International Journal of Advanced and Applied Sciences, 9(11) 2022, Pages: 34-43

Contents lists available at Science-Gate

International Journal of Advanced and Applied Sciences

Journal homepage: http://www.science-gate.com/IJAAS.html

Wildfires damage assessment Via LiDAR

Vivian Sultan *, Taron Sarkysyan, Savita Yadav

College of Business and Economics, California State University, Los Angeles, USA

ARTICLE INFO

Article history:
Received 4 April 2022
Received in revised form
20 July 2022
Accepted 26 July 2022

Keywords:
LiDAR
ArcGIS
Damaged objects
Deep learning

ABSTRACT

This paper examines the phenomenon of wildfires in California and investigates the buildings affected by the Woolsey Fire in Central Malibu in 2018. We focus empirically on machine learning to identify damaged objects from point-cloud data. This project includes a literature review with references to methods used for wildfire research and LiDAR data processing. In this study, researchers trained an existing deep learning model to determine if it offers an effective solution for extracting damaged objects. Data sources for this study include point-cloud data retrieved via the LidarExplorer tool and Kaggle's 2013–2020 California wildfire data. Using two layers of building footprints in the Malibu "T-Zone" revealed 907 structures, of which 435 were damaged or destroyed based on map observations. This analysis of structure identification supports the literature that deep learning can successfully classify objects damaged by wildfires.

1. Introduction

The California Department of Forestry and Fire Protection (Cal Fire) summarized that more than 9,000 fires burned over 4 million acres in 2020 (Knight et al., 2022). The fires destroyed over 11,000 structures and caused over $10 billion in damages. The economic toll of our state's wildfires is still being calculated, but early estimates peg it at $10 billion so far. The prediction for 2021 (as of August) was another severe wildfire season with the changing climate, higher temperatures, limited rainfall, and excess fuels. According to Cal Fire statistics, the number of acres burned in 2021 had increased by 257% compared to the previous year around the same time. As of August 2021, 6,347 fires had burned 959,611 acres.

1.1. Inverse distance weighted tool

One of the datasets that were needed for this project contains 1,636 California wildfires from 2013 to 2020. The dataset is called "California Wildfires (2013–2020)" (Kaggle, 2021). This dataset includes some such basic information on those wildfires as acres of land affected, the year the data was archived, count of structures destroyed. After importing the dataset into ArcGIS Pro, we were able to perform preliminary analyses based on this data. The left side of Fig. 1 shows all the structures destroyed by wildfires along with a power-line map. The right side of Fig. 1 shows the results of using ArcGIS Pro's Inverse Distance Weighted (IDW) tool. IDW allows ArcGIS to identify and create zones based on the dataset. IDW makes it possible to determine cell values by using a linearly weighted combination of a set of sample points. The tool also allows users to set the cell radius. The image on the right is a more accurate representation of the damaged areas compared to the image on the left due to the results of acres burned in the dataset. According to the dataset, 47,402 structures were destroyed, and 15,644 structures were threatened by wildfires. The mean value of structures destroyed per wildfire is 290.8 in 153 wildfires.

1.2. Woolsey fire

The Woolsey Fire was one of the most devastating fires in Southern California. Caused by faulty electrical and communication equipment, the fire started on November 8, 2018, in Los Angeles and Ventura Counties, and burned for 13 days before it was contained. The fire burned 96,949 acres of land and destroyed 1,643 buildings. Three people perished and damages were over $6 billion. Hundreds of homes in Malibu were destroyed or damaged on both sides of the Pacific Coast Highway and thousands of residents were evacuated.

* Corresponding Author.
Email Address: vsultan3@calstatela.edu (V. Sultan)
https://doi.org/10.21833/ijaas.2022.11.004
Corresponding author's ORCID profile:
https://orcid.org/0000-0002-1066-5212

