Using computer vision to detect and segment fire behavior classifications in UAS-captured images

Brett L Lawrence [AB]*, +1-936-581-6833, brett@ravenenvironmental.com; Emerson de Lemmus [C]

[A] Stephen F. Austin State University, 1936 North St, Nacogdoches, Texas 75962, USA

[B] Raven Environmental Services, Inc., 6 Oak Bend Drive, Huntsville, Texas 77340, USA

[C] Independent Researcher

* Corresponding Author: lawrenceb3@jacks.sfasu.edu

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Abstract

The widely adaptable capabilities of artificial intelligence, in particular deep learning and computer vision has led to significant research output regarding fire and smoke detection. Previous studies often focus on themes like early fire detection, increased operational awareness, and post-fire assessment. To further test the capabilities of deep learning detection in these scenarios, we collected and labeled a unique aerial image dataset that determined whether specific types of fire behavior could be reliably detected in prescribed fire settings. Our 960 labeled images were sourced from over 20.97 hours of UAS video collected during prescribed fire operations covering a large region of Texas and Louisiana, U.S.. National Wildfire Coordinating Group (NWCG) fire behavior observations and descriptions served as a reference for determining fire behavior classes during labeling. YOLOv8 models were trained on NWCG Rank 1-3 fire behavior descriptions in grassland, shrubland, forested, and combined fire regimes within our study area. Models were first trained and validated on isolated image objects of fire behavior, and then on segmenting fire behavior in their original parent images. Models trained using isolated image objects of fire behavior consistently performed at a mAP of 0.808 or higher, with combined fire regimes producing the best results (mAP = 0.897). Most segmentation models performed relatively poorly, except for the forest regime model at a box and mask mAP of 0.59 and 0.611, respectively. Our results indicate that classifying fire behavior with computer vision is possible in most fire regimes and fuel models, whereas segmenting fire behavior around background information is relatively difficult. However, it may be a manageable task with enough data, and when models are developed for a specific fire regime. With an increasing number of destructive wildfires and new challenges confronting fire managers, identifying how new technologies can quickly assess wildfire situations can assist wildfire responder awareness. Our conclusion is that levels of abstraction deeper than mere detection of smoke or fire are possible using computer vision, and could make even more detailed fire monitoring possible.

Keywords: YOLO, computer vision, fire behavior, fire detection, UAS

Introduction

The rapid evolution of unmanned aerial systems (UAS) or vehicles (UAV) and their payload capabilities has led to their increased integration into wildland and prescribed fire operations. Some areas of developing use include fire suppression (Lattimer et al., 2023), aerial ignition (Beachly et al., 2016; Lawrence et al., 2023), and real-time or post-fire monitoring (Moran et al., 2019). These innovations are timely, with more severe fires and lengthening fire seasons requiring innovative solutions to managing destructive wildfire events (Flannigan et al., 2013; Bowman et al., 2017; Bowman et al., 2020).

UAS technologies show potential to strategically fit into the operational framework of this challenging fire environment (Ambrosia and Wegener, 2009; Zajkowski et al., 2016). For example, UAS technology proves to be relatively safe, inexpensive, and low complexity when compared to their manned counterparts (Shamaoma et al., 2022; Keerthinathan et al., 2023). UAS-captured information is also relatively fine resolution and temporally flexible when compared to space-borne and airborne remote sensing methods (Muchiri and Kimathi 2016; Pádua et al., 2017). This makes UAS platforms an excellent option for detailed, small spatial extent observations and active-fire monitoring. In this study, we address the increasing interest in utilizing UAS vehicles in conjunction with computer vision, an advanced branch of artificial intelligence, to improve and automate the detection of fire, smoke, and other fire related phenomena (Rahman et al., 2021; Zhan et al., 2021; Chen et al., 2022). Specifically, our aim is to further these developments by employing the latest "You Only Look Once" (YOLO) detection algorithm to identify specific fire behavior descriptions as defined by the National Wildland Coordinating Group (NWCG).

Machine learning (ML) and its associative subclasses, such as deep learning, are continually being developed to provide fire detection and prediction services (Castelli et al., 2015; Hodges and Lattimer 2019; Abid, 2021). The intersection of deep learning and computer vision is where opportunities exist for automating the detection of fire phenomenon with a reconnaissance tool such as UAVs. The YOLO deep learning architecture, known for its accurate and real-time detection capabilities, is a prominent model family in this field. Various studies have already employed YOLO algorithms for fire and smoke detection (Mukhiddinov et al., 2022; Zhao et al., 2022; Bahhar et al., 2023). In several cases, lighter and less processing intensive versions of YOLO architectures have achieved performance and speed suitable for real-time applications (Wang et al., 2021; Wang et al., 2022*b*; Zheng et al., 2023). Speed improvements were achieved by replacing the CSPDarknet backbone network with MobileNet, a lightweight convolutional neural network for mobile and embedded devices.

Modern computer vision algorithms such as YOLOv8 enable both detection and segmentation tasks. Detection involves identifying and locating objects within an image, often represented as traditional bounding box labels. In contrast, segmentation goes a step further by partitioning an image into multiple pixel clusters, or segments. In this study, we separately attempt both detection and segmentation of fire behavior classes. Detection minimally identifies whether fire behavior can be successfully classified, whereas segmentation demonstrates a model's ability to delineate separate fire behavior objects within the context of an entire image. Smoke and flame are amorphous and complex features, and to our knowledge, effort to automate the classification of fire behavior is currently unaddressed. Furthermore, evidence suggests that high-resolution UAS images are well suited for deep learning tasks such as segmentation compared to lower resolution remote sensing images (Osco et al., 2023).

One challenge encountered in developing fire-detection models is the extensive time needed to label images for training effective computer vision models. To address this, some researchers have expedited the process of compiling new datasets by using techniques such as learning without forgetting (Sathishkumar et al., 2023) or semi-supervised learning (Wang et al., 2022*a*). Our goal was to provide a unique dataset of labeled fire behavior classes in UAS-captured images to support continued fire modeling efforts. In addition to the need for large image datasets to train effective models, there are also questions of standardization of labeling techniques. The approach can vary, depending on the method of image acquisition and varying fire settings. One example includes distinguishing between smoke and flame detection, and the context in which one or the other, or both, should be targeted for detection. In some scenarios, such as satellite remote sensing, smoke detection is prioritized as flames are typically not discernable, whereas both flames and smoke can be observed and detected when using an UAS (Barmpoutis et al., 2020). Based on our experience, the ability to detect both is influenced by factors such as landscape type, fire intensity, whether smoke is occluding flames, and altitude of flight. Given that UAS vehicles enable low altitude, high resolution observations, our approach in model development and dataset creation was to attempt detecting both flames and smoke in our classifications.

In summary, our goals for this study were outlined as follows: (1) Train separate YOLOv8 detection models on isolated image objects of NWCG fire behavior for three different major fire regimes and all the fire regimes combined; (2) train separate YOLOv8 segmentation models on entire parent images for the same fire regimes; and (3) generate a unique and previously unavailable labeled image dataset of fire behavior sourced from over five years of UAS-captured prescribed fire videos. For our first two goals, we also generated validation metrics so we could compare model success in various fire regimes and discuss the feasibility of computer vision for successfully classifying fire behavior. Our intention is to determine whether more complex feature abstraction can be detected in fire situations by computer vision, thereby providing even more detailed intelligence to personnel responding to fire incidents. We feel these investigations are highly relevant, as wildland firefighters internationally need new tools and technologies to address the increasingly complex fire environment they are confronted with.

Methods

2.1 Study area

Prescribed fire operations were conducted by Raven Environmental Services from years 2018-2023 throughout a regional area in Texas and Louisiana, U.S.. Dominant sub regional forest and land cover types included Shortleaf Pine (*Pinus echinate*) and Loblolly Pine (*Pinus taeda*) forest in Walker, Montgomery, and Trinity counties of Texas; Live Oak (*Quercus virginiana*) woodland and shrubland in Parker, Brown, and Burnett counties of Texas; Loblolly Pine and Post Oak (*Quercus stellata*) forest and woodland in Bastrop county Texas; Longleaf Pine (*Pinus palustris*) forest in Newton and Jasper counties of Texas, and Vernon Parish of Louisiana; Coastal Prairie in Waller and Harris counties of Texas; and one site-prep burn in Rapides Parish Louisiana. Described ecoregions included Crosstimbers, Post Oak Savannah, Gulf Prairies and Marshes, Piney Woods ecoregions of Texas (Griffith et al., 2007), and historically Longleaf Pine dominant areas of Louisiana. Collectively, this made up a diverse geographic region of fuel types that was desirable when training a computer vision model. When structuring images into major fire regimes for this study, we generalized specific landscapes and vegetation types into three major categories: forest, grassland, and shrubland (Figure 1).

