NORTHWEST NAZARENE UNIVERSITY

Using Pixel-Based Classification and Change Detection to Map Burn Extent & Severity from Hyperspatial Drone and Very-High Resolution Satellite Imagery.

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Submitted to the Department of Mathematics and Computer Science

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Cole Edward McCall

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By

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ABSTRACT

Using Pixel-Based Classification and Change Detection to Map Burn Extent & Severity from Hyperspatial Drone and Very-High Resolution Satellite Imagery.

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Over the past few years, the size and severity of wildland forest fires have continued to increase, causing more damage and destruction around the world. New methods have been developed to utilize machine learning algorithms to map forest fire burn extent and fire severity using aerial imagery. Algorithms such as the Support Vector Machine (SVM) can be used to classify pixels as either black ash, white ash, or unburned, while the Mask Region-Based Convolutional Neural Network (MaskR-CNN) can be used to find and map tree objects. The results from these classifications can be used to help local wildland fire managers assess the burned area and create a recovery plan.

This research has several steps: 1) improving the current method for mapping burn extent with hyperspatial drone imagery, 2) using the same (or similar) methods to determine if wildland fire burn extent can be mapped with high-resolution satellite imagery, 3) evaluating how spatial and spectral resolution impacts the accuracy of the classification, and 4) try to develop new methods that involve less (or no) training data, such as unsupervised change detection. The results of each step were promising, creating much more accurate classifications of wildland fire burn extent than can be obtained by other common products such as LANDFIRE. This research will continue, likely moving in a direction that further examines the use of unsupervised and self-supervised machine learning, which greatly reduces the training data needed.

Acknowledgments

To begin, I would like to thank all my classmates that helped with this research. From the members of Spatial Analysis semester project groups that helped explore mapping burn extent with PlanetScope and Worldview2 imagery to my teammates in Machine Learning, I really appreciate every contribution from Cody Lirazan, Kyle Edgerton, Parker Bartlow, William Gibson, Camden McGath, Kedrick Jones, Daniel Harris, Adrien de Orta, Abigail Brackett, Elliot Lochard, Zachary Smith, and Carter Katzenberger. I would also like to acknowledge several more students who participated in summer or spring FireMAP research opportunities, including Bryn Gautier, Cody Robbins, Kamden Robbins, Tyler Shea, and Timothy Zink.

In addition, I want to thank my professors for a great experience at NNU, both inside and outside of the classroom, with a special shoutout to Dale Hamilton for all his help over the years and for providing so many great opportunities for me to experience.

I would also like to thank my family, specifically my loving parents for always supporting me and encouraging me no matter what. Lastly, I would like to thank my fiancé, Jimena, for all her help during this journey.

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Overview

This research contains four components, each of which is part of Northwest Nazarene University's ongoing FireMAP project. The first component of this research took place from May 2021 to September 2021 as part of NNU's summer research program, intending to improve the process for mapping burn extent from 5cm resolution hyperspatial drone imagery. Based on previous research, machine learning algorithms such as the Support Vector Machine (SVM) have been used to accurately map the burn extent of wildland fires [1]–[3], whereas a Mask Region-Based Convolutional Neural Network (Mask R-CNN) could be used to detect tree objects [4]. Since surface vegetation on the ground may be obstructed by tree crowns above, the aerial imagery captured by drones may produce an inaccurate mapping of the burn extent, observing the tree crown on top instead of the possibly burned vegetation underneath [2], [5]. To enhance the burn extent classification, a program was developed to find all tree objects completely surrounded by burned areas and reclassify those tree objects as burned regions since the areas underneath the tree crown were burned, even though the tree crown itself did not burn. The results of this project were published in an article in the *Remote Sensing* journal titled "Mapping Forest Burn Extent from Hyperspatial Imagery Using Machine Learning" [5].

