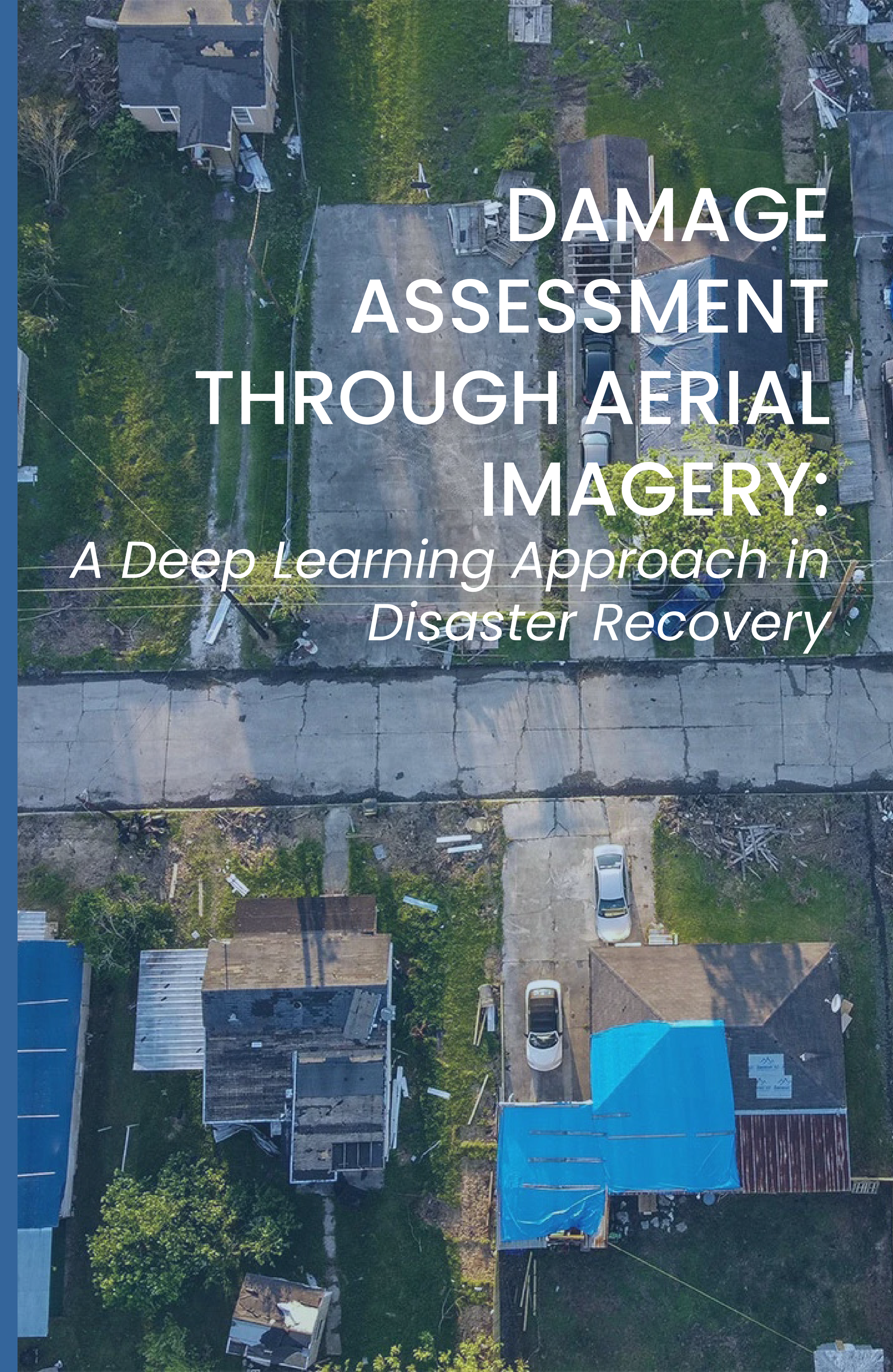
4 white paper series: aerial assessment



DAMAGE ASSESSMENT THROUGH AERIAL IMAGERY:

A Deep Learning Approach in Disaster Recovery

EXECUTIVE SUMMARY

This white paper focuses on the application of deep learning approaches for image classification, object detection, and change detection. Implementation of aerial image analysis and particularly the advanced deep learning analysis is imperative in returning a more accurate, efficient, and consistent damage assessment process. This paper argues that it is a net positive to increase the automation of aerial imagery analysis in order to improve rapid damage assessments. To explain this innovative approach the paper will 1) review relevant literature on the topic; 2) align this process with the Federal Emergency Management Agency (FEMA) framework; 3) address the role of object classification in aerial imagery to rapid damage assessments; 4) review technical processes which can benefit damage assessment; 5) assess the strengths, challenges, and barriers to utilizing such technology; and 6) observe findings and recommendations from experiments using these techniques.

4.1 Introduction

This white paper will focus on how deep learning approaches for image classification, object detection, and change detection can be applied to aerial imagery to improve rapid damage assessments. In order to explain this innovative approach the paper will 1) review relevant literature on the topic; 2) align this process with the Federal Emergency Management Agency (FEMA) framework; 3) address the role of object classification in aerial imagery to rapid damage assessments; 4) review technical processes which can benefit damage assessment; 5) assess the strengths, challenges, and barriers to utilizing such technology; and 6) observe findings and recommendations from experiments utilizing these techniques. Implementation of aerial image analysis and particularly the advanced deep learning analysis is imperative in returning a more accurate, efficient, and consistent damage assessment process. This paper argues that it is a net positive to increase the automation of imagery analysis. Hurricane Ida, which made landfall in late August , 2021 in Southeastern Louisiana, serves as a case study for evaluating this type of analysis. This paper also looks specifically at wind and flooding disaster events such as tornadoes and hurricanes, while also incorporating literature drawn from earthquake and wildfire events. The aim for this research, which includes the technical capacities demonstrated within it, is to aid emergency managers, assessors, and any entity conducting damage assessments in improving damage assessment processes through use of aerial imagery and technical solutions.

Damage assessment following disasters has traditionally been a very manual process which requires significant resources, staff and volunteer time to conduct. As noted by FEMA in the Preliminary Damage Assessment Guide, "A one size-fits-all approach to damage assessments is unrealistic."[1] The use of technology plays a role in fieldwork and in machine learning beyond improving efficiencies in manual data collection and bureaucratic documentation. As the FEMA Preliminary Damage Assessment Guide states, "understanding the technologies available (e.g., aerial imagery and ground-level photography) and ensuring the relevant stakeholders are familiar with the technologies being acquired and used for damage assessments is important for pre-incident readiness."[2] Thus, while challenges remain, FEMA encourages the use of new technologies, aerial imagery, ground-level photography, and other new innovations to improve damage assessment practices.