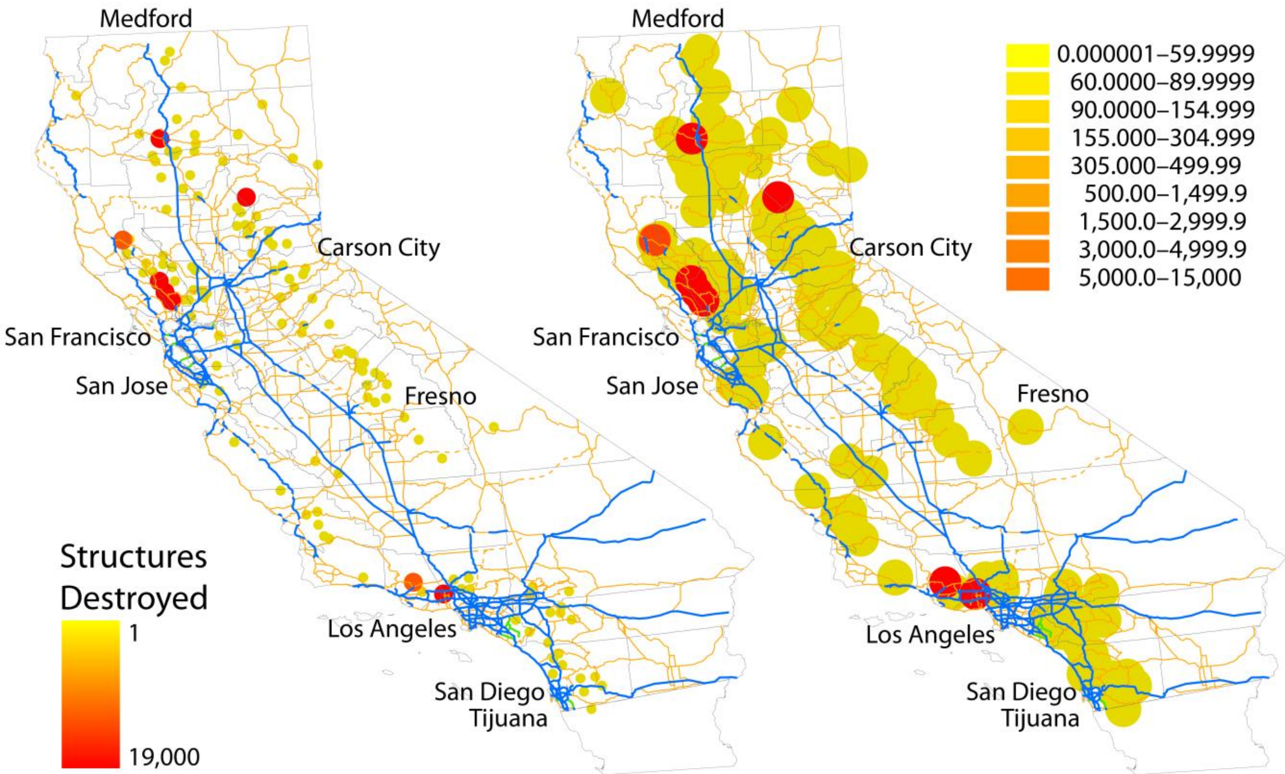

Fig. 1: Structures destroyed and detection of destroyed structures by IDW

1.3. Project goals

The main goal for the project focuses on the buildings impacted in central Malibu. The analysis uses Light Detection and Ranging (LiDAR) data to conduct a risk assessment on the City of Malibu where the buildings are extracted using ArcGIS Pro. A before-and-after analysis compared how that area has changed since the wildfire. We also analyzed the elevation in Central Malibu in relation to wind speed. Higher elevations offer more potential for high wind speeds, which can cause a wildfire to spread quickly toward the vast and dry vegetation throughout the Santa Monica Mountains. Furthermore, ArcGIS deep learning helped the project team detect how many buildings were destroyed. To add more to the research on this wildfire, other observations were considered, such as the power grid and outdated poles still present near central Malibu, which could be hazards in the long term.

2. Literature reviews

Fernández-Álvarez et al. (2019) described a methodology using LiDAR point clouds in forest vegetation characterization to improve protection capabilities in the wildland-urban interface (WUI) and to further prevent wildfires. The author tested the methodology with three LiDAR datasets corresponding to different areas in Galicia, Spain, located next to buildings or roads. The present methodology is based on individual tree detection (ITD), a measurement over a LiDAR point cloud for detection, measurement, and characterization of individual trees and analysis of shrub coverage.

Fig. 2 shows the detection of the biomass-management strips, where the vegetation might be measured and controlled. The biomass management strips are detailed as boundary regions around anthropogenic features in Fig. 2. These features include public communication infrastructures, buildings, recreational areas, and urban and forest roads. The first picture (a) is the infrastructure layer that shows buildings and tertiary and secondary roads. The second picture (b) represents biomass-management strips with purple polygons. The third picture (c) is the legend of both parts (a) and (b), showing the compass, graphic scale, and road, building, and forest-management zone symbols. Fig. 3 illustrates the identified individual trees with the variable-sized window (VSW) algorithm, part of ITD for determining the certainty of estimated maintenance actions and management efficacy for wildfire-prevention purposes.

Schmidt (2020) focused on the relationship between different vegetation variables and structure-loss rates. This study used pre-fire LiDAR data of the vegetation variables to predict the structure losses for the Butte Fire using elevation, topography, structure density, and access as additional variables. The outcome was based on the comparison between the prediction and imagery. According to the report, a 10% increase in vegetation density in the 50-foot buffer zone caused a 10.2% increase in structure loss. Additionally, a 15% increase in structure loss resulted from a 1,000-foot rise in elevation. The study also pointed out that topographic position, structure density, and access are not key predictors of structure-loss rates. Fig. 4 shows most structures were burned in the high-vegetation-density area. The soil-burn severity shows the same result.

Eidenshink et al. (2007) aimed to provide burn-severity information for a national analysis of trends in fire severity for the National Fire Plan. The secondary objectives include providing geographic and fire-specific data at regional and subregional scales to support resource and risk assessments, resource management, monitoring, and research activities.

The normalized burn ratio (NBR) enhances the spectral response of fire-affected vegetation. Differenced NBR images (postfire NBR subtracted from pre-fire NBR) are known as dNBR images. The differenced prefire and postfire NBR images result in a fire-related-change image classified into severity classes to provide an unbiased basis for analyzing additional fire effects. Moreover, the project supplies a valuable data legacy to support a broad range of research and operational uses at multiple scales. Mapping the historical fires and burn severity will enable experts to recognize burn severity trends over time. Fig. 5 shows the processing sequence of LandSat imagery to produce burn severity and fire-perimeter imagery.