The second component is an ongoing process that started immediately after completing the first work. Even though hyperspatial drone imagery can accurately map burn extent, it can be difficult and time-consuming to collect/acquire drone imagery. Additionally, mapping the burn extent involves utilizing an SVM classifier that must be trained to the image, a MaskR-CNN that must be trained to detect trees, and an additional program to enhance the burn extent created by the SVM classifier. For these reasons, the FireMAP research team began to study how substituting 5cm spatial resolution drone imagery for lower 1.5 to 3m spatial resolution satellite imagery affected the accuracy of mapping burn extent. While this high-resolution satellite imagery has a lower spatial resolution (~1.5 to 3m instead of 5cm), the satellite imagery has a higher spectral resolution, containing eight multispectral bands as opposed to the typical Red, Green, and Blue (RGB) bands of an image. When using satellite imagery instead of drone imagery, the higher spatial resolution is swapped for a higher spectral resolution, introducing bands like Red Edge, Yellow, and Near Infrared into the mix.

The changes in resolution between images created a third component in this research: evaluating how spatial resolution and spectral band selection impact the accuracy of a burn extent classification. Two sets of satellite imagery were used to explore these ideas: ~1.8m spatial resolution Worldview2 imagery [6] and ~3m spatial resolution PlanetScope imagery [7]. A manuscript titled "Determination of Multi-Spectral Band Utility for Mapping Wildland Fire Burn Extent and Severity" is currently being developed, which involves evaluating spatial resolution and spectral band selection with Worldview2 imagery. A separate manuscript for mapping burn extent from PlanetScope imagery is expected to begin development this summer.

Finally, a separate component of this research was introduced at Frontier Development Lab (FDL) in 2022, where NNU's summer researchers assisted in the FDL-US 2022

Wildfire Challenge. The wildfire research team was given a challenge by the U.S. Department of Energy to determine if “... ML-enhanced tools can be used to prevent fires from starting or new fires from combining to create mega-fires" [8, p. 2]. Similar to the previous components of this research, the FDL-US 2022 Wildfire team wanted to use machine learning algorithms to map burn extent from satellite imagery. However, this team wanted to use self-supervised learning instead of supervised learning methods that require large amounts of training data. Additionally, the wildfire team partnered with Planet, who gave the team access to ~3m spatial resolution PlanetScope imagery, with near-daily updates, which gave the team even more opportunities. This project aimed to use the PlanetScope imagery to perform daily wildfire change detection, which could then be used to predict wildfire changes in simulation. An advanced deep learning technique called contrastive learning was used to perform unsupervised change detection, which resulted in detecting burn area change. The results of this project were published in “Unsupervised Wildfire Change Detection based on Contrastive Learning” [9].

Background

Currently, local fire managers are overwhelmed by the severity of wildland fires, lacking the resources to make informed decisions in an adequate measure of time. Regulations within the United States require fire recovery teams to acquire post-fire data within 14 days of containment, including mapping burn extent [10]. Fire managers and recovery teams have been using Landsat imagery, which contains 8 spectral bands of 30m spatial resolution along with a panchromatic band (15m) and two thermal bands (100m) [11, p. 9], [12]. Assuming that no clouds or smoke obstruct the view of the fire, Landsat imagery can only be collected for a site once every 16 days, making it challenging to acquire data within the time required.

Fire Monitoring and Assessment Platform (FireMAP)

Over the past decade at Northwest Nazarene University (NNU), the Fire Monitoring and Assessment Platform (FireMAP) research team has successfully employed several methods to investigate and map wildland fire effects. The majority of this work revolved around using sUAS (small Unmanned Aerial Systems) to collect imagery with a spatial resolution of ~5cm and Red, Green, and Blue (RGB) spectral bands [2], then use machine learning algorithms such as the Support Vector Machine (SVM) to classify the imagery into two classes - burned and unburned pixels - creating a burn extent map [1], [13]. For the SVM classifier to work, it must be trained by hand-drawn polygons that inform the classifier what burned and unburned pixels are. Similarly, deep learning algorithms like the MaskR-CNN can be trained to find objects, such as trees, by annotating every object in hundreds of images. The resulting tree objects found by the MaskR-CNN could then be used to calculate the change in canopy cover, or tree mortality, by comparing the area produced from the detected tree objects to the pre-fire canopy cover estimate provided by LANDFIRE [4], [14].