There is a need for rapid methods to be employed in the aftermath of a disaster event. With perishable data and the impacts of the disaster evident following the event, it is necessary to collect data as quickly as possible within the first 72 hours following a disaster before a more extended recovery begins. In this time period, the presence of roof damage including holes or exposed plywood on rooftops, changes to building footprints, and vegetative debris will be most evident.[3]

Aerial imagery is a critical tool in capturing the perishable data and real world impacts of a disaster from a high vantage point. In the initial three days to first two weeks following an event, presence of blue tarps and debris removed from the interior of structures for collection at the curb will become more apparent in aerial and satellite imagery.[4] Thus, aerial imagery collection has a temporal nature which must be considered alongside the hardware technologies deployed to capture the pictures and the software employed to analyze the images. Another key characteristic of aerial imagery is that it is also spatial in nature. Aerial imagery analysis and remote sensing capabilities have the capacity to interpret real world events in time and space through the lens of a camera. Throughout this paper, the nuances of time, spatial complexity, and technical capacity will be considered in each approach.

4.2 Literature Review

Computer vision has achieved significant improvements with deep learning methods, which have been successfully applied to a number of several types of aerial imagery analysis, such as object detection, object segmentation, hyperspectral image classification, and change detection. The use of machine learning and deep learning in damage assessment remains a novel process in the research of disaster recovery. The nature of the existing research remains highly technical and focuses on accuracy and efficiency in algorithm type and training classifiers. This often leaves a gap in understanding how these technical resources effectively shape real-world disaster recovery.[5]

Recent research has worked with building footprint features as a pre-classifier for the damage assessment process. Given that much of damage assessment is focused on damage to structures, this method has contributed to a more efficient and accurate process. The research has emphasized three main methods for incorporating building footprints as a preliminary sorting of the aerial data: with pre-built shape files, ArcGIS Pro, eCognition, and analysis of blue tarps covering damaged structures via Convolutional Neural Networks (CNN). All three of these approaches showed promising results.

OPEN SOURCE BUILDING FOOTPRINTS

Microsoft has produced high quality building footprint datasets with 129.6 million buildings in the United States. These building footprints were computer generated by Microsoft and use AI and computer vision to extract building footprints from Bing Maps imagery. This open data set is available to download for locations with clear imagery available. The vintage of the building footprints can vary widely from 2014 to 2021. The individual footprints are tagged when possible with the known date.[6] These datasets tend to be highly accurate, but have limitations given that the data is more than a few years old. More up-to-date information is needed in disaster prone areas. As in the case of hurricane impacted locations, one storm may follow another and altered building footprints, structure features, and properties can be difficult to measure using a static file from the year prior.

GOOGLE EARTH ENGINE

Google Earth Engine is a free to use open source tool that offers access to extensive remote sensing data. This tool helps practitioners develop CNN frameworks. Multiple CNN frameworks have been created to detect building footprints. The latest Mask R-CNN algorithm developed in 2019 has proven highly effective in detecting detailed building footprints from complex

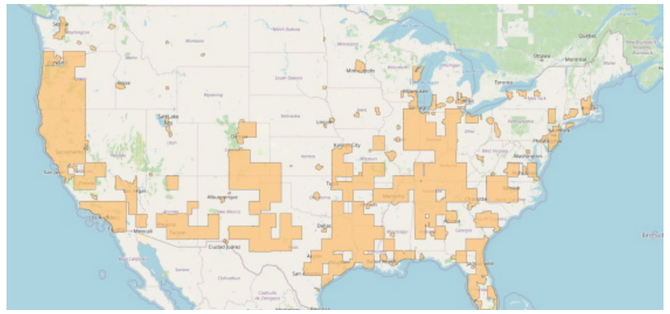


Image 4.1: Areas of the United States with significant building footprint data sets available through Microsoft. Credit Bing Blogs

photographs. While requiring additional effort, this method offers an additional free open source program to supplement existing building footprint datasets (Google, 2022).

ESRI ArcGIS

ESRI has piloted multiple programs to create a visual interface that allows practitioners involved with disaster recovery an easy entry point into the execution of deep learning techniques. Similar to Google Earth Engine, ArcGIS can be utilized to extract building footprints from imagery. ArcGIS Pro has an established prebuilt deep learning process that provides one of the simplest ways to perform building footprint extraction to assist in damage assessments. ArcGIS Pro has created a deep learning package for US based building footprint extraction, making it easy for almost anyone to run the extraction and produce a layer with building footprints detected. ESRI has piloted multiple tutorials on use cases and explanations for practitioners, making a process that can be deployed in minutes and can be fed into the rest of the ArcGIS damage assessment workflow. ArcGIS Pro can also use an existing shapefile where recent building footprint data is available from other sources.[7]

eCOGNITION

A study of the 2018 Woolsey Fire in Southern California performed damage assessment on approximately 1,000 structures in the affected Los Angeles County area. The study used 2017 processed building areas that were then clipped to generate image chips to isolate the target image outlines.[8] The study then used eCognition, an advanced object-based image analysis software for geospatial applications to classify buildings as damaged or undamaged. Notably,

DEFINITIONS

DEEP LEARNING
Deep learning is a class of machine learning algorithms that use artificial neural networks inspired by the human brain's neural networks. These algorithms use raw data to abstract and identify concepts relevant to human understanding. For the purposes of this paper, we employed a supervised deep learning method.

IMAGE CLASSIFICATION
Image classification labels and classifies digital photos. GIS deep learning processes can be utilized to categorize features.

OBJECT DETECTION
Object detection can locate specific features within an image. In GIS this can be used to identify individual objects from satellite, aerial, or drone imagery in a spatial format.

CHANGE DETECTION
Change detection utilizing deep learning identifies changes to structures between pre-event and post-event dates and mapping this change with a spatial component.

IMAGE TRANSLATION
Image translation can improve image quality and resolution. A deep learning process such as image-to-image translation can be employed to improve image quality and prepare an image for an image classification, object detection, or change detection.

REMOTE SENSING
Remote sensing is the process of detecting and monitoring the physical characteristics of an area by measuring its reflected and emitted radiation at a distance (typically from satellite or aircraft).

