Wildfire Risk Classification:
A Computer Vision study of estimating Environmental Resilience using Remote Sensing imagery for Carbon Offset Frameworks

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Extended Abstract

The climate policy landscape has experienced a significant shift since the Paris Agreement in 2015, which stipulated the imperative of constraining the global mean temperature increase to 1.5°C. The urgency to combat global warming has intensified, necessitating the removal of carbon dioxide from the atmosphere (UNFCCC, 2020). Carbon offset projects, particularly those involving forests, are pivotal in this effort as they sequester carbon dioxide. However, these projects face significant risks from wildfires, which can release sequestered carbon back into the atmosphere, undermining their effectiveness.

This study addresses this critical issue by developing advanced wildfire risk classification models tailored for carbon offset projects. Utilizing remote sensing imagery and convolutional neural networks (CNNs), this study integrates techniques like feature extraction and clustering-based undersampling to efficiently handle data imbalance while improving classification performance of classes corresponding to higher risk areas. Furthermore, a framework for on-demand image acquisition is developed and the efficacy of the model in real world carbon offset projects is evaluated. This novel approach aims to enhance the resilience and scalability of carbon offset projects, ensuring their long-term viability and effectiveness in mitigating climate change.

The primary dataset used to train the classification models is the 'FireRisk' dataset, introduced in a 2023 study titled 'FireRisk: A Remote Sensing Dataset for Fire Risk Assessment with Benchmarks Using Supervised and Self-supervised Learning'. This dataset was produced to advance fire risk assessment endeavours by capitalising on the potential of remote sensing imagery. The data includes a total of 91,872 remote sensing images that are acquired from the National Agriculture Imagery Program (NAIP) and labelled into the seven classifications derived from the Wildfire Hazard Potential (WHP) raster dataset (very low, low, moderate, high, very high, non-burnable and water).

In our approach, we utilized techniques such as Local Binary Pattern (LBP) and Grey Level Co-Occurrence Matrix (GLCM) to extract features from various colour channels (greyscale, RGB, and HSV). These features were then clustered using methods including K-Means clustering, Agglomerative Hierarchical Clustering, and Self-Organizing Maps (SOM) to identify patterns across seven fire risk classes. After evaluating the cluster quality both qualitatively and quantitatively, it became evident that some images within each of the seven classes were essentially sparse, lacking discernible features like biomass fuel or urban development. These sparse images were hypothesized to introduce noise into the training data. To address this, we removed all sparse images from the majority classes and created an eighth class labelled 'sparse' for both the training and validation datasets. This adjustment reduced the sample sizes of the remaining classes by over 50%. This decision was further supported by our literature review, which indicated that regions with sparse fuel presence have a very low risk of wildfires. Therefore, accurately classifying these regions as sparse and not misidentifying them as higher risk was crucial for our goal of precisely predicting wildfire risk, particularly for carbon offset projects.

Reduction in original class size (% of initial training sample)	Very Low	Non-Burnable	Low	Moderate	High
GLCM (Greyscale)	54.97%	32.65%	47.43%	48.80%	51.75%
SOM	67.95%	55.55%	44.52%	42.63%	43.77%
GLCM (RGB+HSV+Greyscale)	37.79%	13.32%	21.88%	34.95%	24.97%

Local Binary Pattern (LBP) features were excluded from the study because they did not effectively capture the sparse samples. We then trained pre-trained convolutional neural networks, specifically ResNet-18 and ResNet-50, using the updated training datasets derived the three remaining feature descriptors. To avoid overcomplicating the commercial implementation, model choices were kept simple. It was observed that using the multichannel GLCM feature descriptor combined with K-Means clustering and ResNet-50 achieved the highest classification accuracy.

The selected model underwent hyperparameter tuning and optimization through three different techniques: (1) Optuna Tuning: We used Optuna to fine-tune the model's hyperparameters. This approach led to a slight improvement in the model's performance, (2) Updated Pre-trained Weights: We experimented with updating the pre-trained weights, but this resulted in overfitting, and (3) Fake Class Imbalance and Class Weights: We introduced a fake class imbalance and adjusted class weights to address performance issues with classes exhibiting lower recall rates. This method significantly improved the recall rates for low and moderate-risk classes.

When comparing our study's training classification performance to the baseline performance reported in the original study that introduced the 'FireRisk' dataset, we found notable differences. The original study reported an accuracy of 65.29% with their best-performing model, which

utilized a pre-trained Masked Auto Encoder (MAE). In contrast, our final validation accuracy reached 67.67%. Additionally, the original study's use of a pre-trained ResNet-50 resulted in a validation accuracy of 63.20%, which was lower than our final validation accuracy achieved with the same ResNet-50 model but with tuned hyperparameters.