Machine Learning

This research uses several machine learning algorithms to map burn extent and fire severity from various imagery products. Several terms will be defined to better understand how machine learning is applied in this space. Additionally, explanations of the two particular machine learning algorithms used frequently in the research will be offered: the Support Vector Machine (SVM) and the Mask Region-Based Convolutional Neural Network (MaskR-CNN).

In a presentation in the Advanced Database course, Dr. Dale Hamilton explained data science as “the exploration of data via scientific method to discover meaning or insight, and the construction of software systems that utilize such insight in a business context” [15]. Dr. Hamilton also helped provide some clarity about the terms artificial intelligence (AI), machine learning (ML), and data science (DS), specifically how the three terms are often used interchangeably but have different meanings. Artificial intelligence is an agent that observes percepts in the environment around the agent through sensors, makes a decision or calculation, and then performs an action on/within the environment. Essentially, artificial intelligence produces actions based on data. Machine learning, a subset of artificial intelligence, is a method of AI that learns from data and is used to make predictions.

The MaskR-CNN and the SVM are examples of machine learning that implement supervised classification methods, where the user is required to “train” the model by providing examples of training data. While there are similarities, the MaskR-CNN is a supervised object classification method, whereas the SVM is a supervised pixel classification method.

Using Drone Imagery to Map Burn Extent

Despite Hamilton's success in accurately mapping burn extent from drone imagery with a support vector machine [2], this study did not account for regions that experienced surface fire underneath tree crowns, as shown in Figure 1. Forested areas with high canopy cover can produce a drastic underestimate/underreporting of the burn extent, as tree crowns obstruct burned areas underneath, which can not be observed from aerial drone imagery. While the support vector machine classifier has difficulty mapping forest burn extent by itself, it can be used in combination with a tree object classification, finding all areas completely surrounded by burned pixels and reclassifying these tree objects as part of the burn extent, as shown in Figure 2. To find these tree objects, a Mask Region-Based Convolutional Neural Network (MaskR-CNN) can be trained, then used on the drone imagery. Reclassifying the areas that experience sub-crown surface fire (burned areas underneath tree crowns) produces an enhanced burn extent map, increasing the accuracy by nearly 30 percentage points.