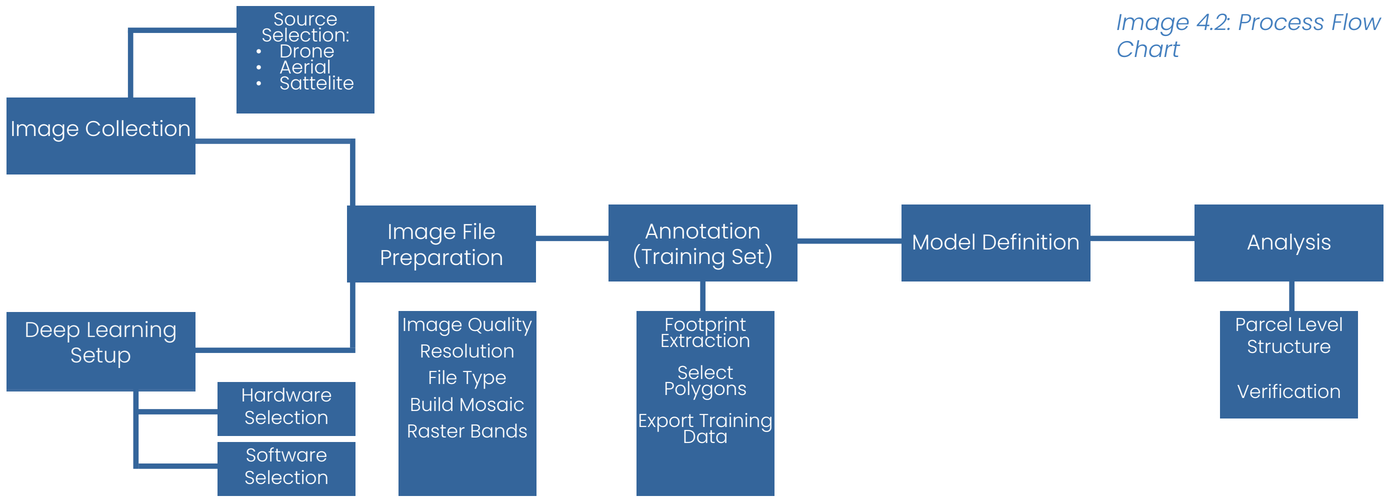


Image 4.2: Process Flow Chart

the footprint objects were classified as 'buildings' and the remaining background was classified as 'background' allowing for the ruleset to consider the changes in texture, mean color, and mean brightness on the 'buildings' only. Using eCognition allows for greater customization in the rulesets and custom feature calculations than the prebuilt ArcGIS Pro mechanism for model training. It is important to note that due to the nature of the fire, structures were either completely destroyed or preserved, which allowed for the binary classification. The results produced an 85% overall accuracy, and a 93% accuracy for damaged buildings.[9]

4.3 Alignment with the FEMA Framework

Almost all disaster recovery in the United States is influenced in some way by the Federal Emergency Management Agency (FEMA). FEMA structures aid and assistance through multiple frameworks and regulations affecting how state, local, and non-profit agencies operate and assist communities and individuals. Therefore, it is important that any damage assessment tool or technical process be aligned with these FEMA frameworks, allowing for their use to be easily adopted into the existing processes.

The National Response Framework outlines the "foundational emergency management doctrine for how the Nation responds to all types of incidents."[10] The key goal for active, effective response is integration and coordination of efforts across sectors and levels of government. Large-scale aerial imagery assessment can readily provide information that creates an understanding of damage at both a macro and micro scale allowing for greater coordination. Local government agencies are specifically tasked with assisting in the rebuilding of housing units. Aerial damage assessment can help local emergency responders understand and prioritize damage in recovery efforts, while also freeing up time and resources enabling them to perform other critical response tasks.

Most pertinent to this process is the FEMA Damage Assessment Operations Manual which promotes three goals: accuracy, efficiency, and consistency.[11] The use of deep learning in aerial damage assessment promotes all three of these goals. Deep learning can improve accuracy in damage evaluation and verify field assessments to ensure consistency. Although there are potential biases in deep learning assessments, there is also the potential for greater consistency in assessment as long as the human annotation is rigorous. Deep learning analysis can apply an "even hand" ensuring that attention is not unevenly distributed within and across communities. Overall, automating what is typically a manual process will increase efficiency. However, that efficiency should not be accepted without accuracy or consistency. That said, there are ways to address concerns of accuracy, consistency, and biases to make the benefits of deploying this process outweigh its limitations.

The onus in damage assessment is largely placed on the individual impacted by the disaster event. FEMA damage assessment guidelines suggest, "potential applicants are encouraged to photograph damage in order to expedite damage assessment verification".[12] Per the FEMA framework, much responsibility is placed on the individual. Individuals whose lives were upended in an instant are expected to fill out pages and pages of forms to comply with government requests. The government operates in a 'pull' mentality. FEMA is pulling information from residents, but only if the information is provided by citizens. Implementing a technical assessment to collect damage imagery can help alleviate the personal burden of documentation on the individual. This burden has the ability to prevent impacted individuals from being able to access much needed funds and resources in order to successfully recover long term.

What if instead of operating under a 'pull' mentality, the government utilizes wide-scale aerial analysis to 'push' aid to impacted individuals and communities? This would mean aid is not contingent on submission of paperwork by impacted individuals, but rather the onus is placed on government, assessing damage and delivering aid. By assessing structures and properties using aerial imagery in an automated fashion, government agencies can quickly assess damage and deliver aid to impacted individuals more rapidly. Under-assessments can be handled in a simplified challenge process. It should be noted that when dealing with structures, this type of aid primarily impacts property owners and more aid benefits should address impacts to renters including displacement and property damage. As a start, multi-family dwellings should receive a larger disbursement of aid relative to the assigned damage score and number of units to be delivered to tenants. This broad aerial damage assessment provides a mechanism to do the most good for impacted areas, delivering significant aid efficiently. It is a paradigm shift in pushing aid out for damage to individual structures rather than pulling information and property assessments from the public.

4.4 Role of Deep Learning in Rapid Damage Assessment

In Louisiana, following Hurricane Ida in 2021, a local assessor reassessed the property value for 20,000 properties in a parish through a process which incorporated aerial imagery into a workflow to assess each property, provide a damage assessment score to each structure, and deliver a discount on the taxes