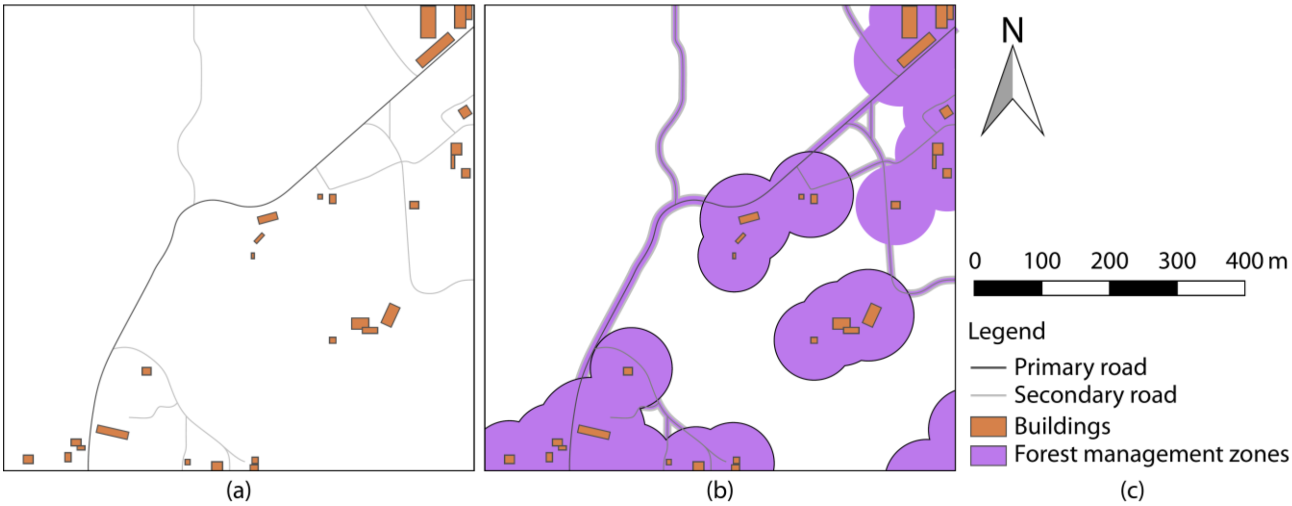

Fig. 2: The process of creating the biomass-management strips. Part (a) is the map of the dataset study, showing buildings and roads. Part (b) is the map including the forest-management zones. Part (c) is the legend

Fig. 3: Trees identified with the estimated crown diameters; trees are represented by red dots