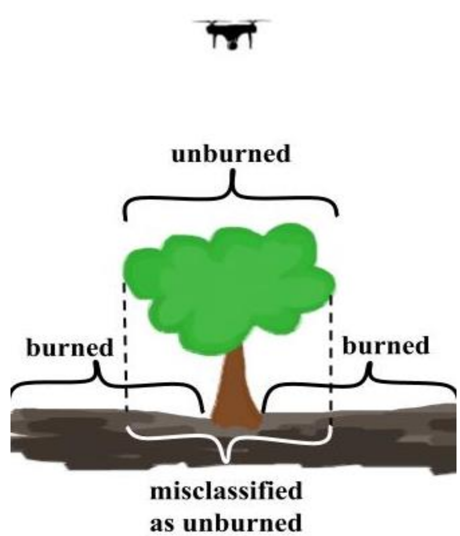

Figure 1 - Misclassified Areas that Experienced Sub-Crown Surface Fire

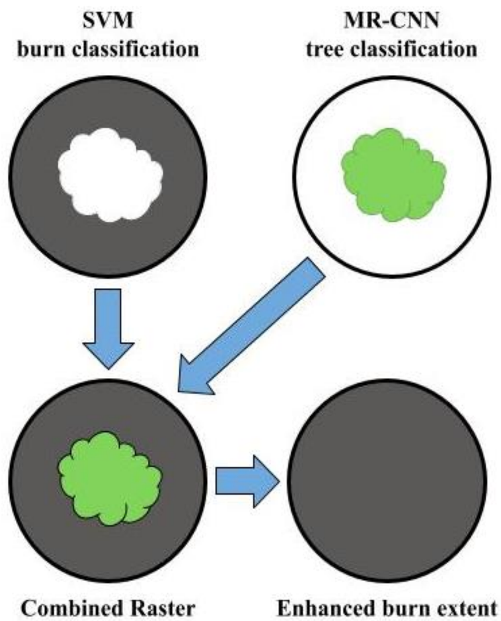

Figure 2 - Reclassifying Areas that Experienced Sub-Crown Surface Fire

Since this project continued the FireMAP research at Northwest Nazarene University, my role included several tasks. First, validation data of the support vector machine classification was created in ArcGIS Pro using the Training Samples Manager. Two classes of polygons were hand-drawn in regions where the team was confident the pixels were either burned or unburned. Included in the burned class were tree crowns completely surrounded by burned pixels, as these regions experience a sub-crown surface fire. Using these polygons, the accuracy of the burn extent classification could be calculated.

As expected, the initial classification produced a low accuracy of only 59%, as areas experiencing sub-crown surface fire were incorrectly classified. To account for this error, the 2-class tree object classification (tree vs. not tree) was merged with the 2-class burn extent classification (burned vs. unburned), resulting in a 3-class (burned, unburned tree, unburned surface) raster with both tree and burn extent classifications. This 3-class raster was then used as input into a program that searched for pixels from the unburned tree class completely surrounded by pixels from the burned class and reclassified those pixels as burned areas. Accuracies were calculated again using the validation data, producing a slight increase in accuracy of 65%.

At this point, the team noticed a crucial feature in the support vector machine that had not been observed previously. Even though the team was working with four different study areas that experienced a fire, the same support vector machine classifier was used to produce the burn extent classification. Since each image was taken at a different time after the fire, in a different location, it is not reasonable to train the classifier on one image and expect it to accurately classify other images, especially since there were noticeable differences in the burned areas of each image. For example, the burned areas in the Mesa fire were light gray pixels, whereas the burned areas in the hoodoo fire were black pixels.

As a result, the team trained new support vector machines in ArcGIS Pro, annotating burned and unburned regions for each image. Once completed, each support vector machine classifier could be used to create a burn extent map of the image it was trained on, greatly improving the accuracy of the map (up to 77%). Once the burn extent enhancement tools (that addressed sub-crown surface fire) were rerun, the accuracy improved even more (to 86%). To read more about the exact methodology used and the results found, please read Mapping Forest Burn Extent from Hyperspatial Imagery Using Machine Learning in Appendix C. Table 1 also briefly summarizes the various classification accuracies.

Table 1 - Enhancing Forest Burn Extent Classification

	Accuracy	Specificity	Sensitivity
Original SVM Surface Burn Extent Classification	59.5%	94.5%	24.3%
Enhanced Reclassification based on Original SVM Classification	65.8%	93.4%	38.4%
Retrained SVM Surface Burn Extent Classifcation	77.6%	95.3%	59.4%
Final Reclassification with Burn Extent Enhancement Tools	86.7%	94.6%	77.7%
Overall Changes	+27.2%	+0.1%	+53.7%

Substituting High-Resolution Satellite Imagery for Drone Imagery

While drone imagery is excellent for mapping the burn extent of small fires (<1000 acres), it can be difficult (or nearly impossible) to acquire large amounts of drone imagery promptly. Fire managers may not have the time or resources to fly drones and obtain imagery, while wildland fires continue to grow in size and severity, making it somewhat impractical to use drone imagery on a larger scale. Even though slightly lower spatial resolution, satellite imagery available to researchers through NASA's Commercial Smallsat Data Acquisition Program [16] and Planet's Education and Research Program [17] can be substituted for hyperspatial drone imagery. Whereas drones capture images with 5 cm spatial resolution, products like PlanetScope and Worldview2 capture ~3m and ~1.8m spatial resolution imagery. These products are fantastic alternatives to drone imagery, allowing users to map much larger wildfires with similar accuracy. The specifications and examples of each image product can be seen in more detail in Appendix A.

