



working paper series: aerial imagery

Getting Started

Aerial Imagery - Deep Learning Approaches for Damage Detection

Introduction

Aerial imagery is utilized by FEMA, assessors, emergency managers, academia, and others in the evaluation and assessment of disaster damage. However, this work has typically been conducted in a manual process by going over each house across large orthophotos to evaluate damage to rooftops. New advances in machine learning offer novel options in the evaluation of such imagery. A deep learning assisted approach can process damage analysis at an unparalleled speed. Deep learning techniques can create an accurate, classified scale of damage by detecting objects such as blue tarps and debris. Capabilities to build a trained model to classify roof damage based on aerial imagery also offers avenues for detecting destruction. There is also potential in detecting change between pre- and post-event imagery.

Given the wide availability of ESRI ArcGIS to planners, assessors, and emergency managers, this paper will focus on deep learning solutions offered in this software. Anyone with access to ArcGIS Pro should be able to follow straightforward steps to analyze aerial imagery to identify damage and objects. Image Classification, Object Detection, and Change Detection are the primary deep learning techniques reviewed in this process recommendation and working paper. There are similarities here to the machine learning concepts laid out in Chapter 2. However, the focus of this paper is on aerial imagery which has a spatial and geographic nature as the photos cover a wider view of the built environment, not just a single structure. Machine learning techniques, tools, and methods (YOLOv5, Roboflow, Lobe.ai) could potentially be applied to aerial photos of single structures if a geographic reference can be coded to each photo. This is not explored in our research but merits further investigation. Additional tips on hardware, imagery collection, and other available and open source tools are also included.

Computing Power Required

Deep learning analysis requires intensive computing power to execute the processes necessary for damage assessment. Most personal computers do not have the necessary hardware required to perform deep learning. Machines powered with a NVIDIA CUDA enabled graphics processing unit (GPU) will optimize the damage assessment within ArcGIS. Even if the local computer in use does not have a GPU there are many cloud computing options available. Google Cloud Compute, Amazon Web Services (AWS), and Microsoft Azure all offer computing options. Additionally, there are other alternatives to these three major suppliers that maintain advanced computing resources accessible through a web browser. Computing costs will vary depending on what source is used. Another condition that must be considered is the availability of the high-powered computing machines through these services.

Setting Up Deep Learning for ArcGIS

To get started you will want to download the ArcGIS Pro Deep Learning Package [here](#).

Also review the deep learning documentation [here](#).

Accessing High Resolution Imagery

NOAA – National Oceanic and Atmospheric Administration
Publicly available aerial photography is provided by NOAA online for certain disaster areas. Only limited geographies may be captured in these photos. Images must be retrieved through the NOAA data access portal, which should not be confused with the NOAA’s Emergency Response Imagery. Imagery can be searched by address or a manually drawn boundary or the predetermined polygons. Blue polygons indicate available imagery from a post-event flyover. Once the imagery is selected the aerial will be added to the cart, once the “checkout” process is completed the file will be sent for download via email.

Other Resources
Private satellite imagery can be acquired from firms such as Planet Labs, Maxar, and others. This will require payment in most cases. Aerial imagery delivered as high resolution orthophotos is offered by firms like EagleView and Nearmap. Access to such photos requires a relationship with these providers and flights to capture these photos can be very expensive.

Image Classification

Image classification labels and classifies digital photos. For example, Image 3.1 shows classification of damage score to the individual photo of a structure. GIS deep learning processes can be utilized to categorize features.



Image 3.1: Image Classification for structural damage undamaged vs. damaged classified in unique colors.Source: Esri

Object Detection

Object detection can locate specific features within an image. For example, Image 3.2 shows building footprints being detected. A bounding box is utilized 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.



Image 3.2: Object detection to identify building footprints. Source: Esri

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. For example, Image 3.3 shows a structure from before Hurricane Ida in Louisiana. The image on the right shows the logical change map where damage to the structure occurred as well as installation of blue tarps which signify temporary repair to damaged roofs.



Image 3.3: Change Detection to identify blue tarps.Source: Planet Labs

Image Translation

To prepare images for evaluation, image translation can improve image quality and resolution. For example, Image 3.4 contrasts an image from Planet Labs before image translation and after. 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.