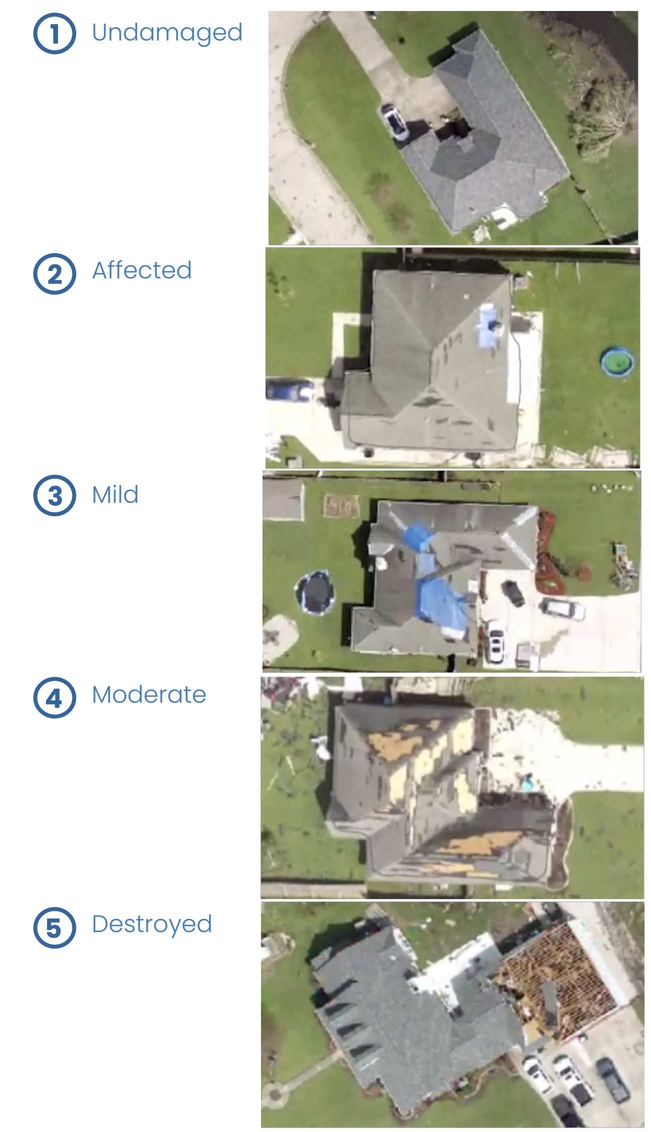


Image 4.2: Aerial photos signifying Level 3 damage included in guidance materials for damage assessment in St. Charles Parish. Level 3 damage indicates visible structural damage with large areas of roof underlayment missing. It also signifies that the property likely has significant water damage. While the damage is not a total loss, it will require significant funds and work to repair.

to that property owner as a form of aid.[13] This process represents an intensive effort to assess damage for an entire community. Relative to the commonly accepted standards, this assessor's office went out of its way to provide aid to a community in need. In a push mentality, this government entity took action on behalf of the community to get the work done through an innovative, time-saving methodology of aerial image review. Any disputes were taken on a case by case basis to address concerns on the assigned damage scores. The records show that very few disputes occurred out of the 20,000 assessments, showing the value of providing for the entire community when in other circumstances many community members may never receive this aid.

Such a manual process deployed in the field provides valuable lessons and insight on available tools for future damage assessments of this kind. A key lesson is that some components of the process deployed in this case study do not need to be abandoned for more automated methods. Images of disaster damage are a representation of real world impacts. The ultimate focus is on delivering aid and resources to residents who require the most assistance. While this should be based on the level of damage sustained to the individual's residence (in alignment with the FEMA framework), the human element consequences cannot be lost in the analysis. A remotely sensed damage assessment or on one conducted in the field can determine the level of damage inflicted by the disaster. But do they conduct this assessment with the same level of accuracy, efficiency, and consistency? In some sense, a remote sensing approach conducted behind a computer screen removed from the disaster site provides a level of protection from bias or serendipitous events on the ground which could alter an assessment. However, this distance from the site removes potential for understanding intangible considerations, connection to the space, and local knowledge. If damage assessments are moving increasingly towards incorporating imagery analysis rather than just field visits, it is appropriate for machines to be engaged more in this work.

Incorporating analysis of aerial imagery along with ground level imagery is a positive direction for emergency managers, assessors, and other disaster response professionals to move in. Utilizing imagery with geospatial qualities to review damage over wide areas can make a traditionally ground level process more efficient by providing a panoramic view of wide scale damage. This can inform need and priority for ground level decisions. With more time and resources, evaluation of damage to individual homes can be conducted. Automation can inform a more advanced model. Yet, if this process moves completely away from a field assessment to a more sterile environment and takes the form of a remote process for a staff member to conduct behind computer screens, then it seems appropriate for the machine to start doing more of the work. Deep learning techniques enable software and computation to evaluate properties, identify structures with signs of damage, and assess changes between a pre-event and post-event images. In the next section, the various available deep learning methods and training approaches will be discussed.

4.5 Technical Process Overview

Deep learning and image classification can assist with rapid assessment by augmenting the integrated data types available in damage assessment methods. Those integrated data types include: aerial imagery from multiple sources, available static files for structures, a recombinant collection of objects to identify, and additional parcel level information to provide a granular understanding of damage and change to structures post-disaster. Using a machine to produce a spatial dataset which identifies roof damage and change in building footprints can enable disaster recovery teams, emergency managers, assessors, and the broader community to optimize and prioritize areas, structures, and families that need assistance thereby enabling more targeted response and recovery. To investigate this further, the various deep learning techniques available to analysts are outlined below:

IMAGE CLASSIFICATION

Image classification labels and classifies digital photos. For example, the image here shows classification by damage score to the individual photo of a structure. GIS deep learning processes can be utilized to categorize features. Image classification can be utilized to label structures in a binary manner such as damaged or undamaged, or on a scale, categorizing based on level of damage. Both methods are most effective when used in tangent with existing building footprints.

Building footprints are then annotated based on the classification model, and the deep learning analysis is limited to the structures. ArcGIS was selected due to its availability in most municipal offices, and also because it offers a visual interface making it easier to maneuver than other GIS tools, however, this process could be performed in an alternative program. The building footprints can be loaded into ArcGIS Pro or other geospatial analysis tools as shapefiles or extracted using the deep learning package for USA building footprints. Once that layer is established, a class field and class name is added to the attribute table and a sample is labeled for damage. The data is then exported using the Export Training Data for Deep Learning tool within the geoprocessing suite of ArcGIS Pro.

That data is then used as an input into the Train Model for Deep Learning module of ArcPro. This

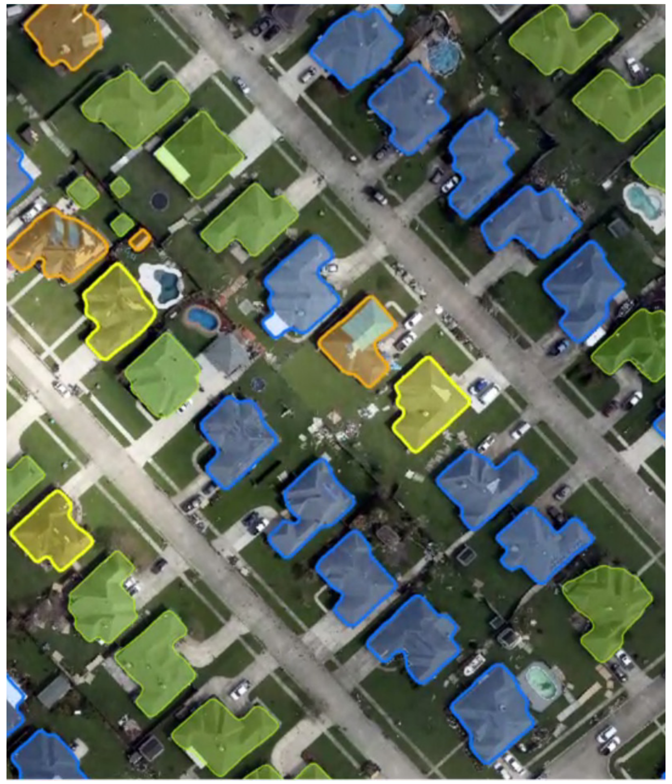


Image 4.3: Image Classification using ArcGIS Pro

Image 4.4: Object Detection using ArcGIS Pro

process makes the intricately technical process more accessible for those unfamiliar with deep learning. The model is then used to classify the objects within the aerial image. Accuracy can vary dramatically depending on the accuracy of the annotation and number of training samples.