To begin this process, pre-fire and post-fire PlanetScope images were downloaded from the Planet Explorer webpage (planet.com/explorer) for the Mesa fire. The team prototyped classifications to determine the feasibility of using ~3m spatial resolution products for mapping burn extent. Like the section above, this process involved training an SVM classifier in ArcGIS Pro with hand-drawn training data, classifying the downloaded PlanetScope images, creating validation data of burned and unburned areas, and calculating the accuracy of the mapped areas.

Additionally, students within the COMP3230 Spatial Analysis course were assigned to semester project groups, two of which included creating training and validation data of PlanetScope imagery. I led and instructed these groups on using the necessary tools in ArcGIS Pro, such as the Training Samples Manager, Image Classification, Tabulate Area, and more. The 2023 summer research team has been taking control of this project and will finish in May 2023, looking to publish soon after.

Evaluating the Impacts of Spatial vs. Spectral Resolution

As mentioned above, high-resolution satellite imagery (~1.8m to ~3m spatial resolution) is a great alternative to (~5cm spatial resolution) drone imagery for mapping burn extent. Despite the lower spatial resolution, satellite imagery contains additional spectral bands compared to the standard Red, Green, and Blue (RGB) bands acquired in drone imagery.

As a result, sacrificing spatial resolution adds spectral resolution (8 bands, including Near Infrared), introducing another question: how does spatial and spectral resolution impact the burn extent mapping accuracy?

To answer this question, Worldview2 imagery of the Mesa fire was downloaded through the cad4nasa.gsfc.nasa.gov portal using NASA's CSDA program. Once the imagery was downloaded, a support vector machine classifier was trained in ArcGIS Pro to map the burn extent in the image. Validation data was also created to compare the classified image to the highly confident hand-drawn polygons of burned and unburned regions to determine the accuracy of the burned area.

At the same time, the team created an Iterative Dichotomiser 3 program that could read in training samples, perform entropy analysis on the spectral bands, and construct a decision tree based on which spectral bands contained the most information content. The bands with the most information content could then be extracted and used as inputs for the SVM classifier, creating another classification. Additionally, all eight bands were reduced to three dimensions using Principle Component Analysis, creating a 3-band raster that could be used as input, along with a simple RGB image and the original 8-band image. While the spectral resolution did not seem to have a significant impact (average burn extent accuracy of 94%), there was an increase in specificity of 6 percentage points when comparing the RGB input to any of the other inputs that contained additional spectral resolution. This increase in specificity, which can be seen in Table 2, may occur in regions where the classifier has difficulty differentiating between shadows and burned areas, with the higher spectral resolution being used to distinguish between those classes more accurately.

Table 2 - Burn Extent Classification Metrics from Various Worldview2 Inputs

Input Layer	Accuracy	Specificity	Sensitivity
Worldview2 RGB Bands	91.37%	86.25%	94.72%
All 8 Worldview 2 Bands	94.44%	92.23%	95.89%
PCA-Transformed Bands	95.25%	92.26%	97.20%
ID3-Selected Bands	94.97%	92.15%	96.81%
Average	94.01%	90.72%	96.16%

The results of this work are currently being published in the *Remote Sensing* journal and a preview of the document is available in Appendix C.

Mapping Wildfires with Unsupervised Learning Methods

Even though high-resolution satellite images can be used for mapping burn extent with a support vector machine, there is a lot of work that needs to be done to train the SVM. For each area of interest that will be mapped, a separate SVM needs to be trained, requiring users to hand-draw training data for every fire, which is fine for a proof-of-concept but is not feasible for product users and creates more work for fire managers. Unsupervised learning allows researchers to develop a complex model with no training data that can be used to map the burned area of a wildfire. Fire managers (or other interested parties) could download/stream satellite images of their location, upload them to a program, and receive an accurate mapping of the wildfire area. With PlanetScope images being taken daily, this process could even be completely automated, sending burn extent maps to the users whenever a fire occurs.