Image 3.4: Image translation to improve image quality
Source: Esri

Further Resources

Hardware

- [NVIDIA CUDA](#)
- [Paper space](#)
- [Amazon Web Services \(AWS\)](#)
- [Google Cloud](#)

Software

- [ArcGIS Pro](#)
- [Geospatial Deep Learning with ArcGIS](#)
- [ArcGIS Hurricane Damage Assessments](#)
- [ESRI Disaster Response Overview](#)

Image Sources

- [NOAA](#)
- [NOAA Ida Aerial Imagery](#)
- [NASA Earthdata](#)
- [NASA Ida Data](#)
- [Maxar](#)
- [Planet Labs](#)
- [Planet Labs in ArcGIS](#)
- [ArcGIS Image Discovery](#)

Aerial Damage Assessment Alternatives

- [ENVI](#)
- [Dewberry](#)
- [EagleView](#)
- [Nearmap](#)

Resolution Considerations

- [Increase Image Resolution ArcGIS/Python](#)
- [ArcGIS Image Preparation](#)

Image Classification

Aerial Imagery Analysis

Introduction

Image classification labels and classifies digital photos. For example, Image 3.5 shows classification of a damage score to the individual photo of a structure. GIS deep learning processes can be utilized to categorize features.

Classification within an image can provide a more detailed understanding of the damage sustained throughout an area or region. Detecting whether an object has been damaged is limiting especially in cases where most structures have sustained some type of damage. With the classification method, emergency managers can understand the degree of damage.

Overview

Image classification, uses convolutional neural networks (CNN) to identify and sort aspects within an image into a predetermined schema. The focal point of image classification within aerial damage assessment remains physical structures. This process classifies objects by programming the model to only classify the structures within a bounding box. Classifying objects within an aerial image provides a union of detail and extensive assessment of damage. This process also offers efficiency in analysis as it eliminates peripheral data for the model to analyze images which creates an easy visual hierarchy for manual analysis.

Post disaster manual classification of structural damage is already occurring in the field. Our team visited Southeastern Louisiana in February, 2022 to assess the disaster recovery process in the wake of Hurricane Ida. This informed our understanding of what kind of tools practitioners in the field currently deploy and those they could use. Interviews with St. Charles



Image 3.5: Image Classification was used to classify the structural damage visible in aerial imagery.

Parish Assessor Tab Troxler detailed a post disaster assessment process where Assessing Department staff members would manually classify the damage of over 20,000 structures. Staff would use aerial imagery to designate a damage score ranging from 0 to 4, with 4 being destroyed (Image 3.6). This process requires extensive labor resources, but even given these costs, the assessing office repeatedly highlighted the utility of this type of damage assessment. The conversation further underscored how paramount roof integrity is to structural soundness, which is one of the reasons this process is so important. In addition, providing an assessment relieves the individual homeowner of the burden of proof that would normally be required to receive aid. In deep learning, damage assessments are typically performed under a binary classification of undamaged versus damaged structures. Our team introduces training to the deep learning model that includes indicators of damage on a scale that reflects the FEMA framework and real world experience.

This process recommendation will walk through the specifics of image classification using a scale of damage for structures. Incorporating this model in the post disaster assessment of major storms can detect levels of roof damage.

Image and Data Collection

In order to perform this process the resolution of the aerial imagery must be of at least a 5 meter per pixel resolution. This type of imagery is available in limited quantities and geographies from NOAA at a 3.5 meter per pixel resolution. Other sources of imagery may be used as outlined in Getting Started with Aerial Damage Analysis. Some local units may have access to professional aerial imagery from flights or drones, however these services remain costly and inaccessible.

Classification of structures requires the objects within the image to already be identified. Identification of structures within an image can take two forms: 1) pre-existing shapefiles of building footprints, 2) extracted building footprints using a deep learning package. Many local governments have already established building footprints within their ArcGIS platform. In addition, Microsoft has compiled an open source data base of multi millions of building footprints throughout the United States. For more information on identifying

building footprints using object detection with deep learning please refer to Object Detection Process Documentation.