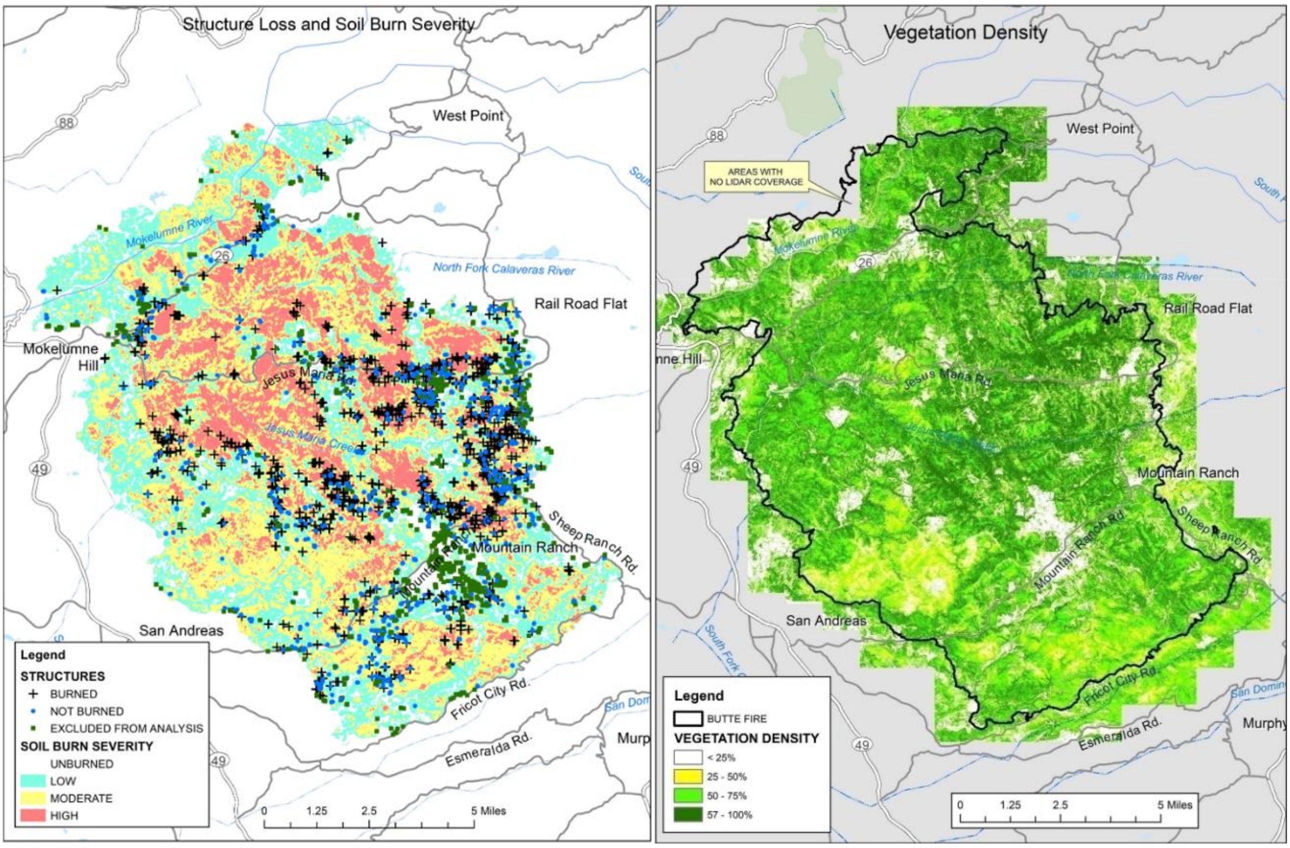

Fig. 4: Vegetation density, structure-loss, and soil-burn severity

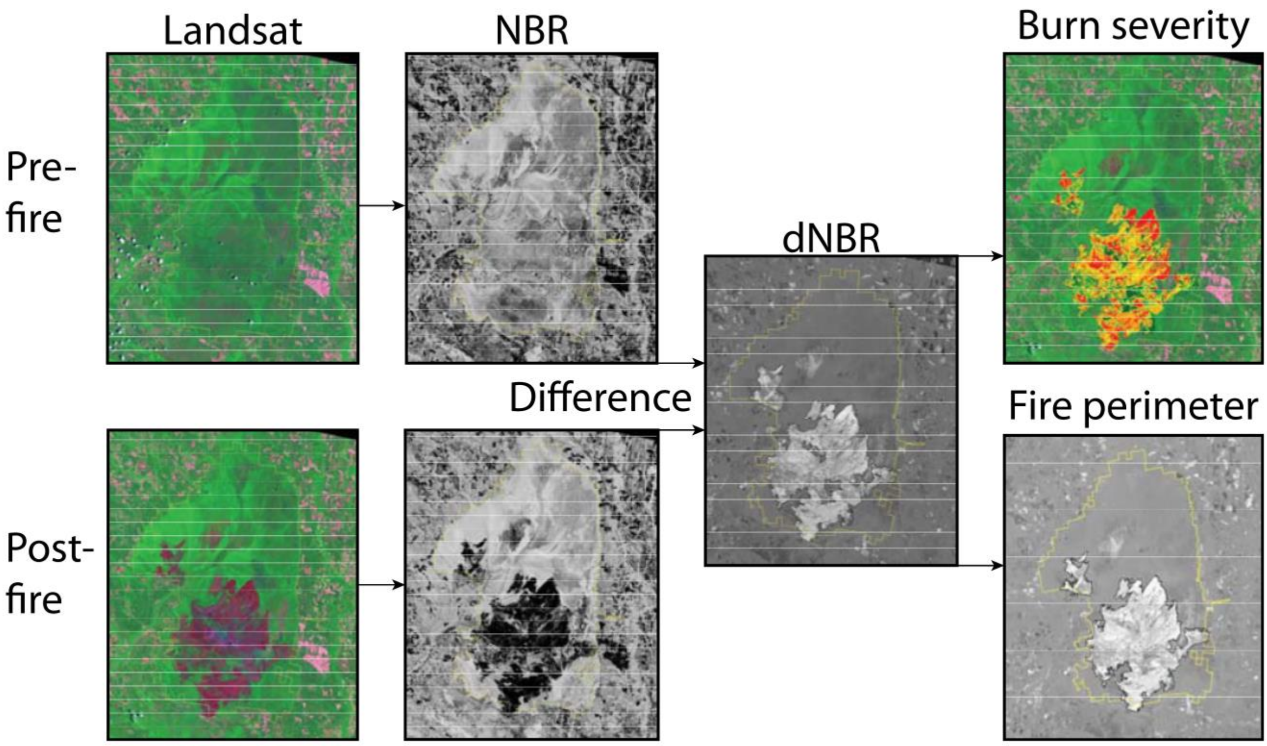

Fig. 5: The processing sequence using Landsat images to map burn severity and a fire perimeter for a fire in the Okefenokee national wildlife refuge (the yellow line is the refuge border)

Schulze et al. (2021) conducted research to understand post-wildfire outcomes for buildings to prevent structures from being damaged or destroyed. The article details an in-depth framework the authors created using multiple layers of field-collected data to assess wildfire damage, including LiDAR data, drone imaging data, and social media photos. The LiDAR scans were used to measure the buildings' structure for deterioration due to fire damage. An assessment was created of post-wildfire damage to infrastructure and the likelihood of buildings collapsing due to the damage. The specific study includes three-compartment fires to examine the influence of the building characteristics on the fire's maximum temperature and duration (Schulze et al., 2021).

The goal explained in this article is to learn from wildfire-damaged buildings, fire hazards, and the buildings' structural responses during the fire. The analysis elaborated in this article is particularly helpful for engineers to determine a more effective construction type so buildings can better resist fires.

The LiDAR scan shown in Fig. 6 demonstrates the exterior and interior of Achieve Charter High School in Paradise, CA after the Camp Fire. The LiDAR scans in the research were used to determine the post-wildfire deformation of the structure and frames. This building included classrooms, offices, and a gymnasium. This type of LiDAR scan shows how useful and powerful LiDAR can be in practice and in research for the details that can be extracted.