This process began by exploring various ways that machine learning could be used to map wildfires. Additionally, all sorts of imagery products were examined, from high spatial resolution products like PlanetScope (~3m) to medium resolution products like Sentinel (10-60m) or lower resolution products like MODIS (250-1000m). After several weeks of research, the NNU FireMAP team traveled to Mountain View, California, to meet the rest of the FDL-US 2022 Wildfire challenge team. This FDL team was sponsored by Frontier Development Lab (FDL), the Department of Energy (DOE), and Planet, and were asked to determine how "...we can use ML-enhanced tools to prevent fires from starting or new fires from combining to create mega-fire" [8]. After 2 weeks of discussion and planning, the team decided to research an unsupervised change detection approach for mapping wildfires.

The first step was to start downloading large amounts of satellite imagery. Unlike the previous projects, where images were downloaded for one study area of ~1000 acres, this research required downloading daily imagery from five different study areas. Each of the fires lasted anywhere from 2 weeks to 4 months, with sizes ranging from ~30,000 acres to ~300,000 acres. Since so much data was required, multiple python scripts were developed to access Planet's developer APIs, downloading up to 1 TB of data daily. Additionally, these scripts could be run from Virtual Machines (VMs) in the Google

Cloud Platform (GCP), keeping all the code and data in the cloud, improving download and access times.

Each team member configured multiple VMs in GCP, with hardware specifications varying from a machine with a 1-core CPU and 2 GB of RAM, to a machine with a 128-core CPU, 512 GB of RAM, and powerful GPUs. The team worked collaboratively worldwide with team members in Washington, California, Idaho, and Massachusetts in the United States, Turkey, the Czech Republic, England, and Portugal. Each team member was a subject matter expert in slightly different fields, so the team shared each other's knowledge and experience to complete each task.

Using contrastive learning, the team developed and trained a model for mapping wildfires with unsupervised change detection. This project's exact methodology and results have been submitted for publication and can be read in Unsupervised Wildfire Change Detection based on Contrastive Learning.

Future Work

Finding Ideal Spatial Resolution

Despite the team's success in mapping burn extent from drone and satellite imagery, there are still questions regarding the ideal spatial resolution. Using 5cm hyperspatial drone imagery requires acquiring imagery by conducting aerial flights over burned areas instead of downloading or streaming imagery captured by a satellite. Even though the spatial resolution decreases when using satellite imagery instead of drone imagery, burned areas can still be mapped with high accuracy using machine learning. More fine features, such as individual trees or small pockets of white ash, could be easily observed with drone imagery but are difficult to notice even with a human eye in satellite imagery. It is unreasonable to expect a machine learning approach to detect these regions when the subject matter experts have difficulty mapping them.

This raises the question: what is the “sweet spot” for spatial resolution? 5cm imagery is great, but it may include more detail than necessary, and the acquisition process is not feasible for larger fires, requiring manual acquisition flights. At 1.8 meters, much of the detail that can be observed at 5cm is lost, and at 3 meters, it can be even more difficult to recognize. Future work could be conducted to analyze the different imagery products on the same fire and explore newer imagery products such as Planet’s Pelican [18] satellites, which provide 30cm satellite imagery anywhere in the world from 12 to 30 times per day.

Daily Imagery

Through Planet’s Education and Research Program, the university can download 5000 square kilometers of PlanetScope imagery per month [17]. Since PlanetScope satellites can acquire imagery anywhere in the world at least once a day, it is possible that additional insights can be obtained from daily images. Additional work may involve using day-by-day imagery to predict where a fire will spread in the future.

Unsupervised Learning

The FDL wildfire team successfully mapped wildfires from satellite imagery without training data. While these models are very complex, require large computational power to train, and can be difficult to explain, unsupervised learning has very good potential to map burned areas or predict wildfire behavior. Once completed, end users can detect wildfire in images not used in training or trained on. More work should be done to continue to explore how unsupervised learning can be used to detect and prevent wildfires.