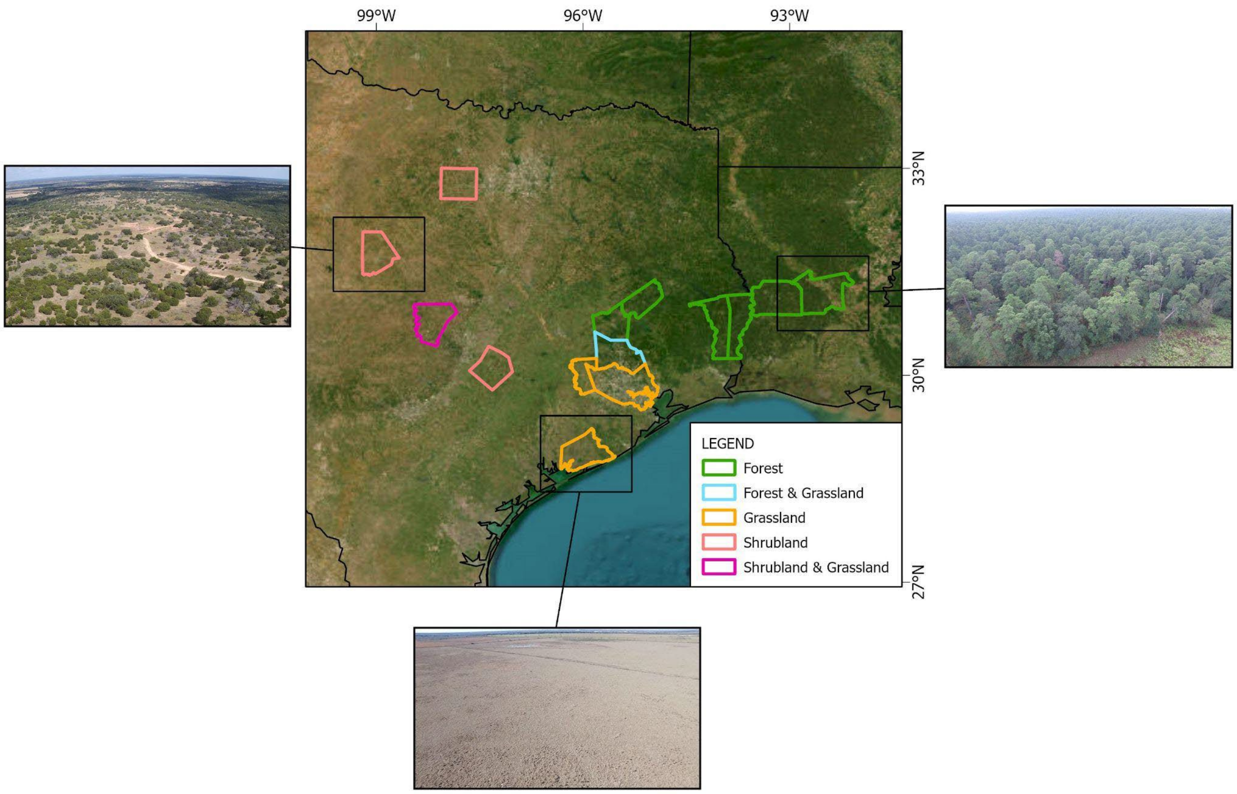


Fig. 1. The distribution of counties and parishes in Texas and Louisiana, U.S. where fire behavior images were extracted from prescribed burn videos. Each location is symbolized to reflect the type of fire regime images collected from that area.

2.2 Image Dataset Description and Labeling

2.2.1 Image Extraction from Fire Videos

Images were extracted from a total of 20.97 hrs of video captured during UAS aerial ignition flight missions on 36 total prescribed burns. Videos were reviewed in Adobe Premiere Pro 2022 (Adobe Inc., San Jose, California, US) and individual frames were captured at their original video resolution of 3840 x 2160 pixels. Deliberate effort was made to diversify the image dataset by collecting a balance of Rank 1-3 fire behavior classifications in each fire regime. Individual frames were also captured in a multitude of luminosity settings, cloud cover, varying altitude, and gimbal angle. Moreover, frames of different positioning of the fire (i.e. foreground, background, etc.), positioning of smoke dispersal, prevailing wind and smoke travel relative to the UAS, the distance of the fire from the UAS, and the amount of fire and smoke in the field-of-view (FOV) all contribute to a dataset containing a variety of fire situations. Our image dataset development, labeling, and eventually model training workflow is visualized in Figure 2.

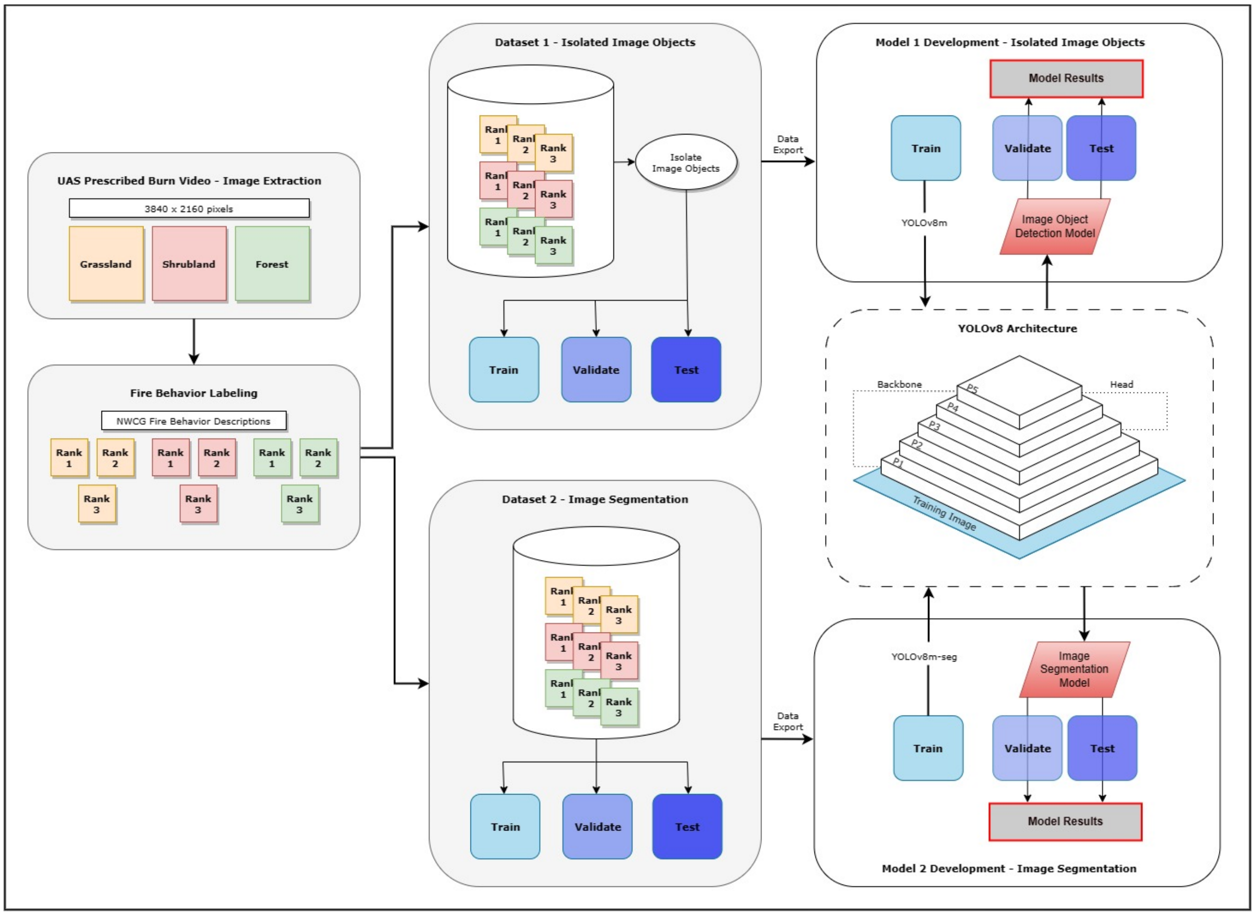


Fig. 2. Fire behavior dataset and model development workflow.

