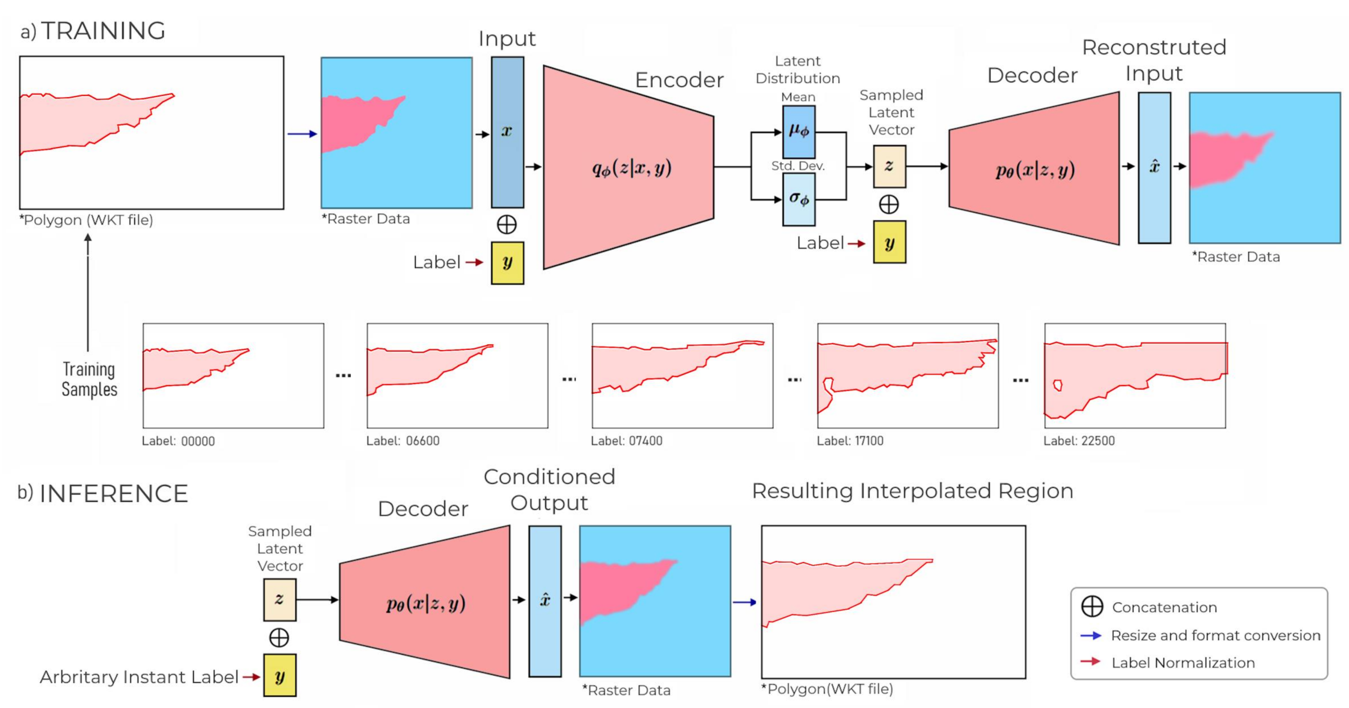
Average Temporal Inconsistency.

Key takeaways

- U-Net models perform well on the *BurnedAreaUAV* dataset.
- U-Net *Base* shows superior classification and temporal consistency.
- Generalization to other wildfires footage remains untested.

III. Representing burned area fire evolution with C-VAEs

C-VAEs are deep learning models that extend VAEs by learning a conditional distribution. They are capable of learning a conditional distribution, allowing to generate in-between representations by *smoothly* interpolate the latent space. We compare the performance of the C-VAE with alternative models from the literature. We evaluate these models on the *BurnedAreaUAV* dataset and compare the generated interpolations with the U-Net segmentations in the entirety of the wildfire video.



Employed C-VAE Architecture:. a) each region stored in WKT format is converted to raster image to be processed by the model b) a new image is generated conditioned by a label and converted to WKT format.

Results

Data	Algorithm	IoU	Hausdorff Dist.
Periodic Sampling			
U-Net Samples	*Shape-Based*	**0,96**	42,5
	Mackenney	0,89	72,2
	C-VAE	0,95	**41,9**
BurnedAreaUAV Test Set	*Shape-Based*	**0,96**	**48,4**
	Mackenney	0,82	113,2
	C-VAE	0,95	60,8
Distance Based Sampling			
U-Net Samples	*Shape-Based*	**0,93**	**68,3**
	Mackenney	0,88	85,4
	C-VAE	0,91	76,5
BurnedAreaUAV Test Set	*Shape-Based*	0,91	**60,8**
	Mackenney	0,85	103,1
	C-VAE	**0,93**	85,2

Similarity metrics for the tested models.

Algorithm	Temp. Consistency
Periodic Sampling	
Shape-Based	0,986
Mackenney	0,970
C-VAE	**0,993**
Distance Based Sampling	
Shape-Based	0,994
Mackenney	0,983
C-VAE	**0,999**

Average Temporal Consistency.

Key findings

- C-VAE shows competitive results in terms of Similarity metrics.
- C-VAE outperforms in terms of Temporal Consistency.
- C-VAE show promising results and may be an alternative for applied earth sciences continuous time polygon interpolation applications.

Conclusion and Future Work

In this project, we have developed novel methodologies for the creation of high-quality burned area datasets. These dataset enabled us to effectively utilize U-Net networks to capture representation of the evolution of the burned area. Additionally, we propose a straightforward Autoenconder-based model that performs competitively against classical models
In the future, we intend to augment BurnedAreaUAV by incorporating additional drone-captured videos from diverse locations and varying conditions. We aim to continue testing AE-based models' capabilities to generate continuous spatiotemporal interpolations. Furthermore, we plan to apply these approaches to study other phenomena, such as artificial reef monitoring, iceberg tracking, cloud segmentation, and other spatiotemporal database applications.

Papers, Code, Demo Videos

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