Develop Applications that Implement Burn Extent Mapping Tools

There is also room to develop software that allows end users to perform these mappings of burned areas much more quickly. For example, an app with a Graphical User Interface (GUI) could be created so that users can specify an input image and receive a classified image showing the burned area. The source could be a downloaded satellite image or an image in the cloud. The selected image will be used as input for an already trained support vector machine or a trained deep learning model that uses unsupervised learning (like change detection with contrastive learning).

Conclusion

At this point, the FireMAP research team at Northwest Nazarene University has accurately mapped burn extent from drone imagery and high-resolution satellite imagery, using supervised and unsupervised machine learning methods. The past few years have been full of amazing opportunities to learn about data science, machine learning, remote sensing data, and wildlife ecology. As someone who has always loved maps and data, these projects offer a unique opportunity to combine personal passion and interests with skills and knowledge obtained in various computer science courses. The Spatial Analysis and Artificial Intelligence courses taught many necessary skills to complete the research tasks, while courses like Advanced Database Management and Machine Learning provided hands-on learning opportunities through semester group projects. Additionally, courses like C++ Programming, Database Design/Programming, Data Structures, Algorithm Analysis, and Python Programming were needed to gain a foundational understanding of the most complex concepts used in the research.

Additionally, working with Dr. Hamilton and Dr. Myers for almost three years on research created room for developing great relationships with the professors, the ability to present the team's work at conferences and in published papers, and collaboration with students and professionals all over the world. It is incredible to be graduating from Northwest Nazarene University as an author of two published articles with two more publications in development.

References

[1] D. Hamilton, M. Bowerman, J. Colwell, G. Donohoe, and B. Myers, “Spectroscopic analysis for mapping wildland fire effects from remotely sensed imagery,” *Journal of unmanned vehicle systems*, vol. 5, no. 4, Art. no. 4, 2017.

[2] D. Hamilton, R. Pacheco, B. Myers, and B. Peltzer, “kNN vs. SVM: a Comparison of Algorithms,” in *Proceedings of the Fire Continuum - Preparing for the future of wildland fire. 2018 May 21-24*, Missoula, MT: Proceedings RMRS-P-78. Fort Collins, CO: U.S. Department of Agriculture, Forest Service, Rocky Mountain Research Station., 2020, p. 95. [Online]. Available: https://www.fs.usda.gov/treesearch/pubs/60581

[3] J. Branham, B. Myers, Z. Garner, and D. Hamiton, “Evaluation of Texture as an Input of Spatial Context for Machine Learning Mapping of Wildland Fire Effects,” *Idaho Conference on Undergraduate Research*, Jul. 2017, [Online]. Available: https://scholarworks.boisestate.edu/icur/2017/Poster_Session/27

[4] D. A. Hamilton, K. L. Brothers, S. D. Jones, J. Colwell, and J. Winters, “Wildland Fire Tree Mortality Mapping from Hyperspatial Imagery Using Machine Learning,” *Remote Sensing*, vol. 13, no. 2, Art. no. 2, Jan. 2021, doi: 10.3390/rs13020290.

[5] D. Hamilton, K. Brothers, C. McCall, B. Gautier, and T. Shea, “Mapping Forest Burn Extent from Hyperspatial Imagery Using Machine Learning,” *Remote Sensing*, vol. 13, no. 19, Art. no. 19, Jan. 2021, doi: 10.3390/rs13193843.

[6] European Space Agency (ESA), “WorldView-2 - Earth Online,” *WorldView-2 Instruments*, Feb. 13, 2023. https://earth.esa.int/eogateway/missions/worldview-2 (accessed Feb. 13, 2023).

[7] “Understanding PlanetScope Instruments.” https://developers.planet.com/docs/apis/data/sensors/ (accessed Apr. 02, 2023).