The dataset was subsequently imported into Roboflow (Roboflow, Des Moines, Iowa, US) for annotation. Utilizing the labeling tool powered by the Segment Anything Model (SAM), regions exhibiting varying fire behaviors were annotated in accordance with fire behavior descriptions and observations defined by the NWCG. SAM has recently been introduced as an excellent remote sensing image processing technique that harnesses zero-shot learning capabilities (Osco et al., 2023).

SAM was trained on the SA-1B dataset consisting of 1 billion masks and 11 million images, allowing downstream users to transfer learning to new image datasets (Kirillov et al., 2023). For this work, SAM's efficiency in annotating complex phenomena such as fire behavior, typically a labor intensive task, was significantly enhanced. The NWCG classifies fire behavior from Rank 1 ("smoldering") to Rank 6 ("erratic"). For example, Rank 1 fire behavior or "smoldering" consists of "no open flames in surface fuels", "white smoke", and a "smoldering ground fire" (National Wildfire Coordinating Group, 2021). Throughout the annotation process, descriptions and images provided by the NWCG were consistently referenced to ensure accurate labeling of fire behavior types. Given that all images originated from UAS video footage of prescribed fires, behaviors classified as Rank 4 ("torch/spot") were observed sporadically, while Rank 5 ("crowning") and Rank 6 ("erratic") were not observed. Due to the necessity for balanced classes in computer vision model training , Rank 4 was excluded from the annotation process to maintain dataset integrity, leaving Ranks 1 through 3 for subsequent model training.

2.2.1 Image Preprocessing, Augmentation, and Splits

A total of 1,025 images were extracted from UAS prescribed burn videos for our study. Some of the extracted frames were designated as null images or images that did not contain any of the targeted fire behavior classes. Negative examples are important when training certain object detection or classification models. They assist in the learning process by improving its ability to distinguish between relevant and irrelevant information. Out of the initial collection, 960 images were annotated into the final dataset and split into training, validation, and testing subsets (Table 1). Before their inclusion into the dataset, these original 960 images were classified into distinct categories based on the fire regimes they represent: grassland, shrubland, and forested areas (Table 1). This categorization was followed by a series of preprocessing and augmentation steps to enhance the dataset's robustness and variability. Augmentation steps included cropping, saturation, and exposure changes to original images, which provides the added benefit of artificially increasing the image dataset size. The entire curated image dataset has been made publicly available on Roboflow Universe, an open-source platform dedicated to sharing computer vision datasets (Fire Behavior, 2024). This initiative aims to facilitate further research and advancements in the field of fire behavior analysis using computer vision.

Table. 1. Original image dataset sizes and the size of training, validation, and testing splits after preprocessing and augmentation.

Dataset	**Original Images**	**Image Splits after Augmentation**		
		Training	**Validation**	**Testing**
All – Isolated Image Objects	960	9585	279	243
All – Instance Segmentation	960	3555	141	92
Grassland – Isolated Image Objects	264	3470	121	63
Grassland – Instance Segmentation	264	985	45	22
Shrubland – Isolated Image Objects	354	3470	101	128
Shrubland – Instance Segmentation	354	1340	48	38

Forest – Isolated Image Objects	364	3095	83	65
Forest – Instance Segmentation	364	1365	56	35

2.2.3 Unique Labeling Scenarios

Labeling was an iterative process because of the variety of fire situations and settings. This necessitated careful consideration of how to standardize the labeling methodology. We list some prominent examples here, and how we addressed them. For the grassland fire regime, dot ignition sites could arguably be categorized as Rank 2 fire behavior during early ignition, but eventually develop into Rank 3 on the downwind side as they radiate outwardly (Figure 2). Determining when to begin dividing grassland fires into multiple fire behavior classifications was usually straightforward, although not always. Additionally, grassland fires frequently presented visible flames and smoke that could be labeled together. This was manageable at high oblique and horizontal camera perspectives, but less so at low oblique or nadir perspectives. In the latter scenarios, the smoke's organization relative to the flame source was complex, scattered, and sometimes disjunct. We chose to label only flames in some low oblique or nadir perspectives because this might be the most helpful to a potential end-user.

In situations where the UAS was a considerable distance from the fire's progression, flames might only be visible in the foreground or not at all. This was true of shrubland and forest fire regimes, where trees and vegetation often occlude or block the flame front. This could result in a mosaic of smoke and/or flame features within one image (Figure 2). For example, the foreground of a shrubland fire might have Rank 2 flames and smoke, and the background has Rank 2 and 3 smoke only. High-oblique or horizontal shots often contained two or all three fire behavior ranks. Where to delineate the transition from one to another was not always straightforward and could potentially vary between different labelers. We continually reference our NWCG fire descriptions to provide clarification in these situations. A challenge unique to forested regime labeling was strongly occluded smoke in both oblique and nadir gimbal angles. We made an effort to be consistent when labeling smoke in these scenarios (Figure 2).