OBJECT DETECTION

Object detection can locate specific features within an image. For example, the Image 1.3 shows a blue tarp being detected on a rooftop. A bounding box is used to identify the specific object feature as distinct from the other objects in the image. In ArcGIS Pro this can be used to identify individual objects from satellite, aerial, or drone imagery in a spatial format. This technique can be applied to other types of damage such as debris piles, fallen trees, and exposed plywood roofs. Identification of these features can functionally serve as a heatmap for damage assessment.

This process can be performed using the deep learning object detection tools in ArcGIS Pro. Practitioners can identify the desired features using polygons within their imagery to create a new training set that will be saved within the project folder. Similar to the classification tool, this training set is exported to create a model. The model is then used when running the Detect Object

Deep Learning geoprocessing. Ideally, the analysis then produces a new layer with all objects detected.

CHANGE DETECTION

Change detection utilizes deep learning to identify changes to structures between pre-event and post-event dates while mapping this change with a spatial component. Change detection can be performed as a stand alone process or coupled with one of the above methods. ArcGIS Pro has a prebuilt change classification wizard that can determine the type, magnitude, and location of change. At least two raster image datasets or a time series set of imagery must be provided. The change detection wizard tool then allows these to be saved as a new raster image that shows the differences. If two raster images are being used, the output change detection can be saved as a raster function template that can be used for further geoprocess. This allows for polygon feature classes to be added as an additional step in tandem with object detection or classification. In fact, in order to tailor change detection to structural damage assessment most efficiently it should be used with object detection or object classification.

4.6 Strengths and Challenges of Technology

Advancing the use of these technologies is imperative in returning a more accurate, efficient, and consistent damage assessment process. Yet, there are challenges and drawbacks to the approaches of analyzing aerial imagery and utilizing machines to assess damage which should be considered. However, concerns for 1) human error; 2) resolution and image quality; 3) geospatial nature of aerial imagery; 4) proprietary and temporal aspects of aerial imagery; 5) hardware constraints; 6) software limitations; and 7) secondary data access should be evaluated when incorporating this approach into rapid damage assessments.

HUMAN ERROR

Manual aerial imagery analysis leaves room for human error in the inspection of each home. In this process, staff members will review aerial images of each structure to determine the integrity of the roof and note any signs of damage. This primarily impacts the consistency and accuracy of the assessment. There can be mistakes made in the analysis of each individual parcel, particularly as fatigue sets in.

Running an automated analysis can reduce human error with regard to consistency and accuracy, and should also improve efficiency. However, in an automated analysis utilizing deep learning techniques and other feature detection capabilities, decisions in choice of analysis, geoprocessing tools, as well as image and evaluation criteria can result in poor results. Mistakes made in training the algorithm or model in selection of objects or placement of bounding boxes can have significant impacts. Choices made at the outset can produce domino effects at later steps resulting in cascading impacts. Here, the use of robust testing, statistical observations, and spot checking can reduce wide-scale error. The entire intent of remote sensing or aerial imagery analysis utilizing deep learning techniques is to relate image data to features on the ground. Validation by means of comparing output from the analysis with damage assessments collected via field work, comparable secondary data, or manual review of the imagery can help reduce this error.

IMAGERY OVERVIEW

Passive

- Uses the Sun as a source of illumination that measures energy that is reflected back
- Aerial photography, infrared, thermal

Active

- Sends out pulse that has the capability to penetrate objects/surfaces that gets reflected back
- Radar, Sonar, LiDAR, SAR

Multi-Spectral

- Between 3-10 spectral bands

Hyper-Spectral

- As many as 200 or more spectral bands
- The narrower the wavelength, the finer the spectral resolution

RESOLUTION AND IMAGE QUALITY

Imagery data collection must include close quality assurance which inspects the image for resolution issues. This is particularly true of satellite images which may not have a high enough image quality and resolution for deep learning analysis of individual structures. To truly conduct a granular damage assessment of buildings located on individual parcels, high resolution imagery at 1.5 meters will be necessary. Commercially available satellite photos may only provide 3 meters resolution which is not a well-defined image for this analysis. Firms like Planet Labs, Maxar, or even publicly available information from NASA will provide images which can be utilized for change detection if the resolution is closer to 1.5 meters, particularly for distinct colors such as blue tarps, at the census tract level but not for individual properties.

Aerial photography collected by airplane flyovers will likely deliver a higher resolution for this type of inspection, however such photography is often proprietary to firms such as EagleView or Nearmap and can be costly. Drone photography may also offer high quality enough imagery, though for a smaller geographic area. The National Oceanic and Atmospheric Administration will take photos in the aftermath of disaster events to monitor impacts to coastal areas and infrastructure. For instance, following Hurricane Ida, images were taken over interstates, highways, and coastlines in Louisiana. Firms like EagleView offer a proprietary solution which tracks new developments using an aerial image technology which can also measure dimensions of structures. While the primary use case for this offering is assessment of structures for valuations and property taxes, the aerial orthophotos are high resolution enough to be used for a deep learning analysis.

GEOSPATIAL NATURE OF AERIAL IMAGERY AND ORTHOPHOTOS

When evaluating imagery from a satellite, plane, or drone for disaster recovery and damage assessments it is critical to account consider the geolocation of certain features. The image of a rooftop must be tied to a certain set of coordinates, address, or parcel in order for that resident to receive appropriate relief. Certain file types such as a GeoTIFF provide a spatial element to the photograph. Orthophotos are aerial photographs which have been geometrically corrected, or orthorectified, in order to follow a specific map projection and measure true distance[14] Aerial images, when compiled in a mosaic can cover vast swaths of a geographic region. It is critical that the spatial aspect of this type of photography be evaluated in the collection of imagery and the following analysis.

PROPRIETARY AND TEMPORAL ASPECTS OF AERIAL IMAGERY

All imagery analysis must consider the temporal nature of any photography which is procured. Images are collected at a specific point in time. The conditions of light, shadow, contrast, alterations to photos, and weather should be recognized in not just the taking of the photos but in the selection of such. Satellite images of a certain geography are collected at a point in time when the orbiting device and its cameras are thousands of miles above those coordinates. The orbit controls the schedule for collection of photography and can result in the presence of clouds obfuscating structures. Aerial photography taken by a plane has much more flexibility in terms of timing as flights can be arranged to follow disaster events or if demand for coverage over a certain region is critical to observe. Alongside more flexibility in timing, there is less land coverage when compared with satellite photos. Access to such photography may also be more difficult to procure as public entities may not arrange flights over all territory while private providers do so at the behest of clients. Drone systems may provide an alternative to damage assessment teams to conduct such evaluations. However, these systems require an operator either in house or contracted with a longer timeframe required for collecting such photos than a satellite or plane.