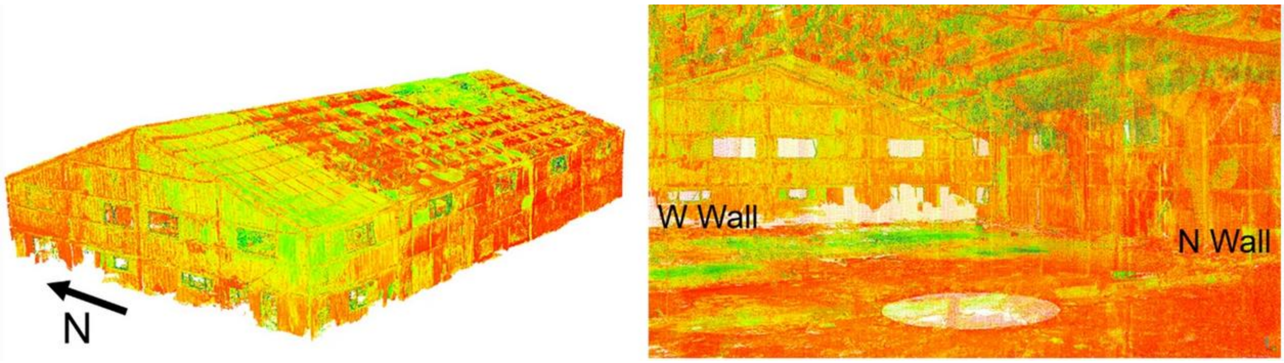

Fig. 6: LiDAR scan of achieving charter high school in Paradise, CA

Platt (2014) included metrics that characterize land cover, a burned area, and topography in the home ignition zone (HIZ). The HIZ is the area that includes a structure and its surroundings within a specific range (30 to 60 yards). Many specific studies of wildfire hazard focus on the WUI instead, which is the area where natural vegetation crosses or blends with structures. One reason that studies of the HIZ are so scarce is the cost or limited availability of LiDAR data and very high resolution (VHR) multispectral imagery. Object-oriented image analysis (OBIA) was used on an HIZ metric, pre-fire land cover, to obtain information about vegetation and fuel. The OBIA uses both ethereal and contextual data extracted from remotely sensed imagery to detect significant objects at multiple dimensions. The average study uses supervised categorization to categorize each pixel into discrete classes (Objects from terrain) based on the spectral response compared to a training sample.

The study took place in Fourmile Canyon, an area west of Boulder, Colorado, partially because of Fourmile Fire. From September 6 through 16, 2010, the Fourmile Fire burned about 6,180 acres and destroyed 168 homes. Most of the fire growth and home destruction took place during short bursts of extreme fire on September 6. About 83% of the destroyed houses were caused by low-intensity fire along with the degree of consumed vegetation surrounding each home. To learn from the Fourmile Fire background, the diagrams in Fig. 7 present the most accurate visual representations of the study's results. The left diagram is known as the Local Moran's I map. This diagram shows that HIZs in this area tend to score high in the hazard index due to the steep slopes, narrow canyon topography, and contiguous forest canopy. The HIZ Hazard Index on the right is used to evaluate or classify individual HIZs. Box A was rated "more hazardous" for canopies to structures and ridges.

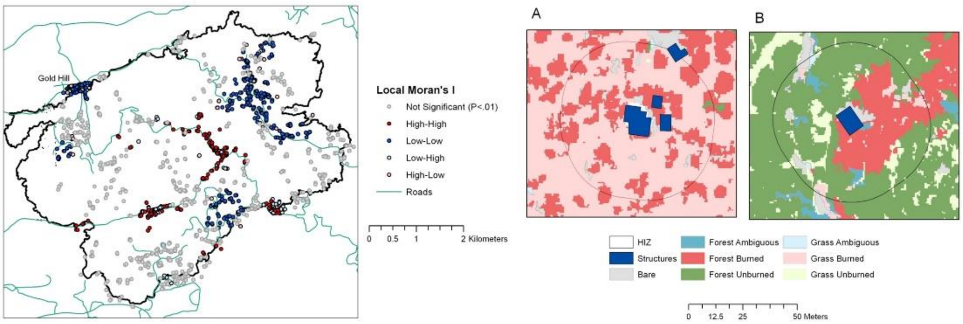

Fig. 7: Left: Local Moran's HIZ hazard index within the four-mile fire perimeter; Right: HIZ hazard index

3. Tools and data source

The tools used in the LiDAR/Imagery project are ArcGIS Pro, Microsoft Excel, LASzip, Google Maps, and Earth Pro. With ArcGIS Pro, the team explored, visualized, and analyzed data, creating 2D maps and 3D scenes. From LiDAR data, 3D buildings were extracted, a Raster layer was created for the terrain, Deep Learning analysis was performed to assess damaged buildings, and destroyed structures were predicted by IDW. Microsoft Excel was used to load the Kaggle dataset of wildfires that occurred in California between 2013 and 2020. The LASzip tool was used to compress point cloud data files and to decompress a merged ".laz" file into a ".las" file. Google maps were needed to choose between locations based on building damage and to discover the power grid and poles using Street View to know which area files to download from the LidarExplorer website. LidarExplorer provides LiDAR point-cloud data files to anyone for research. The dataset accessed on this site was known as "CA Los Angeles 2016" (USGS, 2021). The Google Earth Pro software offers the most comprehensive set of publicly available geospatial data, including high-resolution imagery, 3D cityscapes, detailed road maps, panoramic imagery at street level, and historical imagery. The Woolsey Fire satellite imagery that was taken in April 2019 was downloaded and used for the project.

4. Observations and analysis

4.1. Observations

The analysis focuses mainly on the Woolsey Fire, 17 miles from central Malibu by the measure tool in ArcGIS. About 96,949 acres were burned as shown in Fig. 8, in which the yellow patch is the fire's extent. The image shows how the devastating fire began in an area controlled by a major utility company in Southern California, between Simi Valley and Canoga Park. Then, the fire spread south to all areas of Malibu. One key observation for this project was to find out which houses were damaged or destroyed in central Malibu. This was shown by creating two layers of a building footprint using LiDAR data representing the outlines of structures. This layer is useful for determining the damaged area of each building, a valuable resource for future research.