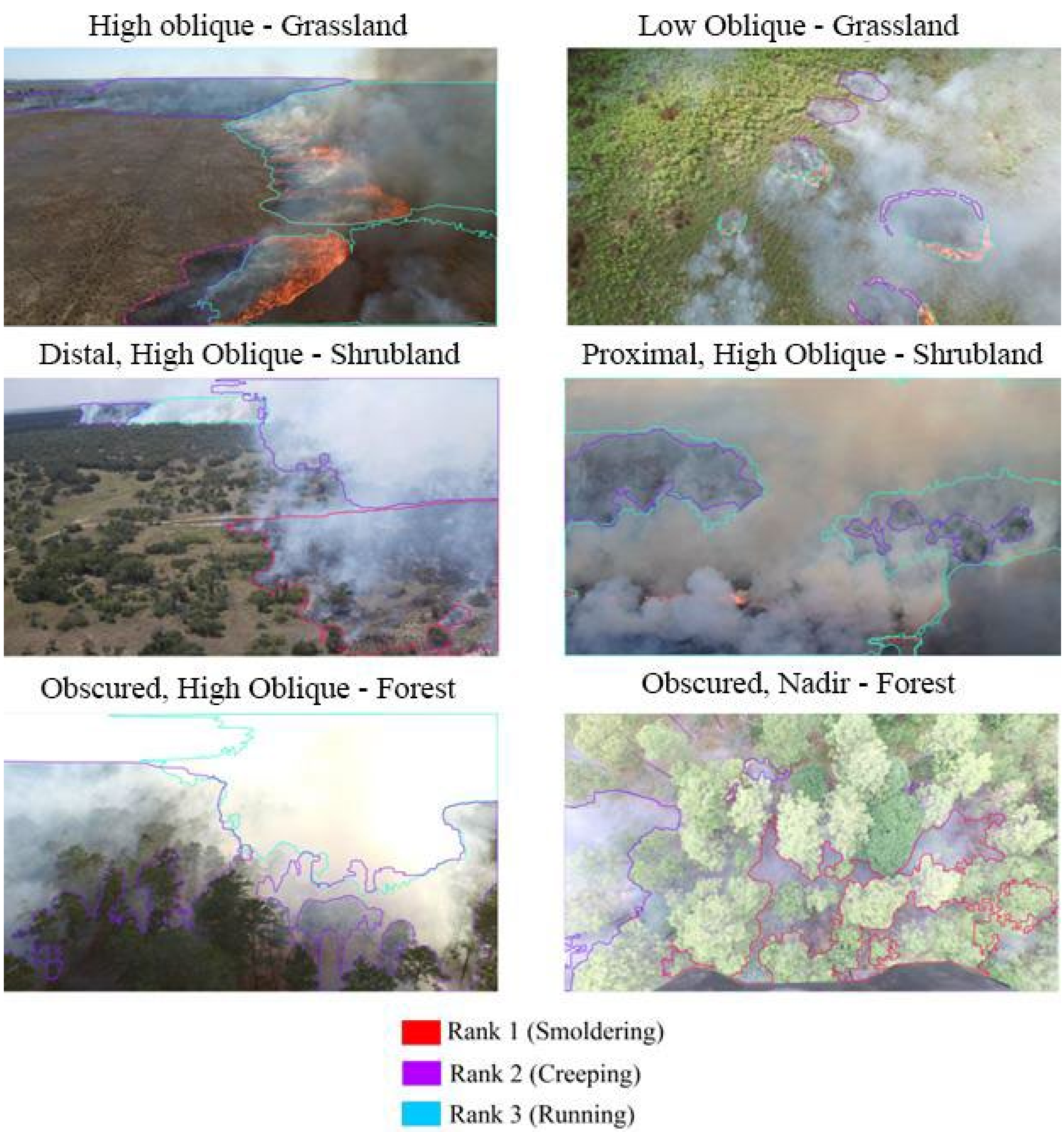


Fig. 3. Examples of fire behavior labeling in all three fire regimes. Images of high oblique and low oblique grassland fires demonstrate how developing spot fires can consist of multiple types of fire behavior. Flames were often visible and labeled in grassland fires, but smoke could be difficult to label at nadir or close to nadir gimbal angles. High oblique gimbal angles of shrubland fires when the UAS was

distal or proximal to the fire front presented situations with multiple types of fire behavior in one image. Forested settings could be difficult to label because of smoke occluding tall trees.

2.3 Model Selection and Training

YOLO deep learning architecture was used to train and develop our fire behavior classification model. YOLO is known for its fast detection times and suitability for potential real-time applications (Redmon et al., 2016). The YOLO family has undergone several version improvements since its introduction as YOLOv3. Our model training was conducted in Google Colaboratory or Colab (Bisong 2019) using the latest version, Ultralytics YOLOv8 (Jocher et al., 2023; Ultralytics, 2023*b*). Google Colab provides cloud-based and open-source computing services for managing the large processing requirements needed for model training. We used Python 3 runtime type with a NVIDIA T4 GPU. Training was performed using 100 epochs, and an input resolution of 640 x 640 pixels. Medium sized model options YOLOv8m-cls and YOLOv8m-seg were used to train the classification and segmentation models respectively because of their balance of accuracy and training time.

2.4 Model Validation

Model validation was performed using the “val” mode, which introduces the trained models to a new set of images not used during training. Validation metrics included precision, recall, mean average precision (mAP), and F1-Score with their values determined as follows:

$$\text{mAP} = \frac{\Sigma \quad AP}{N\ (Class)} \tag{1}$$

$$\text{Precision} = \frac{TP}{(TP+FP)} \tag{2}$$

$$\text{Recall} = \frac{TP}{(TP+FN)} \tag{3}$$

$$\text{F1 Score} = 2\ x\ \frac{(Precision \times Recall)}{(Precsion+Recall)} \tag{4}$$

Model validation metrics were used to assess and compare model performance between our classification and image segmentation model. Testing data predictions were made last, and represented a real-world example of model deployment.

Results

3.1 Isolated Image Object Detection

For all fire regimes and combined regimes, YOLOv8 models trained using isolated image objects performed at a mAP of 0.808 or higher for all fire behavior classes (Table 2). Combined fire regimes performed the best for all classes at a mAP of 0.897 and F1-Score of 0.84 at a 0.494 confidence interval. Individual fire behavior classes typically performed better for the combined fire regime model, except for Rank 1 behavior, which performed best in the forest regime model. The lowest performing individual class was Rank 2 fire behavior for the forest regime at an average precision of 0.605. The combined regimes and forest regime discontinued training at 69 and 83 epochs respectively because of stalled learning for several epochs.

Table. 2. Validation results for detection of isolated image objects of fire behavior in grassland, shrubland, forested, and combined fire regimes.

Dataset	Class	Precision	Recall	mAP@50	F1-Score
Combined	All	0.83	0.842	0.897	

	Rank 1	0.872	0.877	0.912	**0.84 @ 0.494**
	Rank 2	0.822	0.824	0.879	
	Rank 3	0.798	0.827	0.902	
Grassland	All	0.818	0.696	0.814	0.74 @ 0.804
	Rank 1	0.839	0.533	0.784	
	Rank 2	0.822	0.868	0.86	
	Rank 3	0.792	0.686	0.798	
Shrubland	All	0.733	0.874	0.867	0.80 @ 0.337
	Rank 1	0.736	0.903	0.865	
	Rank 2	0.731	0.848	0.843	
	Rank 3	0.731	0.87	0.894	
Forest	All	0.729	0.808	0.808	0.72 @ 0.514
	Rank 1	0.857	**0.92**	**0.926**	
	Rank 2	0.377	0.883	0.605	
	Rank 3	**0.952**	0.621	0.892	

Normalized confusion matrix results for all four models demonstrate 0.73 or greater prediction accuracy of fire behavior classifications, with some exceptions (Figure 3). These include Rank 2 for the combined fire regimes, Rank 1 & 3 for grassland, and Rank 3 for forest. The only instance of less than 0.5 prediction accuracy was for Rank 1 fire behavior detection in grassland areas. Interclass prediction inaccuracies for all models were less than 0.26, except for grassland areas where over predictions of Rank 2 in cases of Rank 1 (0.33) and Rank 3 (0.31) were relatively frequent.

It is important to note that when interpreting a normalized YOLOv8 confusion matrix, the instances of predictions for each class (Rank 1- 3) versus true background is the false positive rate per class. This is the right-most column of the confusion matrix, and the sum of all classes is always one because they have been normalized. In this way, they are not a visualization of the number of false positives – that number per class might be very low – but their values are instead the number of false positives relative to other classes. For example, when considering our model trained using data for combined fire regimes, the amount of false positives was much higher for Rank 2 fire behavior (0.67) than Rank 1 (0.22) or Rank 3 (0.10).