There is ample documentation available that provides step-by-step guides on how to perform damage assessment with [ArcGIS deep learning](#). This project followed the steps provided by ESRI in a tutorial on automated fire damage assessment with deep learning. The purpose of the rest of this document is to provide critique, clarification, and explanation for process improvements. Practitioners wishing to implement this process on their own should follow the aforementioned tutorial supplemented by this documentation.

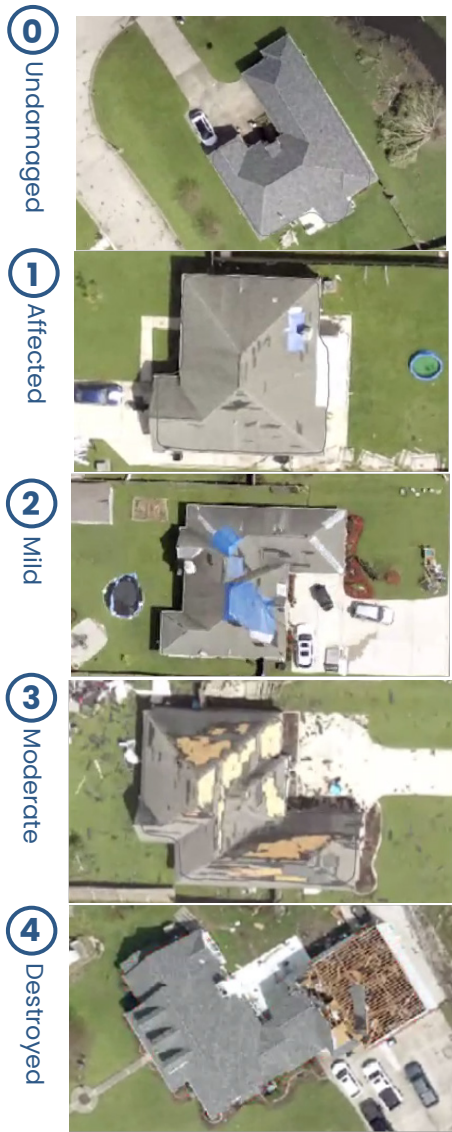


Image 3.6: Damage Assessment Scale created based off FEMA and St. Charles Parish Assessment Framework

Annotation

Once the building footprints have been established, the objects must be annotated manually, which can be done using ArcGIS Pro. Annotation must be normalized using a standard scale with individuals trained to ensure high quality and accurate input for the model. The annotation scale created for this project incorporates feedback from on the ground practitioners as well as the FEMA framework for damage assessment. This classification ranged from undamaged to level 4 damage, which indicated almost complete destruction. Below is an image of examples of the annotation scale.

Annotation for this method takes place in the attribute table of the building footprint layer. Codes should be added for all five levels of damage that will be annotated: 0) undamaged 1) affected 2) mild 3) moderate 4) destroyed. The criteria for these categories is as follows. Undamaged displays no visible damage to the roof integrity, all shingles remain in place. Affected structures may have some shingle loss or less than 5% of the under roofing exposed. Structures with mild damage have less than 30% of the under roofing exposed. Moderately affected structures have less than 70% of the under roofing exposed. Destroyed structures are classified as more than 60% roof damage or complete exposure with all under roof material missing. Once the class value has been created it can be added to the layer in the contents panel by right clicking the layer and adding the appropriate field from the data drop down. This will make the features viewable on the map. The symbology then can be adjusted from the content panel to designate a useful visual hierarchy of damage. No less than 100 features per class should be annotated, additional samples will benefit the accuracy of the model. This training sample can then be exported as chips using the Export Training Data for Deep Learning module as outlined in the ESRI tutorial.

The predefined export process is an easy to navigate click-through process. Be sure to delete any null values in the class field prior to export otherwise you will not be able to create a training set. An alternative method of annotation was attempted, this workflow followed the training samples manager in ArcGIS. This process forgoes using the attribute table of the building

footprint layer and labels both the polygons and the damage. While this method exported training samples consistently, it did not yield usable results once the model was run. Therefore, it is our recommendation that further research be conducted into alternative annotation and training sample creation.