All forms of aerial photography have some proprietary constraints. This makes much of the highest quality imagery taken of specific sites at specific times very inaccessible. Unless the entity doing the damage assessment has total control over the source of such photos, there will likely be a delay in the retrieval of photos. Satellite photo providers and aerial

Image 4.5: Aerial Imagery captured following a disaster. Source: Planet Labs

photography have control over such imagery and unless a public entity such as NASA, NOAA, or otherwise is releasing the files, the entity conducting the damage assessment will need to access photos from a private firm which requires a financial commitment. Drone operation will require the purchase of a drone system and attainment of a trained operator, in-house or outsourced.

SOFTWARE LIMITATIONS

A critical inaccessibility of these softwares is the perceived black box nature of deep learning or other techniques which fall under the manifold of artificial intelligence. These tools consist of a complex algorithmic design but can be layered over with buzzwords and oversimplifications. The complexity involved should not be a restraint to engaging with such tools, nor should they be given only cursory attention. Deploying this technology should warrant a deeper investigation into ins and outs of the algorithm in order to understand these technical components. Deep learning is a powerful force for interpreting real world patterns. This process should be made accessible to geographic information system (GIS) analysts everywhere. Analysis of this nature should not be under lock and key only for advanced computer scientists. There are avenues both in traditional enterprise software systems such as ESRI ArcGIS Pro as well as other open source options which can make this analysis more readily available. This paper focuses on how ArcGIS can be deployed to conduct this analysis. In addressing next steps and how to move forward in advancing this type of analysis, open source options are raised as alternatives and future methods.

ESRI's ArcGIS Pro product has made deep learning techniques more accessible to GIS analysts, however technical challenges remain. Most governmental authorities which operate with a clear political boundary maintain some kind of GIS staff whether on payroll directly or via a consulting relationship. Disaster management agencies, counties, local municipalities, and regional authorities typically have access to a GIS capability. The dominant software used by these analysts is the ESRI ArcGIS suite, thus the deep learning tools for imagery analysis included in ESRI tools should be more readily available to any GIS analyst. However, barriers to entry remain as the deep learning techniques require training outside of standard GIS curriculum. Additionally, this software is proprietary in nature and requires a contract with ESRI in order to have access to its toolset. ArcGIS Pro has constraints in file inputs and particularities which must be reckoned with in an advanced analysis such as this. Beyond this, hardware constraints remain which limit deep learning process speeds.

HARDWARE CONSTRAINTS

Hardware constraints can limit the level of analysis a GIS professional conducting a damage assessment may achieve. Several operations to prepare image files and other geospatial information can be run on a CPU which are provided on standard personal computer systems which typically run ArcGIS. However, the deep learning processes available through ArcGIS deep learning libraries and packages require a more robust computing system with a graphics processing unit (GPU) in order to efficiently and rapidly analyze photos using object detection, image classification, and change detection processes. NVIDIA CUDA is one such GPU and complementary software platform recommended for and capable of running this analysis, there are others.

These hardware constraints can also be overcome by the use of virtual computing services, which offer GPU powered processing through a web browser. Cloud computing will allow for the deep learning processes to be performed quickly and efficiently, potentially creating better process outcomes. However, these services, such as Amazon Web Services, Google Cloud Compute, and Microsoft Azure, can be costly and need to be closely monitored to ensure excess costs are minimized.

SECONDARY DATA ACCESS

Challenges also exist in access to secondary sources of data and geospatial files which can validate deep learning methods and results. Shapefiles, JSONs, and other geospatial information may not be available or up to date for a specific structure or unit of analysis. This kind of information can aid in the analysis by providing a reference point to verify analysis of the imagery. Typically, this will be publicly available data from a local county assessor's office or other governmental entity. For instance, in building footprint extraction, a polygon file of building footprints can verify the presence of a structure against the extracted footprint from the photo. A static polygon file of this type can be useful in change detection as well. However, while a file of this kind is useful in terms of providing a large dataset, there may be discrepancies in the file such as lack of building footprints for mobile homes, out of date information, or discrepancies on specific parcels.

4.7 Findings

Utilizing deep learning in aerial damage assessment requires some technical knowledge, but can be deployed by almost anyone with enough resources, capacity, and time. The unit of analysis is at the parcel level as the focus is on indicating damage impacting structures on individual properties.

ArcGIS Pro provides a guided workflow and many tutorials for practitioners to use deep learning for aerial damage assessment. These visual based workflows make this technology much more accessible to those who may not be technical experts. Alternative methods require knowledge of coding languages and a steeper learning curve to get started. However, ArcGIS Pro does not allow for as much flexibility to refine the model for accuracy and efficiency. This can lead to a cap on accuracy expectations with ArcGIS Pro that could be potentially overcome through other methods.

Pixel Classification

In an attempt to cut down on annotation and pre-work, our team performed classification trials outside of the predetermined building footprint polygons. The hypothesis was that practitioners could classify damaged and undamaged structures with polygons using the training classification tool to eliminate the building footprint detection or import. Through this training the aim was for the tool to capture other damaged or undamaged structures. However, the results proved almost unmanageable. We believe the tool has difficulty distinguishing pixel groups when having to calculate for other materials which produces large swaths of rectangles with very little of meaning identified.

Classification of Objects

Using the pre-built deep learning model to extract building footprints has proven highly accurate using Arc Pro. This method, however, potentially biases away from impermanent structures such as mobile homes. These types of structures may be excluded from historic data in open source or institutional files as their footprints do not require permanent footings such as a basement. Additionally, when using the building footprint extraction, especially on post-event imagery, there is a higher likelihood of the non-permanent structures being missed because they may already be destroyed. This is more likely to occur when mobile homes are on large lots or outside of planned developments. Deep learning must be accompanied with human supervision to ensure that these types of structures are not missed. Special attention should be paid to areas that are known to have these types of structures, exemplifying why local knowledge is important in the assessment process.

Classification Scale

Classification of damaged structures through an attribute table of the existing buildings resulted in the most usable classification. An image annotation guideline was created based on the input of the local assessment workflow and the FEMA damage assessment framework. This scale ranges from a 0 indicating no damage to a 4 indicating complete destruction. These guidelines should be used in the future to create cohesive training sets that ensure the FEMA framework is being emulated and allowing for easier incorporation of multiple training sets. Standardization of the classification system also minimizes potential bias as it gives structure to the humans annotating images.