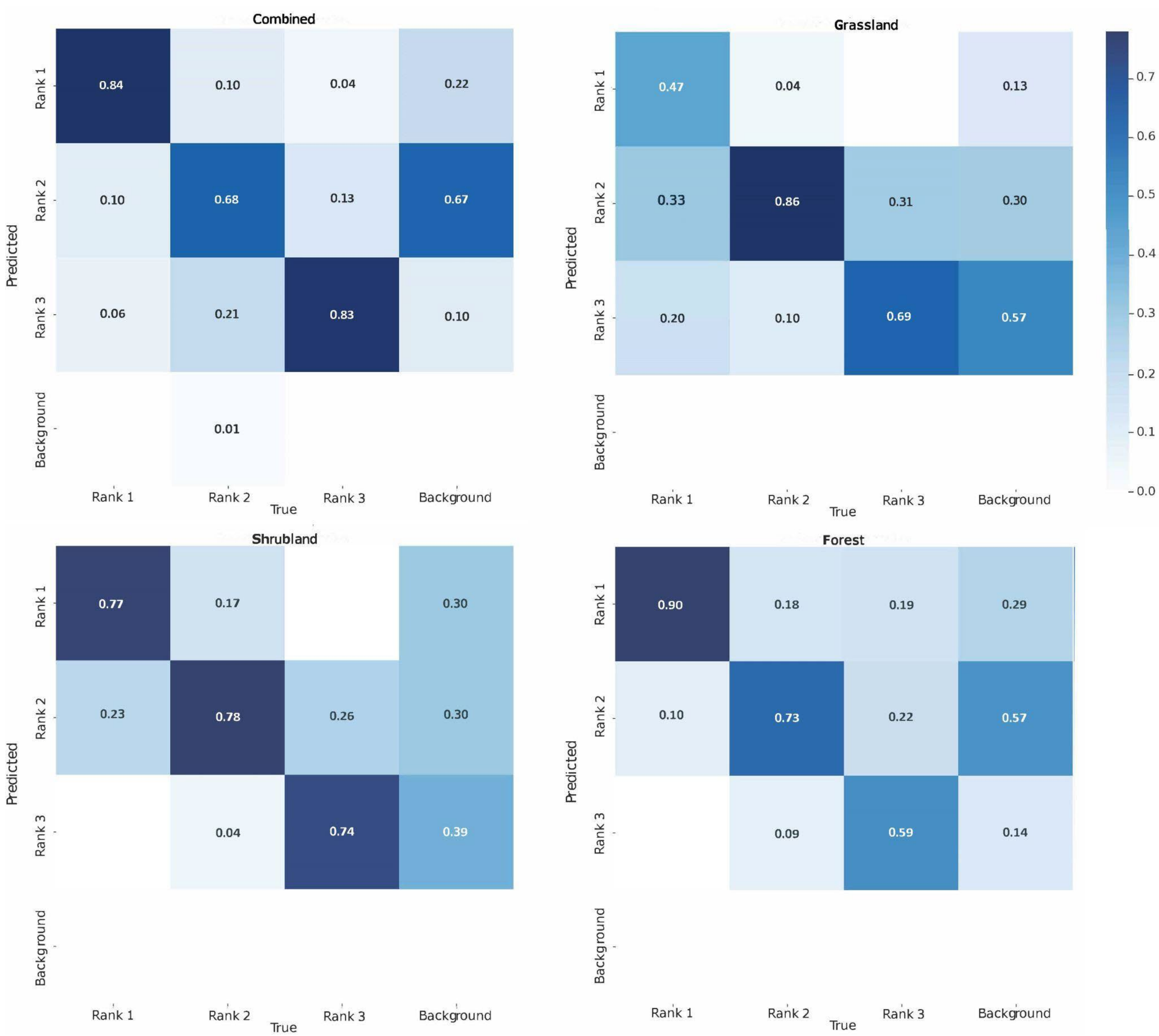


Fig. 4. Normalized confusion matrix results for detection of isolated image objects of fire behavior in grassland, shrubland, forested, and combined fire regimes.

3.2 Segmentation

YOLOv8 segmentation of fire behavior in original parent images resulted in relatively low performance when compared to isolated image object counterparts. The highest mAP for all classes was accomplished with the forest regime dataset and resulted in a box mAP of 0.590 and mask mAP of 0.611 (Table 3). The forest regime model also produced the highest F1-Score of 0.64 at a confidence interval of 0.637. The next highest box and mask mAP for all classes was 0.343 and 0.290 in the case of the grassland segmentation model. Contrary to isolated image objects, the combined fire regimes model's average precision per class underperformed several of the regime specific models. For example, the forest segmentation model outperformed for all classes in the case of both box and mask, and grassland out performed in Rank 2 & 3 for both, too. The shrubland segmentation model performed the worst for all three metrics; average precision per class, mAP, and F1-Score. It also discontinued training at 77 epochs because of stalled learning. Compared to detection models using isolated image objects, recall was disparately lower than precision across all segmentation models. Average box and mask precision for all four segmentation models was 0.52 and 0.55, whereas average box and mask recall was 0.36 and 0.33, respectively.

Table. 3. Validation results from segmentation of fire behavior in parent images of grassland, shrubland, forested, and combined fire regimes.

Dataset	Class	Box				Mask			
		Precision	**Recall**	**mAP@50**	**F1-Score**	**Precision**	**Recall**	**mAP@50**	**F1-Score**
Combined	All	0.431	0.314	0.302	0.37 @ 0.135	0.467	0.267	0.288	0.34 @ 0.490
	Rank 1	0.431	0.295	0.267		0.41	0.232	0.245	
	Rank 2	0.459	0.339	0.327		0.539	0.289	0.299	
	Rank 3	0.403	0.307	0.313		0.454	0.28	0.32	
Grassland	All	0.545	0.316	0.343	0.38 @ 0.539	0.442	0.273	0.29	0.32 @ 0.538
	Rank 1	0.434	0.125	0.113		0.216	0.0625	0.0705	

	Rank 2	0.644	0.31	0.379		0.616	0.298	0.342	
	Rank 3	0.557	0.514	0.537		0.493	0.457	0.459	
Shrubland	All	0.447	0.229	0.202	0.31 @ 0.294	0.475	0.24	0.2	0.32 @ 0.304
	Rank 1	0.385	0.188	0.162		0.324	0.156	0.132	
	Rank 2	0.42	0.196	0.164		0.476	0.217	0.162	
	Rank 3	0.537	0.304	0.28		0.624	0.348	0.305	
Forest	All	0.666	0.599	0.59	**0.62 @ 0.648**	0.8	0.547	0.611	**0.64 @ 0.637**
	Rank 1	0.58	0.414	0.436		**0.833**	0.425	0.505	
	Rank 2	0.585	**0.727**	0.618		0.746	**0.636**	0.656	
	Rank 3	**0.834**	0.656	**0.717**		0.822	0.578	**0.673**	

Confusion matrix results for segmentation models demonstrated a significant number of errors in the form of underpredicting fire behavior for background (Figure 4). The only exception was the forest regime model, which managed to keep false background predictions under 0.5. The shrubland regime's lack of validation performance was reinforced in the confusion matrix results. Under prediction of fire behavior was significant for all classes (>0.70). The grassland segmentation model demonstrated more mixed interclass accuracy, with Rank 3 fire behavior being predicted moderately (0.6) and Rank 1 fire behavior predicted poorly (0.12). The combined fire regimes, while poor performing, were relatively balanced amongst classes and ranged from 0.27-0.33 prediction accuracy. A significant outcome was the small amount of interclass prediction errors. The largest amount of error was found when the grassland regime model was mistaking Rank 2 for Rank 3 fire behavior (0.07). Overall, background prediction errors were significant for all models except for the forest regime, whereas interclass prediction errors were minimal.