Training and Running the Model

Once the training set has been exported it can be used to train a deep learning model, as can be viewed in the tutorial ArcGIS Pro. This creates a model that is tailored to classified damage assessment. Practitioners who decide to use their own annotated training samples can benefit from the fact that the model was presumably trained on the specific kind of damage that has occurred by using a subset of the post-event imagery. This is because the pre-trained model could have been trained only on structures affected by tornado damage but is being used to assess earthquake damage. Different disaster events produce different damage typology and practitioners should be mindful of this when selecting a model. Alternatively, using a pre-trained model that has been trained on a wide variety of damage, of thousands of images, can offer validity that is not seen from models trained on smaller subsets. Special attention should be given on the distribution of training samples. Every class should have an even distribution of training samples

Additional options for training the model should be explored. These include ArcGIS Notebooks, Google Earth Engine, Pytorch Vision, and Keras. These methods require additional computer programming knowledge and a fluency in Python to be able to execute these trials. The additional knowledge and skill allows for the models to be designed with more customization. Further customization could create stronger models and higher rates of validity, and therefore trust in the assessment process.

Object Detection

Aerial Imagery Analysis

Introduction

Object detection can locate specific features within a sample set of images that can train a deep learning model to detect those features in a larger dataset. For example, Image 3.7 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 geographic information systems (GIS) methods, this training set will then be fed into a model to identify individual objects from satellite or aerial imagery in a spatial format. The identification of features such as blue tarps, exposed plywood, and household debris in the aftermath of a disaster can highlight hotspots or areas of significant damage. This type of object detection can output information at the parcel level or structure level to determine the presence of such features feeding into a damage assessment framework or score.



Image 3.7: Object detection was used in this image to identify building footprints in a given location. Source: Esri

Overview

In order to evaluate and assess damage at a more granular level, a process of detecting objects in satellite imagery can provide insight on the impact of a disaster. By analyzing both pre-event imagery and post-event imagery, the presence of certain elements which illustrate disaster damage can be analyzed in ArcGIS Pro to evaluate the damage level for a given structure. This process recommendation focuses on ArcGIS Pro as the software tool with the capability to run this object detection, however some alternative methods are also explored.

After a disaster with substantial wind damage, presence of blue tarps and exposed plywood are two primary indicators of roof damage to a property. As such, object detection for exposed plywood or extensive damage can be a powerful method. Additionally, presence of household debris can indicate a level of damage from flooding and/or potentially wind damage and rain. Other variables of interest could include RVs or trailers housing those rebuilding and recovering. These indicators can be identified from aerial imagery using deep learning techniques.

However, identifying the presence of a blue tarp is a straightforward feature for detection given the coloration and known presence in the aftermath of hurri-

canes (relevant to the Hurricane Ida case study). Blue tarps are not always immediately installed to roofs but are applied in the relief stage. These “band-aids” prevent more water damage and protect property. Tarping of roofs (often blue), can also be an indicator of a lagging recovery. It should further be noted that these tarps are not always the color blue and not all damaged structures will be patched, as they may have been totally destroyed or lack a response from a property owner or otherwise. However, these tarps can be a strong indicator of hotspots for wind damage which need relief and recovery support. This process recommendation will walk through the particulars of object detection in identifying blue tarps as a particular feature.

Image and Data Collection

Identifying blue tarps can be done at the parcel level or at a larger unit of analysis. However, this is largely dependent on the resolution and quality of the imagery available. NOAA provides high quality imagery at 3.5 meter per pixel resolution which is a high enough quality to see individual roofs and allows the possibility of identifying blue roofs at the parcel level. Other sources include NASA, Planet Labs, and those sources outlined under Further Resources. However the highest quality photos are likely to be aerial imagery which can include high resolution orthophotos taken from planes. These photos, however, can be costly and inaccessible. Firms like EagleView or NearMap are often contracted for the capture of such imagery.



Image 3.8: Aerial Imagery can highlight where blue tarps have been deployed. Source: NOAA

Training and Analysis

Object detection can locate specific features within an image. For example, Image 3.9 shows detection of a blue tarp 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. In the disaster context, 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, determining where instances of blue tarps exist in the aftermath of a storm. One further step is to investigate the potential for object detection to inform damage assessments directly.

The object detection 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 will then produce a new output with all objects detected. A simple analysis at the parcel or structure level could then be conducted to determine the presence of a detected object in that exact polygon. This could then inform the weighted damage score on a property.