These classifications offer something novel to practitioners and researchers alike. Studies thus far have focused on binary classification of damaged or undamaged structures. Classification based on a scale created from the FEMA framework offers greater nuance and potential for the expedition of a disaster declaration. The scale is translated into color coded polygons making it visually easy to understand types of damage and clusters or trends. Coupling this method with change detection offers a particularly strong methodology that can hopefully extend to more accurate assessments and insurance processing.

Damage classification on a scale can create the potential for greater biases in the deep learning analysis. Training sets of annotated structures must be much larger to provide an adequate sample of each category to the model. This can create a heavy burden on practitioners attempting to create datasets individually. In addition, it can be difficult to discern between levels of damage, leading to greater levels of human error. However, given the fact that assessors and the FEMA framework use a scale for structural damage assessment, this method can create greater value for practitioners. Understanding the level of damage on individual structures can help create a faster assessment process for residents, allowing individuals to access aid more quickly and begin rebuilding sooner. It also allows for a more equitable assessment process in states (such as Louisiana) that require property reassessment post-disaster. Rather than a one size fits all property assessment deduction the classification of levels of damage can create a right size approach.

In an attempt to cut down on annotation and pre-work this team performed classification trials outside of the predetermined building footprint polygons. The hypothesis was that practitioners could classify damaged and undamaged structures with polygons with the training classification tool to eliminate the building footprint detection or import. Through this training the hope was the tool would be able to pick up other damaged or undamaged structures. However, the results proved almost unmanageable. It appears the tool has difficulty distinguishing pixel groups when having to calculate for other materials and produces large swaths of rectangles with very little of meaning identified.

Alternatively, annotation and training for a binary classification model can be less labor intensive and potentially reduce biases. When labeling a training set of images it is simpler to detect whether damage exists creating more accurate models for deep learning to use. However, it is important to remember the context, certain disaster types are more likely to accurately follow binary outcomes. For instance, wildfire response tends to leave homes destroyed or intact, whereas wind events may only partially destroy a structure making it more difficult to annotate and assess damage. Detecting damaged or undamaged structures can give emergency responders a quick visual cue to allow for prioritization of areas of need.

Image 4.6: Deployment of blue tarps following Hurricane Ida
Source: New York Times

Object Detection

Object detection can be utilized to detect debris areas as well. This can serve as another useful aspect of general aerial damage detection as it can capture types of damage that may not be evident based off of roof analysis. Just as roof detection is most useful after wind events, damage detection could also be useful in capturing flooding and internal structural damage. Debris damage is potentially more temporally sensitive and must be captured quickly as individuals are likely to clear out damaged personal property from their homes. If performed in real-time there is potential that this information could benefit trash haulers as well, but further research is needed to determine its usefulness.

Detecting exposed plywood on roofs can aid in the immediate recovery response and aid in disbursement of blue tarps. Plywood and blue tarp detection can offer an alternative overview of damage assessment. Given that roof integrity is one of the most essential aspects of structural integrity, detection of damage and exposed roofing can highlight structures that can be efficiently preserved from continued damage especially during rain events. Further evolution of blue tarp and plywood detection could create a percentile index where calculations and prioritization during aerial assessment are based on the percentage of exposed roof. However, since tarping sometimes occurs preemptively to a storm it is important to look at pre and post event imagery. In addition this method may not accurately capture the area of damage when tarps cover significantly larger portions of the roof than the area of damage.

Blue tarp detection should be conducted with a focus on identifying the presence of a tarp on a rooftop to indicate a binary presence (0 or 1) at the parcel level. This can assist in identifying areas which need assistance and closer assessment of disaster damage. Additionally, a parcel level score can include the presence of blue tarps as a weighted factor in a score. Analyzing images for blue tarps is useful in that the sharp blue coloration of these tarps has a distinct contrast to other land cover and structural imagery. This makes for a straightforward analysis to quickly capture damaged areas in the aftermath of a storm. Of course, concerns with this process include the failure to capture tarps of other color, exposed plywood, or distinct instances of roof damage.

Change Detection

Change detection is a simple, straightforward deep learning technique as it does not require annotation of a training set or training of a model. This single click can take a macro level assessment of the damaged areas, going beyond structure specific assessment. If emergency responders are looking to understand trends and clusters of damage within the area this can be a useful approach. The usefulness may be limited by the timing of the pre-event imagery, the further back dated the image is from the event the more non-event related change could be detected adding non-pertinent visual clutter. Using change detection can help verify the damage in post-event imagery. Incorporating pre-event imagery allows emergency responders to understand if the damage was caused by the event or if it was a pre-existing condition, ensuring that resources are not misallocated. This could significantly strengthen the confidence in deep learning damage assessment.

4.8 Recommendations

Deep learning models require less human input than machine learning algorithms that may only utilize a linear regression or decision tree because of the nature of the artificial neural network that is complex and intertwined like the human brain. Deep learning requires much more data to feed these algorithms, where machine learning potentially works with a thousand data points, deep learning often uses millions.[14] This ensures that the complex multi-layer structure has enough data to eliminate fluctuations and make high quality interpretation. Therefore, there is a need to increase the size and amount of training samples available in the disaster response context. Training sets can also be created pre-disaster using previous disaster imagery. While there are some existing image sets for training, most are not open source or readily available to be utilized within ArcGIS. Expanding on the established image sets that the National Disaster Preparedness Training Center has previously created and making them available to emergency managers could significantly reduce the time it takes to perform deep learning aerial damage analysis, by reducing the need for emergency managers to create their own training sets and models.

Exploration of other machine learning techniques would also benefit this area of study. Analysis of aerial imagery containing individual structures could be conducted utilizing an approach deployed for street level imagery. However, a critical piece of the work conducted utilizing aerial imagery is the geospatial nature of the analysis. Thus, a unique geospatial identifier such as coordinates or parcel number will need to be assigned to each individual aerial structure. Practitioners could potentially use ArcGIS Pro to manipulate the imagery and clip the building images and use the individual images in Google Colab or a similar software to analyze the individual structures. Additionally, use of other spatial softwares should be explored including Google Earth Engine and QGIS. Alternatively, exploration of options like change ChangeOS and other open source methodologies available to the general public is worth the time in each new analysis as the deep learning landscape is changing rapidly and new tests, experiments, and tutorials become available frequently.