Our study's best-performing model demonstrated higher recall rates in the higher-risk classes compared to the original study. For instance, the original study's pre-trained MAE achieved a recall rate of 49.58% for the 'Very High' class and 24.92% for the 'High' class. In contrast, our final ResNet-50 model, without hyperparameter tuning, achieved recall rates of 97% and 72% for these classes, respectively. This improved performance is crucial for wildfire risk classification, where higher-risk classes typically indicate areas with significant combustible material and conditions conducive to rapid fire spread. Accurate classification of these areas is vital for effective fire management strategies and for decision-making in carbon offset projects, ensuring that high-risk areas are identified and addressed appropriately.

	Original Study	***Our Study***		
	No Undersampling: MAE	Intentional Undersampling: ResNet-50	Intentional Undersampling: ResNet-50 (Optuna)	Random Undersampling: ResNet-50
Validation accuracy	65.29%	67.25%	67.67%	62.81%
	Recall Rates			
0. Non-burnable	0.87	0.77	0.79	0.78
1. Very Low	0.79	0.65	0.67	0.51
2. Low	0.3	0.29	0.26	0.41
3. Moderate	0.29	0.23	0.23	0.29
4. High	0.25	0.72	0.66	0.37
5. Very High	0.5	0.97	0.99	0.48
6. Water	0.88	0.95	0.95	0.89
7. Sparse		0.81	0.86	

The two top-performing models (ResNet-50 without hyperparameter tuning and with hyperparameters tuned using Optuna) were evaluated on 50 images of the Green Diamond Resource Company's Klamath-East IFM project area extracted using publicly available NAIP aerial imagery from 2020 and 2022, processed independently with QGIS. This project was selected as it experienced a significant drop in carbon stocks during its sixth reporting period (2020-21), falling to 12.4 million tons of CO2 equivalent (tCO2e)—almost 1 million tCO2e below the baseline of 13.4 million tCO2e due to the Bootleg Fire, which began on July 6, 2021, and was contained by August 15, 2021. The fire, which burned through a quarter of the project's 449,902 acres (182,069 hectares), released over 3.8 million tCO2e back into the atmosphere. This case highlights the real-world implications of carbon offset projects, the impact of natural disturbances on carbon stocks, and provides insights for improving temporal project management, and resilience.

Model 1 (No Hyperparameter Tuning): Predicted 'High' wildfire risk in 78% of the selected area in 2020 and 'Moderate' for 20% of the site, with changes in risk categories for 30% of the 50 test images between 2020 and 2022. These adjustments delineated that, in 2022, post the occurrence of the Bootleg fire, 58% of the site was categorized as 'High' risk, 36% as 'Moderate' risk, and 6% as 'Sparse' areas.

Model 2 (Hyperparameters Tuned): Classified 94% of the area as 'High' risk, and 6% of the site in 'Moderate' risk in 2020, with 80% of risk classifications remaining unchanged in 2022, indicating improved stability and accuracy over time. In 2022, post the occurrence of the Bootleg fire, 76% of the site was categorized as 'High' risk, 18% as 'Moderate' risk, 4% as 'Low' risk, and 2% as 'Sparse' areas.

In an overall comparison of the performance between the two classification models, Model 2 demonstrates a superior ability to discern nuances, and transitions in classifications compared to Model 1. This suggests that the hyperparameter tuning applied to Model 2 facilitated a more effective learning of patterns and a better comprehension of the aerial imagery data. This observation leads to the conclusion that given more time and computational resources, further enhancements in classification performance could be achieved through additional rounds of hyperparameter tuning.

Despite the limitations of the WHP dataset, its synergy with NAIP imagery in the 'FireRisk' dataset enhances its effectiveness. This collaboration allows for a better approximation of relative wildfire risk on on-the-ground assets captured in the NAIP imagery. This is further substantiated by the 2020 WHP raster dataset's classifications for our test site where only 10% of the 50 test site images are categorized as high risk, 70% as moderate risk, 16% as low risk, and 4% as very low risk. However, when our classification model employing both NAIP and WHP dataset via the 'FireRisk' dataset was used, 94% of the area was classified as 'High' risk, and the remaining 6% was categorized as 'Moderate' risk in the 2020 classifications of the model with tuned hyperparameters. (Figure 63) This classification better represents the real-world scenario, marked by the extensive wildfires across the entire site, emphasizing the 'FireRisk' dataset's effectiveness.

While we acknowledge the ongoing nature of this study and recognize the need for further refinement to boost performance, the strategic undersampling of our dataset, guided by unsupervised learning and instance selection approaches, lays the foundation for continual improvement and seamless implementation within carbon offset frameworks by not only facilitating enhanced performance but also offering the practical advantage of reduced computational requirements associated with the use of an undersampled dataset. Further, the results obtained from the CNN models not only underscore the models' proficiency in providing realistic risk classifications based on aerial imagery but also offer valuable insights into the practicality and feasibility of incorporating such methodologies within carbon markets for effective risk mitigation.

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