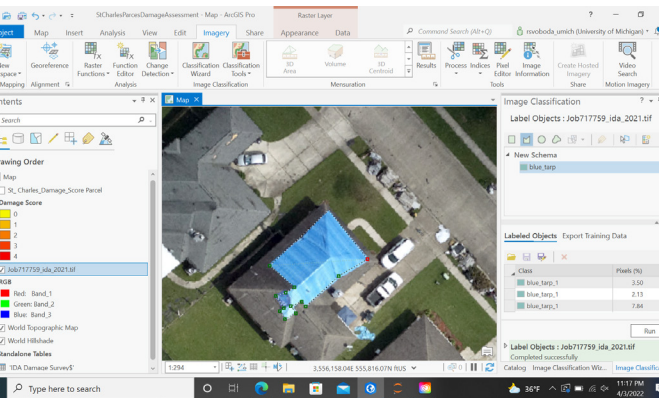


Image 3.9: A blue tarp is labeled using the image classification deep learning tool.

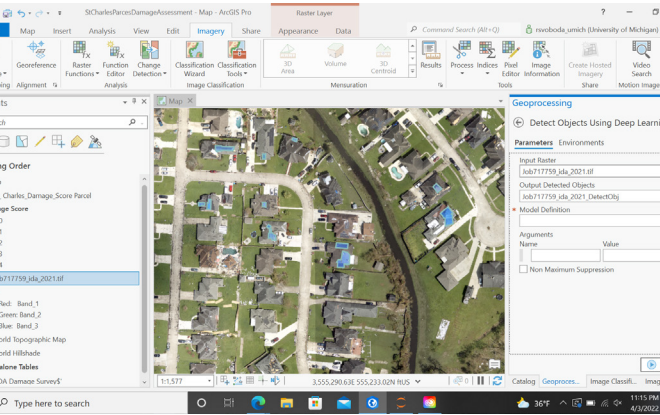


Image 3.10: Once the data has been trained, the model is run using the detect objects using deep learning

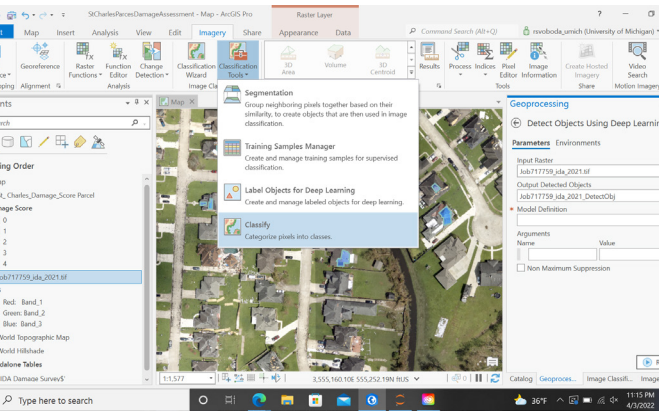


Image 3.11: The classify option categorizes pixels into classes.

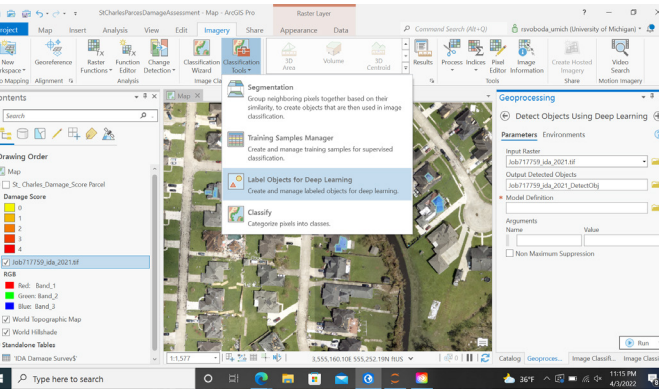


Image 3.12: The label object for deep learning object allows users to label objects.

Other Methods

Beyond the ArcGIS approaches delineated here, certain methods are availalbe for object detection, image classification, and segementation. These include RetinaNet architecture, convolutional neural networks, and Mask R-CNN. Techniques that exist outside of proprietary platforms such as ArcGIS should be considered in future evolutions of this research to incorporate open sourced tactics for aerial imagery analysis.