For this project, a "T-Zone" was created by merging the ".laz" files in LASzip. A specific zone was needed instead because covering the entire area of central Malibu would require too much processing time. Then the merged ".laz" file was converted to a .las file in LASzip to be loaded into ArcGIS Pro. Fig. A1 in Appendix A shows a screenshot of the LiDAR data. When loading the LiDAR data in ArcGIS Pro, one must first make sure that the ground, noise, and building points are classified. Otherwise, it will not be possible to create the building footprint layer or extract 3D buildings. After classifying the points, the LAS Point Statistics as Raster tool can build a raster corresponding to the location of the LiDAR building points. Then the Raster to Polygon can convert the building raster to a polygon layer. Fig. 9 shows two screenshots of the building footprint layer. The left image shows that 907 structures in the T-Zone were detected by LiDAR in 2016. The right image shows that 435 structures were damaged or destroyed by the Woolsey Fire. Most of the polygons were deleted in ArcGIS Pro by observing the map carefully. A more professional layout for the project was to extract 3D buildings by running the LAS Building Multipatch tool (Appendix A, Fig. A2).

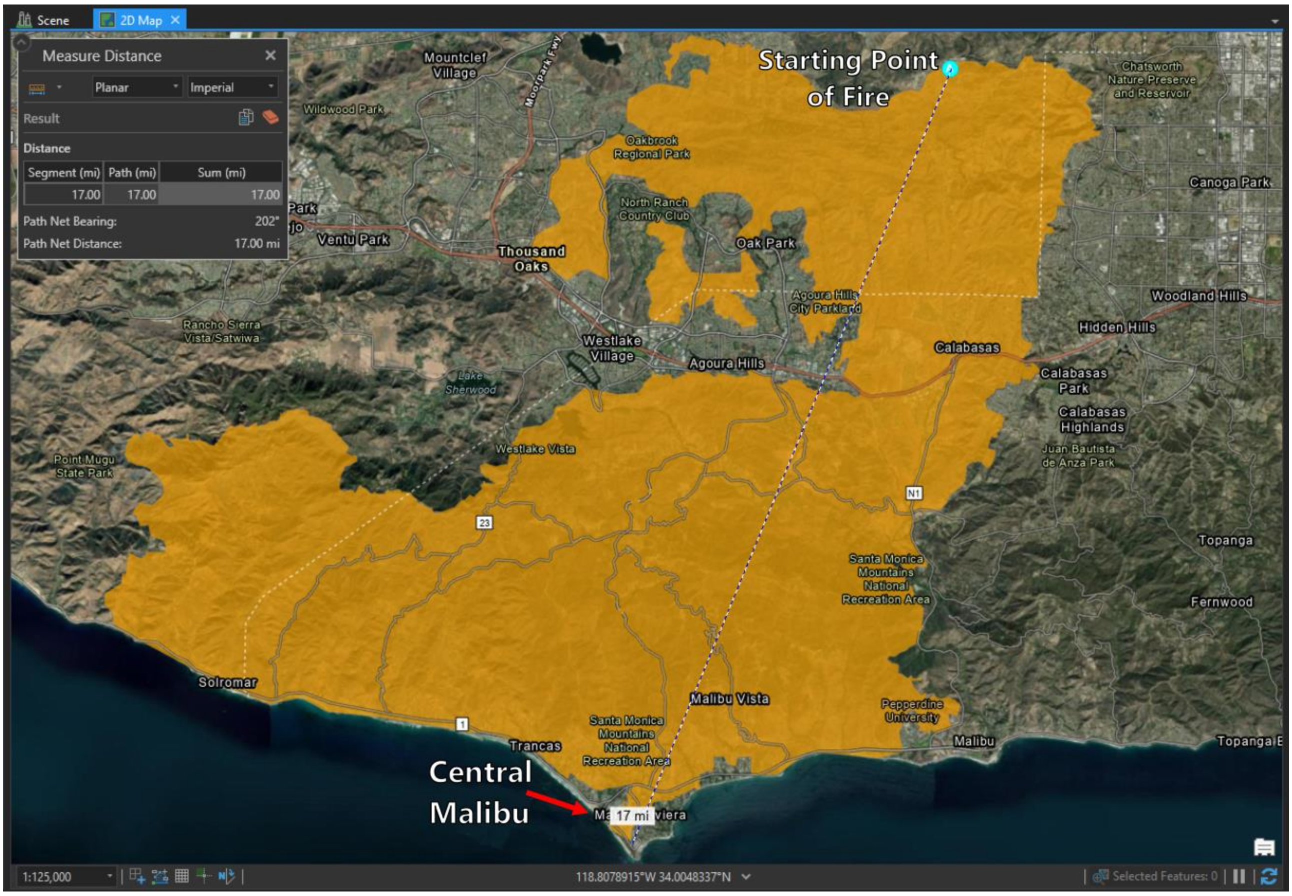

Fig. 8: Woolsey fire's affected area

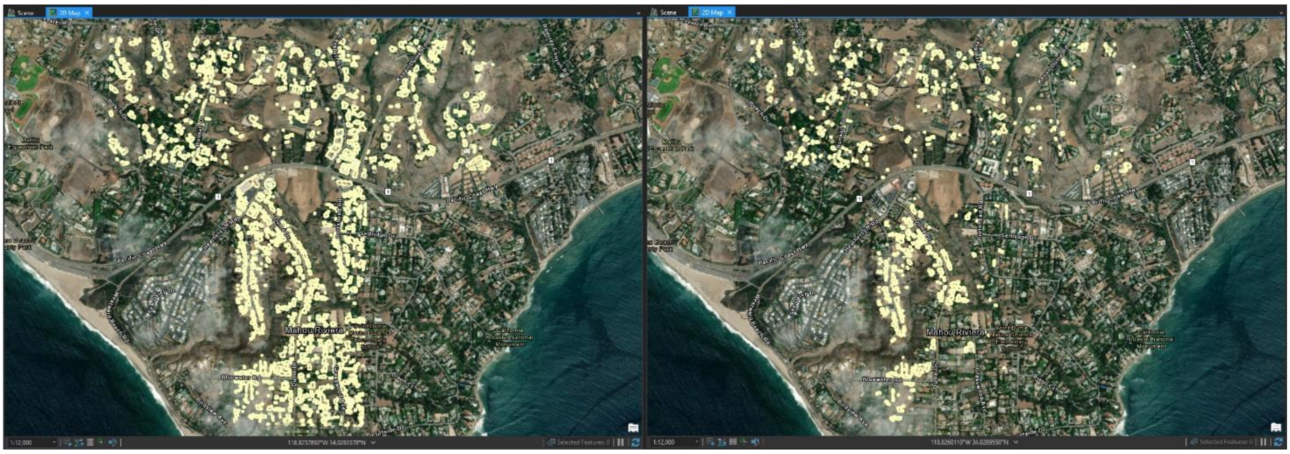

Fig. 9: Left: Structures detected by LiDAR; Right: Structures affected by the Woolsey fire

The elevation in the DEM (Fig. 10) layer made for central Malibu shows an interesting observation. The orange and brown areas indicate high elevation, and the yellow and green indicate low elevation. The mountains get higher in elevation toward the northeast where the fire started. The Santa Ana winds are another factor: They cause low humidity and can blow faster than 40 mph. These winds caused the fire to spread toward the coast. The Santa Ana winds are categorized as strong and extremely dry downslope winds that form throughout the land and blow towards the coast in Southern California. These winds blow at their worst during the fall. These dangerous winds made matters worse for the thousands of firefighters working to contain it.