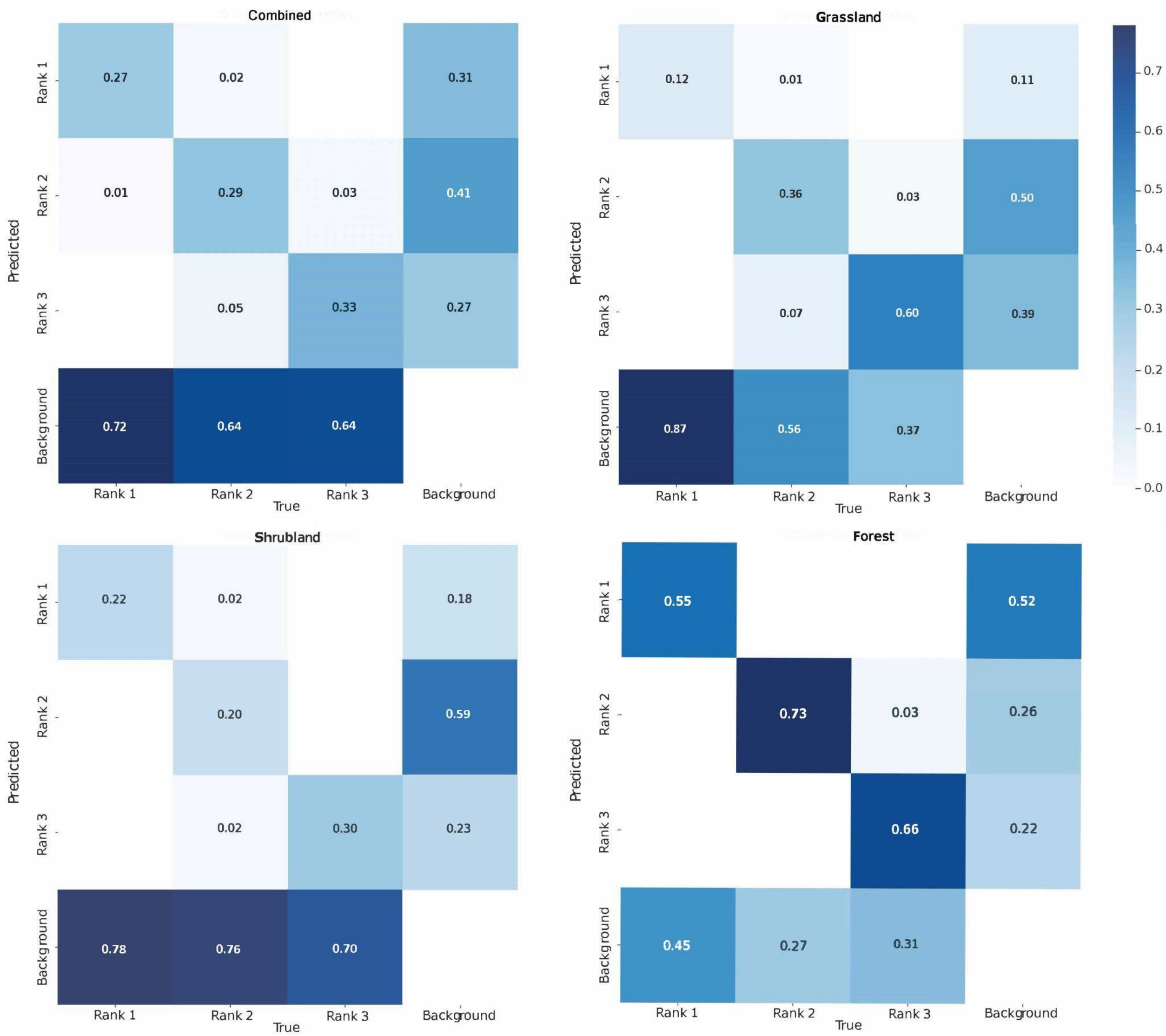
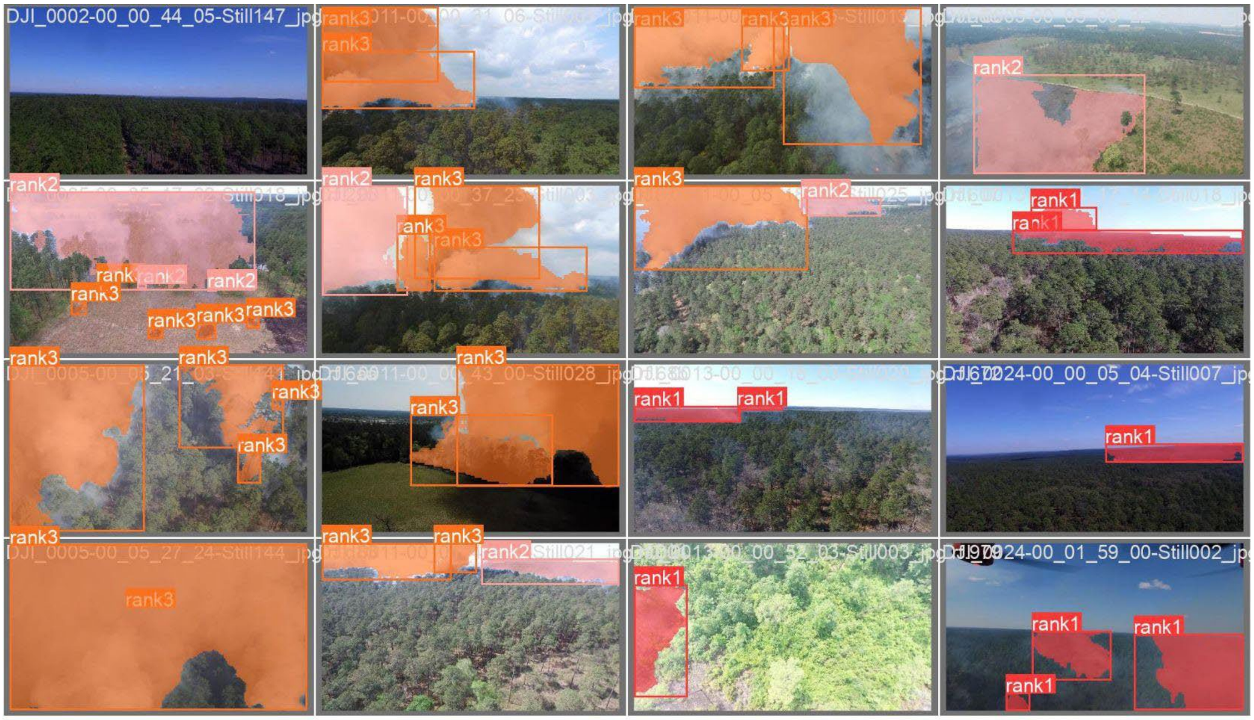
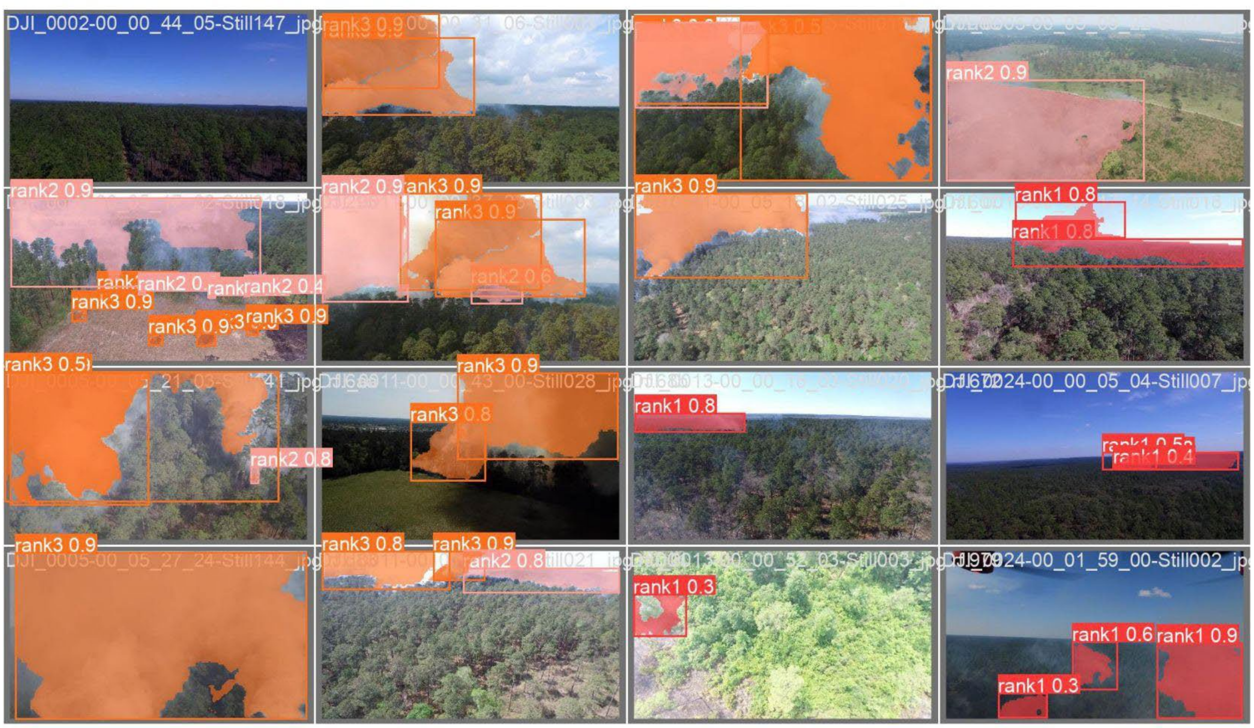


Fig. 5. Normalized confusion matrix results for segmentation of fire behavior in parent images of grassland, shrubland, forested, and combined fire regimes.

We also provide some examples of images labels versus box and mask predictions during the forest regime segmentation model validation (Figure 6).



(a)



(b)

Fig. 6. Examples of (a) images labels and (b) predictions made during validation of our forest segmentation model.

Discussion

1.1 Interpretation of results

Assessing fire situations quickly and accurately is an important requirement for fire managers responding to wildfire situations or conducting prescribed fire operations. An understanding of general classifications of on-scene fire behavior can immediately inform fire managers about the type of situation they are dealing with and the appropriate response. We focused on (1) Training separate YOLOv8 detection models on isolated image objects of NWCG fire behavior for three different major fire regimes and all the fire regimes combined; (2) training separate YOLOv8 segmentation models on entire parent images for the same fire regimes; and (3) generating a unique and previously unavailable labeled image dataset of fire behavior sourced from over five years of UAS-captured prescribed fire videos.