[8] “FDL USA 2022 Technical Results and Findings.” Accessed: Apr. 02, 2023. [Online]. Available: https://www.calameo.com/read/0055032805743f9fd8bf6

[9] B. Zhang *et al.*, “Unsupervised Wildfire Change Detection based on Contrastive Learning.” arXiv, Nov. 26, 2022. doi: 10.48550/arXiv.2211.14654.

[10] D. Hamilton, “Improving Mapping Accuracy of Wildland Fire Effects from Hyperspatial Imagery Using Machine Learning,” The University of Idaho, 2018.

[11] National Aeronautics and Space Administration (NASA), “Landsat 9 Instruments,” *NASA*, Feb. 13, 2023. http://www.nasa.gov/content/landsat-9-instruments (accessed Feb. 13, 2023).

[12] National Aeronautics and Space Administration (NASA), “Landsat 8 Bands,” *Landsat 8 Bands*, Jul. 21, 2020. https://landsat.gsfc.nasa.gov/landsat-8/landsat-8-bands/ (accessed Jul. 22, 2020).

[13] L. B. Lentile* *et al.*, “Remote sensing techniques to assess active fire characteristics and post-fire effects,” *Int. J. Wildland Fire*, vol. 15, no. 3, pp. 319–345, Sep. 2006, doi: 10.1071/WF05097.

[14] LANDFIRE, “Landfire Program,” 2020. https://landfire.gov/ (accessed Nov. 25, 2020).

[15] D. Hamilton, “What is Data Science?,” Sep. 02, 2022. Accessed: Apr. 02, 2023. [Online]. Available: https://docs.google.com/presentation/d/17FDm2j-Y_OaiEKnUDxhRp9gJyYVU5bg3

[16] National Aeronautics and Space Administration, “Commercial Smallsat Data Acquisition (CSDA) Program | Earthdata,” 2023. https://www.earthdata.nasa.gov/esds/csda (accessed Mar. 29, 2023).
[17] “Education and Research Program | Planet.” https://www.planet.com/markets/education-and-research/ (accessed Apr. 02, 2023).
[18] “Pelican,” *Planet*. https://www.planet.com/products/pelican/ (accessed Apr. 02, 2023).

Appendix A – Specifications of Different Imagery Products Used

Imagery Product	Spatial Resolution	Spectral Resolution
Drone (Hyperspatial)	5 centimeters	3 Bands (RGB) ● Red ● Green ● Blue
Worldview2	~1.8 meters	8 Bands ● Coastal Blue ● Blue ● Green ● Yellow ● Red ● Red Edge ● Near Infrared 1 ● Near Infrared 2
PlanetScope	~ 3 meters	8 Bands ● Coastal Blue ● Blue ● Green I ● Green ● Yellow ● Red ● Red Edge ● Near Infrared

Figure 3 - 5cm Hyperspatial Drone Imagery subsection of the Mesa Fire

Figure 4 - ~1.8m Worldview2 Imagery subsection of the Mesa Fire

Figure 5 - ~3m PlanetScope Imagery subsection of the Mesa Fire

Appendix B - Resources for Code and Documentation

All code, data, resources, and documentation can be found on the FireMAP Google Drive. In addition, several pieces of software are stored in GitHub repositories for easy access.

Links to Source Code, Data, and Related Materials for Mapping Forest Burn Extent from Hyperspatial Drone Imagery Using Machine Learning: Materials

Links to Source Code, Data, and Related Materials for Determination of Multi-Spectral Band Utility for Mapping Wildland Fire Burn Extent and Severity: ID3 Source Code, Materials

Link to Source Code and Related Materials for Unsupervised Wildfire Change Detection based on Contrastive Learning: Source Code

Link to Additional Resources on FireMAP Google Drive: FireMAP Software, FireMAP Presentations

Appendix C - Published Papers

- Mapping Forest Burn Extent from Hyperspatial Imagery Using Machine Learning
- Determination of Multi-Spectral Band Utility for Mapping Wildland Fire Burn Extent and Severity (In Progress)
- Unsupervised Wildfire Change Detection based on Contrastive Learning