4.2. Analysis: Deep learning to assess damaged buildings

The deep learning workflow includes four steps:

I. Image classification: Image classification involves assigning a label or class to a digital image. The classification tool is used to search the labeled objects with the deep-learning option. With all the buildings selected, the result appears like the image in Fig. 11.

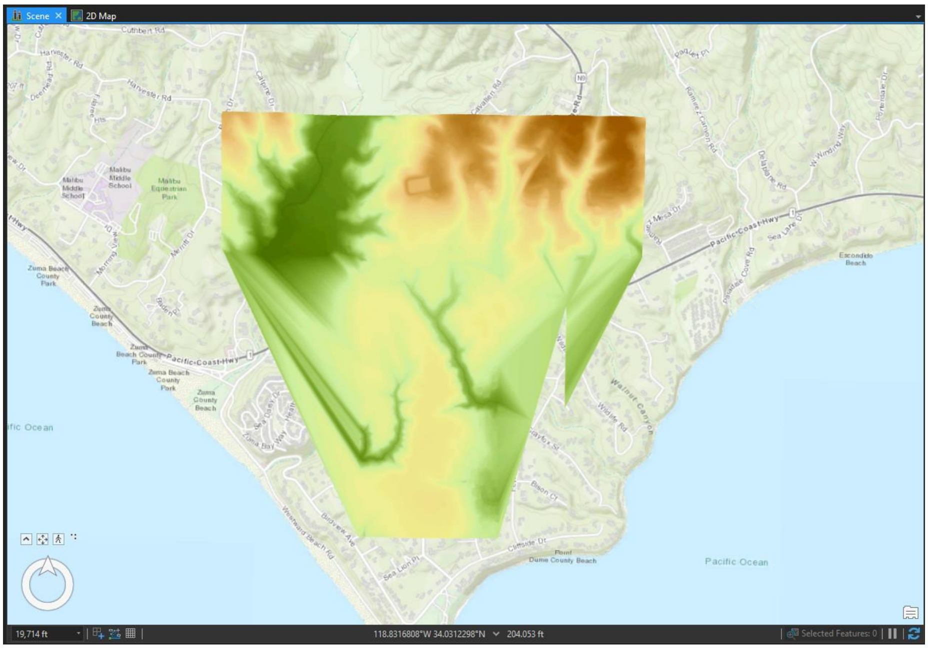

Fig. 10: Digital elevation model layer for central Malibu, 2018

II. Exporting training samples: Deep-learning training samples are small subimages known as "image chips." They contain the feature or class of interest. This tool creates folders containing image chips for training the model and labels.

III. Train the deep learning model: From the Geoprocessing pane, one searches and opens the Train Deep Learning Model tool. This step creates an ESRI model definition ".emd" file. The file contains the trained model, class names, model type, and image specifications of the image used for training.

IV. Object detection using single shot detector model: Object detection is the process of locating features in an image and typically requires multiple tests to achieve the best results. Several parameters are used to get better results. The current generation of object-detection networks such as SSD (single-shot detector) uses a fully convolutional approach in which the network can find all objects within an image in one pass (i.e., a single shot). Fig. 12 is the result of this process showing the destroyed buildings.

Fig. 11: Image classification step to label damaged-building objects

Fig. 12: Detected destroyed buildings

Fig. 13 shows the result of the image chips folder that was also referenced in the export-training sample. The sample step contains all the selected damaged-building features.