When analyzing isolated image objects of fire behavior, YOLO detection models reasonably classified NWCG Rank 1-3 fire behavior in all our fire regimes (mAP > 0.6, $\underline{x}$ = 0.85). While there were some examples of classes within fire regimes that performed relatively poorly, the overall results suggest that fire behavior is a visual phenomenon that can be trained and reliably detected using computer vision methods. Furthermore, combining datasets and training a detection model from images in all fire regimes resulted in increased model performance. This suggests that when excluding background information the type of fire regime is not necessarily important when classifying fire behavior with computer vision.

Model performance reduced significantly when training segmentation models on fire behavior with parent images. The main explanation for this drop in performance in all four models was low recall, or instances of missing fire behavior objects. Meanwhile, precision metrics were relatively high compared to recall for all our segmentation models. This is also evidenced by normalized confusion matrices for segmentation models, with instances of interclass errors being low but underpredicted fire behavior being high for all classes (Figure 4). Ultralytics attributes low recall to the need for improved feature extraction or lack of data (Ultralytics, 2023*a*). High-performing computer vision models are often trained with image datasets on the scale of thousands to millions of labeled images, so our lack of recall performance is likely attributable to our relatively small datasets. Unfortunately, labeled image datasets of fire behavior are not readily available, and generating new data is time-intensive. Despite this, our forest regime segmentation model still generated results of a potentially deployable model.

Our conclusion is that fire behavior is a detectable phenomenon using computer vision, but making accurate detections in a variety of scenarios is either difficult or requires more labeled image data for some fire regimes. Moreover, fire behavior classification and masking within those regimes can be variable because of circumstances unique to each fire regime described in our labeling methodology. For example, Rank 3 fire behavior was predicted with reasonable accuracy by the grassland segmentation model. One possible explanation is because flames are consistently visible in grassland settings, and our labeling of flames allowed for an outlier in class performance.

Given this information, one of our most significant findings is that our results indicate computer vision models are better developed for a specific fire regime, rather than several simultaneously. The strongest indicator of this is the reduced performance in the combined fire regimes segmentation model compared to the forest regime. Despite using around a third the amount of labeled images, the forest regime model still outperformed its combined regime counterpart.. It is possible that differences in feature extraction amongst fire regimes led to a diversity of scenes that negatively impacted performance.

1.2 Future Considerations

A more clearly defined standard for labeling fire behavior could benefit the continued development of computer vision modeling of fire behavior in different fire regimes. Creating a standardized system might lead to complementary datasets, helping with the issue of data availability and the time intensiveness of labeling. For our work, data size was a limiting factor for segmentation model performance in most fire regimes.

UAS platforms are making a strong foray into the operational framework of fire management agencies, but their continued rapid evolution poses several challenges. Much of the work on UAS vehicles is experimental, and their impact is usually constrained by their small-scale capabilities. Furthermore, the presence of UAS vehicles in wildland fire airspace could arguably inhibit, or even endanger, some of the manned flight operations that will always be necessary during wildfire response. Managing interagency communication, understanding regulatory requirements, and creating protocols for UAS response and where they fit in the larger operational effort are all important challenges for UAS operators in fire. Examples of large unmanned vehicle deployment for fire monitoring (Hall et al., 2008) and the use of edge-device computing (Fouda et al., 2023) both demonstrate the operational possibilities of large and small UAS monitoring of fire. It is probable that fire behavior detection could serve as an additional feature extraction tool during these types of efforts.

Conclusions

Our study demonstrated that YOLOv8 computer vision modeling is capable of successfully detecting and classifying NWCG fire behavior descriptions. Our images were sourced from low-altitude UAS flights during prescribed burn operations and focused on relatively low-severity fire behavior (Rank 1-3). Furthermore, we have provided an open-sourced dataset for future modeling efforts. Model precision, or successful detection of different classes of fire behavior, was high for different major fire regimes and all of them combined when training YOLO models on isolated image objects. Model precision remained acceptable when training YOLO segmentation models, but the introduction of background information around image objects led to a drastic reduction in recall and performance for all models but forested areas. For the forest regime, the segmentation model performed well enough to serve as a potentially useful model for real-time deployment, and minimally demonstrated that fire behavior can be segmented reliably in some circumstances using our methods. Our results suggest that future modeling efforts might be more successful if they are developed for a specific fire regime. This is especially important, considering the lack of data available and the time-intensiveness of developing new datasets. Lack of datasets consisting of several thousand labeled images was most likely the primary reason for low segmentation model performance. Overall, our study has demonstrated that in addition to smoke and flame detection, computer vision technologies can extract and identify even more nuanced fire phenomena. This development represents a step towards several opportunities available for leveraging deep learning, computer vision technology for advanced fire monitoring purposes.

Declarations

Ethics approval and consent to participate: Not applicable

Consent for publication: Not applicable

Availability of data and material: The labeled image dataset of combined fire regimes is available at: https://app.roboflow.com/raven-environmental-services/fire-behavior/9

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Authors' contributions: BL: conceptualization, data curation, formal analysis, methodology, validation, writing - original draft, and writing - review and editing. EdL: formal analysis, methodology, validation, and writing -review and editing.

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References

1. Abid, F., 2021. A Survey of Machine Learning Algorithms Based Forest Fires Prediction and Detection Systems. Fire Technol 57, 559–590. https://doi.org/10.1007/s10694-020-01056-z
2. Ambrosia, V.G., Wegener, S.S., 2009. Unmanned Airborne Platforms For Disaster Remote Sensing Support, in: Peter, P.-G. (Ed.), Geoscience and Remote Sensing. InTech. https://doi.org/10.5772/8302
3. Bahhar, C., Ksibi, A., Ayadi, M., Jamjoom, M.M., Ullah, Z., Soufiene, B.O., Sakli, H., 2023. Wildfire and Smoke Detection Using Staged YOLO Model and Ensemble CNN. Electronics 12, 228. https://doi.org/10.3390/electronics12010228
4. Barmpoutis, P., Stathaki, T., Dimitropoulos, K., Grammalidis, N., 2020. Early Fire Detection Based on Aerial 360-Degree Sensors, Deep Convolution Neural Networks and Exploitation of Fire Dynamic Textures. Remote Sensing 12, 3177. https://doi.org/10.3390/rs12193177
5. Beachly, E., Higgins, J., Laney, C., Elbaum, S., Detweiler, C., Allen, C., Twidwell, D., 2017. A micro-UAS to Start Prescribed Fires, in: Kulić, D., Nakamura, Y., Khatib, O., Venture, G. (Eds.), 2016 International Symposium on Experimental Robotics, Springer Proceedings in

Advanced Robotics. Springer International Publishing, Cham, pp. 12–24. https://doi.org/10.1007/978-3-319-50115-4_2

6. Bisong, E., 2019. Google Colaboratory, in: Building Machine Learning and Deep Learning Models on Google Cloud Platform. Apress, Berkeley, CA, pp. 59–64. https://doi.org/10.1007/978-1-4842-4470-8_7
7. Bowman, D.M.J.S., Kolden, C.A., Abatzoglou, J.T., Johnston, F.H., Van Der Werf, G.R., Flannigan, M., 2020. Vegetation fires in the Anthropocene. Nat Rev Earth Environ 1, 500–515. https://doi.org/10.1038/s43017-020-0085-3
8. Bowman, D.M.J.S., Williamson, G.J., Abatzoglou, J.T., Kolden, C.A., Cochrane, M.A., Smith, A.M.S., 2017. Human exposure and sensitivity to globally extreme wildfire events. Nat Ecol Evol 1, 0058. https://doi.org/10.1038/s41559-016-0058
9. Castelli, M., Vanneschi, L., Popovič, A., 2015. Predicting Burned Areas of Forest Fires: an Artificial Intelligence Approach. fire ecol 11, 106–118. https://doi.org/10.4996/fireecology.1101106
10. Chen, X., Hopkins, B., Wang, H., O'Neill, L., Afghah, F., Razi, A., Fulé, P., Coen, J., Rowell, E., Watts, A., 2022. Wildland Fire Detection and Monitoring Using a Drone-Collected RGB/IR Image Dataset. IEEE Access 10, 121301–121317. https://doi.org/10.1109/ACCESS.2022.3222805
11. Fire Behavior Image Dataset [WWW Document], 2024. Roboflow Universe. URL https://app.roboflow.com/raven-environmental-services/fire-behavior/9 (accessed 1.24.24).
12. Flannigan, M., Cantin, A.S., De Groot, W.J., Wotton, M., Newbery, A., Gowman, L.M., 2013. Global wildland fire season severity in the 21st century. Forest Ecology and Management 294, 54–61. https://doi.org/10.1016/j.foreco.2012.10.022

13. Fouda, M.M., Sakib, S., Fadlullah, Z.M., Nasser, N., Guizani, M., 2022. A Lightweight Hierarchical AI Model for UAV-Enabled Edge Computing with Forest-Fire Detection Use-Case. IEEE Network 36, 38–45. https://doi.org/10.1109/MNET.003.2100325

14. Griffith, G., Bryce, S., Omernik, J., Rogers, A., 2007. Ecoregions of Texas. Texas Commission on Environmental Quality.