Another area of rapid transformation relevant to this research and methodology are trends in availability of open source satellite imagery and aerial photography. Following the advent of digital cartography and GIS in the 1960s "the abilities of geospatial data collection and problem-solving have exploded. Innovations in digital tools for gathering, visualizing and analyzing geospatial information created new possibilities for public and private sector organizations alike."[15] Now, a proliferation of satellites has grown the number of devices orbiting Earth for photography collection purposes into the thousands.[16] Private firms like Maxar, Planet Labs, SPOT, Airbus, and others have launched numerous satellites and innovated in this sector alongside government programs like the NASA and USGS landsat program. As space launch and satellite component costs fall, there is potential that higher quality imagery of large geographic areas will become more readily available with greater frequency. Given that, "companies that once had to pay hundreds of thousands of dollars to put a satellite into orbit can now do the same for a fraction of that price," imagery may quickly become more available at lower prices with these economies of scale.[17] With this potential, privacy concerns may also escalate which should be monitored and evaluated in advancing rapid damage assessment solutions.[18] However, while this concern should be taken seriously, the need for delivering aid quickly is real and these trends in imagery availability should be seen positively with potential for community benefit.

Further research should explore creating linkages between aerial analysis and street level view of structures. The street level imagery would need to have location data attached either by parcel or by coordinates. Combining aerial data with street level imagery would not only create a more complete understanding of structural damage, but also further expedite insurance claims. Allowing residents to click on individual parcels and print a report with street view imagery and the official damage assessment would create a uniform damage report that would take the guesswork out of requesting aid. This could significantly increase the level of aid to individuals in socioeconomic groups that typically lose out. Often lower income individuals do not have access to the resources or understanding to request aid, allowing their homes to remain damaged until the next disaster occurs compounding even more damage.

Nonprofits and community based organizations regularly try to bridge these gaps, but they are often overtaxed and under-resourced as well. Producing a public facing tool powered by both aerial and street level assessment would create greater cross-sector integration and improve equity in disaster recovery.

4.9 Conclusions

Although these technical solutions are complex and require advanced computing workloads and skills, there remains a net positive increase to the accuracy, efficiency, and consistency of rapid damage assessment. These advances further the goals of the Federal Emergency Management Agency and assist emergency managers, assessors, and community leaders to make informed decisions for better recovery. However, these solutions should be made more accessible with attention given to both hardware and software constraints. The current ArcGIS Pro deep learning framework provides a visual based tool that allows practitioners with an intermediate level of digital literacy an entryway into deep learning assessment work. While this is a good step, these tools need to continue to evolve to be more inclusive and create an impactful tool for the community at large. Disaster Managers, emergency managers, assessors who might not have mapping, machine learning, or an intermediate level of digital literacy. Implementation of aerial image analysis and particularly the advanced deep learning analysis should be advanced as a method in returning more accurate, efficient, and consistent damage assessment results.

ENDNOTES

1. *Preliminary damage assessment guide - fema.gov. (2021, August). Retrieved April 11, 2022, from https://www.fema.gov/sites/default/files/documents/fema_2021-pda-guide.pdf*

2. *FEMA (2021).*

3. Tab Troxler Intervew, St. Charles Parish Assessor, lives in Louisiana, USA personal communication, March 2022

4. Troxler (2022).

5. *Dell'Acqua, F., & Gamba, P. (2012). Remote Sensing and earthquake damage assessment: Experiences, limits, and perspectives. Proceedings of the IEEE, 100(10), 2876–2890. https://doi.org/10.1109/jproc.2012.2196404*

6. Microsoft. (2022, January 14). *New and Updated Building Footprints.* Bing. Retrieved April 11, 2022, from https://blogs.bing.com/maps/2022-01/New-and-updated-Building-Footprints

7. Microsoft. (2022).

8. Kulbacki, J. (2019, October 14). *Building Damage Assessment: 2018 Woolsey Fire, Southern California.* ArcGIS StoryMaps. Retrieved April 11, 2022, from https://storymaps.arcgis.com/

9. Kulbacki, J. (2019)

10. *National Response Framework.* (2019). Retrieved April 11, 2022, from https://www.fema.gov/sites/default/files/2020-04/NRF_FINALApproved_2011028.pdf Preliminary damage assessment guide - fema.gov. (2021, August). Retrieved April 11, 2022, from https://www.fema.gov/sites/default/files/documents/fema_2021-pda-guide.pdf

11. *Damage Assessment Operations Manual: A Guide to Assessing Damage and Impact.* FEMA. (2016, April 5). Retrieved April 11, 2022, from https://www.fema.gov/sites/default/files/2020-07/Damage_Assessment_Manual_April62016.pdf

12. *FEMA (2016).*

13. Troxler (2022).

14. *Deep learning in arcgis pro. Deep learning in ArcGIS Pro-ArcGIS Pro | Documentation. (n.d.). Retrieved April 11, 2022, from https://pro.arcgis.com/en/pro-app/2.7/help/analysis/image-analyst/deep-learning-in-arcgis-pro.htm#:~:text=Deep%20learning%20is%20a%20type,object%20classification%2C%20and%20image%20classification.*

15. *Wolfewicz, A. (2022, April 21). Deep Learning vs. machine learning – what's the difference? Levity. Retrieved April 24, 2022, from https://levity.ai/blog/difference-machine-learning-deep-learning#:~:text=Machine%20learning%20works%20with%20a,and%20make%20high%2Dquality%20interpretations.*

16. *Maxar Technologies. (2020). Advances in Satellite Imagery and Technology Cause a Basemap Evolution. Maxar Blog. Retrieved April 25, 2022, from https://blog.maxar.com/earth-intelligence/2020/advances-in-satellite-imagery-and-technology-cause-a-basemap-evolution*

17. *UNOOSA. (2022). United Nations Office for Outer Space Affairs. Search OSOidx. Retrieved April 25, 2022, from http://www.unoosa.org/oosa/osoindex/search-ng.jspx?lf_id=*

18. *Chow, D. (2022, April 8). To cheaply go: How falling launch costs fueled a thriving economy in orbit. NBCNews.com. Retrieved April 25, 2022, from https://www.nbcnews.com/science/space/space-launch-costs-growing-business-industry-rcna23488*

19. *Brown, S. (2019, October 29). If you're worried about surveillance from space, read this. CNET. Retrieved April 25, 2022, from https://www.cnet.com/science/turns-out-satellite-surveillance-only-sounds-like-a-major-privacy-concern/*

RISING ABOVE THE DELUGE

DAMAGE ASSESSMENT THROUGH AERIAL IMAGERY

Authors: Jane Dixon, Jon Haadsma, Rob Svoboda

about this project

This project is a joint effort by students and faculty within the Master of Urban and Regional Planning program at the University of Michigan and the National Disaster Preparedness Training Center (NDPTC) as a Capstone project for the Winter 2022 semester.

A key focus of the University of Michigan team is to work in a manner that promotes the values of equity, uplifting local voices, transparency and honesty. As a result, the outcomes of this capstone aim to speak to both our collaborators at the NDPTC and the local communities impacted by disasters across the United States. Our responsibilities as researchers will also include the implementation and/or recommendation of innovative solutions to issues surrounding machine learning, damage assessments, prioritization determinations, and social infrastructure networks.

UNIVERSITY OF MICHIGAN