Fig. 13: Image chips and real building predictions

5. Discussion and conclusion

A background on wildfires in California provided a strong introduction. This environmental issue has yet to be resolved. Since June 14, 2021, its actual cause is under investigation, but the fire was most likely caused by faulty equipment. The news came as a major utility company reported to the California Public Utilities Commission [CPUC] that its "equipment may have been involved in the start of the big Dixie Fire burning in the Sierra Nevada." Yet another wildfire occurred from another power company just three years after the Woolsey Fire. This project shows the importance to our daily lives in California of emphasizing which structures are destroyed by wildfires. Displaying information about wildfires in California from 2013 to 2020 and running this analysis using the IDW tool is important because so many wildfires are a huge threat to the environment. Creating visuals in ArcGIS Pro to develop building footprint layers can help researchers determine how much of an area has been deeply affected by wildfire. Observations like elevation and wind factors will help power companies consider alternatives to prevent more environmental disasters. Finally, spending less time creating a visual by letting the program run a deep-learning analysis can be very useful and more accurate for research. The four steps of the deep-learning workflow can help develop better research for business intelligence. The main difficulty in the project was getting the LiDAR point cloud data files to work in ArcGIS Pro. The location for this project was originally going to be in Butte County to cover the 2018 Camp Fire which was also devastating. When the files in that location were loaded to ArcGIS Pro, the coordinates were missing, preventing the necessary tools from running. Regardless, the project turned out to be a success, but it signals the substantial work needed to provide adequate research about wildfires in California.

Appendix A. ArcGIS analysis with built-in tools

The screenshots below show features of ArcGIS that help you provide visual data for your analysis. The first part of Fig. A1 shows LiDAR data in the T-Zone. The second part of Fig. A1 shows a much closer look at the LiDAR data by demonstrating the elevation of buildings and objects. Fig. A2 shows buildings rendered in 3D.

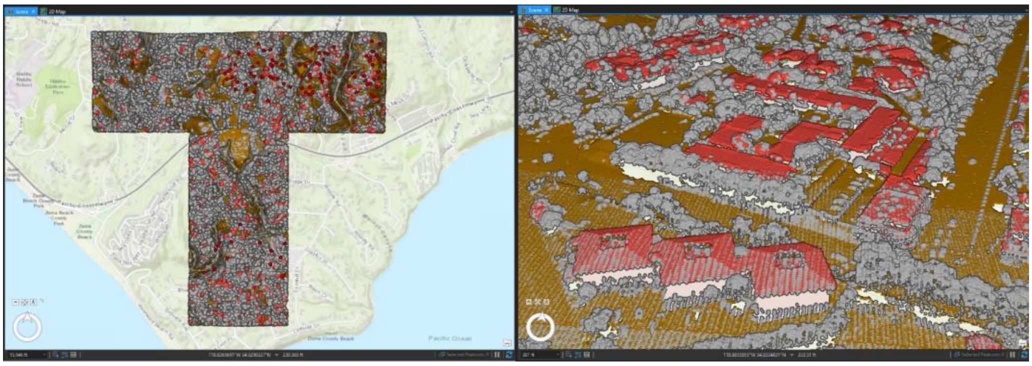

Fig. A1: Screenshots of LiDAR data layer in the T-zone

Fig. A2: Extraction of 3D buildings in the T-zone

Acknowledgment

This research is based on students' course project work at the graduate school, Information Systems department of California State University, Los Angeles. The second and the third author would like to acknowledge Professor Vivian Sultan for her guidance and contribution to this research project. This research received no external funding.

Compliance with ethical standards

Conflict of interest

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

References

Eidenshink J, Schwind B, Brewer K, Zhu ZL, Quayle B, and Howard S (2007). A project for monitoring trends in burn severity. Fire Ecology, 3(1): 3-21. https://doi.org/10.4996/fireecology.0301003

Fernández-Álvarez M, Armesto J, and Picos J (2019). LiDAR-based wildfire prevention in WUI: The automatic detection, measurement and evaluation of forest fuels. Forests, 10(2): 148. https://doi.org/10.3390/f10020148

Kaggle (2021). California wildfire incidents (2013–2020): List of Wildfires in California between 2013 and 2020. Available online at: https://www.kaggle.com/ananthu017/california-wildfire-incidents-20132020

Knight CA, Tompkins RE, Wang JA, York R, Goulden ML, and Battles JJ (2022). Accurate tracking of forest activity key to multi-jurisdictional management goals: A case study in California. Journal of Environmental Management, 302: 114083. https://doi.org/10.1016/j.jenvman.2021.114083 **PMid:34800763**

Platt RV (2014). Wildfire hazard in the home ignition zone: An object-oriented analysis integrating LiDAR and VHR satellite imagery. Applied Geography, 51: 108-117. https://doi.org/10.1016/j.apgeog.2014.03.011

Schmidt J (2020). The butte fire: A case study in using LiDAR measures of pre-fire vegetation to estimate structure loss rates. MPRA Paper No. 99699, Munich Personal RePEc Archive, Munich, Germany.

Schulze S, Fischer EC, and Mahmoud H (2021). Framework for post-wildfire investigation of buildings: Integrating LiDAR data and numerical modeling. Fire Technology, 57(5): 2407-2432. https://doi.org/10.1007/s10694-021-01124-y

USGS (2021). 3DEP LidarExplorer. Available online at: https://prd-tnm.s3.amazonaws.com/LidarExplorer/index.html