15. Hall, P., Cobleigh, B., Buoni, G., Howell, K., 2008. Operational Experience with Long Duration Wildfire Mapping: UAS Missions Over the Western United States, in: AUVSI Unmanned Systems North America 2008. National Oceanic and Atmospheric Administration & NASA Dryden Flight Research Center, San Diego, CA.

16. Hodges, J.L., Lattimer, B.Y., 2019. Wildland Fire Spread Modeling Using Convolutional Neural Networks. Fire Technol 55, 2115–2142. https://doi.org/10.1007/s10694-019-00846-4

17. Jocher, G., Chaurasia, A., & Qiu, J. (2023). YOLO by Ultralytics (Version 8.0.0) [Computer software]. https://github.com/ultralytics/ultralytics

18. Keerthinathan, P., Amarasingam, N., Hamilton, G., Gonzalez, F., 2023. Exploring unmanned aerial systems operations in wildfire management: data types, processing algorithms and navigation. International Journal of Remote Sensing 44, 5628–5685. https://doi.org/10.1080/01431161.2023.2249604

19. Kirillov, A., Mintun, E., Ravi, N., Mao, H., Rolland, C., Gustafson, L., Xiao, T., Whitehead, S., Berg, A.C., Lo, W.-Y., Dollár, P., Girshick, R., 2023. Segment Anything.

20. Lattimer, B.Y., Huang, X., Delichatsios, M.A., Levendis, Y.A., Kochersberger, K., Manzello, S., Frank, P., Jones, T., Salvador, J., Delgado, C., Angelats, E., Parés, M.E., Martín, D., McAllister, S., Suzuki, S., 2023. Use of Unmanned Aerial Systems in Outdoor Firefighting. Fire Technol. https://doi.org/10.1007/s10694-023-01437-0

21. Lawrence, B.L., Mundorff, K., Keith, E., 2023. The impact of UAS aerial ignition on prescribed fire: a case study in multiple ecoregions of Texas and Louisiana. fire ecol 19, 11. https://doi.org/10.1186/s42408-023-00170-x
22. Moran, C.J., Seielstad, C.A., Cunningham, M.R., Hoff, V., Parsons, R.A., Queen, Ll., Sauerbrey, K., Wallace, T., 2019. Deriving Fire Behavior Metrics from UAS Imagery. Fire 2, 36. https://doi.org/10.3390/fire2020036
23. Muchiri, N., Kimathi, S., 2016. A Review of Applications and Potential Applications of UAV, in: 2016 Annual Conference on Sustainable Research and Innovation. Presented at the Proceedings of the Sustainable Research and Innovation Conference.
24. Mukhiddinov, M., Abdusalomov, A.B., Cho, J., 2022. A Wildfire Smoke Detection System Using Unmanned Aerial Vehicle Images Based on the Optimized YOLOv5. Sensors 22, 9384. https://doi.org/10.3390/s22239384
25. National Wildfire Coordinating Group, 2021. Fire Behavior Observations/Descriptions [WWW Document]. Fire Behavior Observations. URL https://www.nwcg.gov/publications/pms437/cffdrs/fire-behavior-observations (accessed 11.13.23).
26. Osco, L.P., Wu, Q., de Lemos, E.L., Gonçalves, W.N., Ramos, A.P.M., Li, J., Junior, J.M., 2023. The Segment Anything Model (SAM) for Remote Sensing Applications: From Zero to One Shot.
27. Pádua, L., Vanko, J., Hruška, J., Adão, T., Sousa, J.J., Peres, E., Morais, R., 2017. UAS, sensors, and data processing in agroforestry: a review towards practical applications. International Journal of Remote Sensing 38, 2349–2391. https://doi.org/10.1080/01431161.2017.1297548

28. Rahman, E.U., Khan, M.A., Algarni, F., Zhang, Y., Irfan Uddin, M., Ullah, I., Ahmad, H.I., 2021. Computer Vision-Based Wildfire Smoke Detection Using UAVs. Mathematical Problems in Engineering 2021, 1–9. https://doi.org/10.1155/2021/9977939
29. Redmon, J., Divvala, S., Girshick, R., Farhadi, A., 2016. You Only Look Once: Unified, Real-Time Object Detection, in: 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR). Presented at the 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), IEEE, Las Vegas, NV, USA, pp. 779–788. https://doi.org/10.1109/CVPR.2016.91
30. Sathishkumar, V.E., Cho, J., Subramanian, M., Naren, O.S., 2023. Forest fire and smoke detection using deep learning-based learning without forgetting. fire ecol 19, 9. https://doi.org/10.1186/s42408-022-00165-0
31. Shamaoma, H., Chirwa, P.W., Ramoelo, A., Hudak, A.T., Syampungani, S., 2022. The Application of UASs in Forest Management and Monitoring: Challenges and Opportunities for Use in the Miombo Woodland. Forests 13, 1812. https://doi.org/10.3390/f13111812
32. Ultralytics YOLOv8 Docs [WWW Document], 2023*a*. Performance Metrics Deep Dive. URL https://docs.ultralytics.com/guides/yolo-performance-metrics/ (accessed 1.24.24).
33. Ultralytics YOLOv8 Docs [WWW Document], 2023*b*. The New Frontier of Vision AI. URL https://docs.ultralytics.com/ (accessed 11.13.23).
34. Wang, J., Fan, X., Yang, X., Tjahjadi, T., Wang, Y., 2022*a*. Semi-Supervised Learning for Forest Fire Segmentation Using UAV Imagery. Forests 13, 1573. https://doi.org/10.3390/f13101573
35. Wang, S., Zhao, J., Ta, N., Zhao, X., Xiao, M., Wei, H., 2021. A real-time deep learning forest fire monitoring algorithm based on an improved Pruned + KD model. J Real-Time Image Proc 18, 2319–2329. https://doi.org/10.1007/s11554-021-01124-9

36. Wang, Y., Hua, C., Ding, W., Wu, R., 2022*b*. Real-time detection of flame and smoke using an improved YOLOv4 network. SIViP 16, 1109–1116. https://doi.org/10.1007/s11760-021-02060-8

37. Zhao, L., Zhi, L., Zhao, C., Zheng, W., 2022. Fire-YOLO: A Small Target Object Detection Method for Fire Inspection. Sustainability 14, 4930. https://doi.org/10.3390/su14094930

38. Zajkowski, T.J., Dickinson, M.B., Hiers, J.K., Holley, W., Williams, B.W., Paxton, A., Martinez, O., Walker, G.W., 2016. Evaluation and use of remotely piloted aircraft systems for operations and research – RxCADRE 2012. Int. J. Wildland Fire 25, 114. https://doi.org/10.1071/WF14176

39. Zhan, J., Hu, Y., Cai, W., Zhou, G., Li, L., 2021. PDAM–STPNNet: A Small Target Detection Approach for Wildland Fire Smoke through Remote Sensing Images. Symmetry 13, 2260. https://doi.org/10.3390/sym13122260

40. Zheng, H., Duan, J., Dong, Y., Liu, Y., 2023. Real-time fire detection algorithms running on small embedded devices based on MobileNetV3 and YOLOv4. fire ecol 19, 31. https://doi.org/10.1186/s42408-023-00189-0