RetinaNet

RetinaNet architecture, outlined in a 2017 paper, contains two categories of object detection: single-stage and two-stage. Two-stage categorizes objects into foreground or background categories (Faster-RCNN is an example of this two-stage architecture). Single-stage architecture does not classify foreground objects. This architecture trades accuracy for efficien-

Segmentation

The next level of object detection is segmentation of aerial imagery. There can be interest in only some portions or features within an image representing different objects, rather than the entire photo. Segmentation is the best technique for identifying specific components of an image. In disaster recovery and damage assessments this would mean identification of multiple features including but not limited to blue tarps, exposed plywood, and household debris. Image segmentation can classify each pixel of an image into a meaningful classes related to a specific object. Those classified pixels represent independent features in the output. Identifying each feature or a combination thereof can then factor into a damage assessment score.

There are multiple options outside of ArcGIS deep learning that can implement image segmentation or object detection (Retinanet, CNN). However, these technologies are typically applied to street-level imagery with one house or structure in each frame. Aerial images present a challenge with complex foreground and background compositions. A potential avenue for evaluating aerial images with such methods is to take a geoTIFF and extract only the image geolocated within a certain parcel. Then running that image through these frameworks with a parcel ID (or other unique geolocated ID) in order to conduct object detection or segmentation. This also offers up the possibility of matching the aerial image damage assessment with the street-level damage assessment based on a join of unique identifiers. That is a critical next step in the effort to establish a more robust damage assessment score for individual structures.

CNN for Blue Roof Object Detection

Blue roof object detection is a method for identifying damage structures following a disaster using convolutional neural network (CNN) technology. This process was used to explore a damaged building inventory in a 2020 paper by Miura, Aridome, and Matsuoka that analyzed the 2016 Kumamoto and 1995 Kobe, Japan earthquakes. Roofs which are damaged but not entirely destroyed are covered with blue tarps after disasters. Aerial images and the building damage data obtained in the aftermath of these disasters show the blue tarps and the level of damage for structures, respectively. Collapsed, non-collapsed buildings, and buildings covered with blue tarps were identified using this method. CNN architecture deployed in this research correctly classifies building damage with 95% accuracy. The CNN model was later applied to aerial images in Chiba, Japan following a typhoon in September 2019. Results showed 90% of the building damage classified with the CNN model.

Change Detection

Aerial Imagery Analysis

Introduction

Change detection utilizing deep learning techniques can identify changes to structures between pre-event and post-event photography. This process compares multiple raster datasets from the same geospatial location across a temporal spectrum to determine the magnitude of change. Change detection brings both the temporal and spatial elements of aerial photography together in one process. In disaster recovery, mapping this change with a spatial component in comparison with a pre-disaster photo can provide insight on areas of concern which need further ground-level damage assessment. Beyond this, change detection analysis can assist in building a parcel or structure level damage assessment by factoring in impact of wind or flooding damage.

Overview

The image below shows a structure from before Hurricane Ida in Louisiana and the image on the right shows the logical change map where damage to the structure occurred illustrated by installation of blue tarps which signify temporary repair to damaged roofs.

Change detection can be a useful analysis in determining differences in the make up of structures as visible in aerial images. Automated change detection can be based on the building footprint or other features on roofs of structures. Analyzing this type of change requires a pre-event image and post-event image for the comparative analysis. The ChangeDetector model workflow in ArcGIS Pro can identify change in satellite imagery or aerial photography taken during two different time periods.

In damage assessment, this type of imagery can be utilized to identify areas which have experienced this persistent change. It is also a method in damage assessment that can be used for improving damage assessments and speeding up the identification of spatial units which need to be evaluated more closely. Analyzing areas of concern for active field assessments or further imagery analysis can save time and

resources, providing aid to residents more expeditiously.

When working with ArcGIS Pro, there are three possible workflows: categorical change, pixel value change, and time series change. For disaster recovery purposes, pixel value change is likely the needed workflow as the pre-event and post-event imagery will most likely be orthophotos which are continuous raster data. The output of this workflow can be a raster dataset, polygon feature class, or raster function template which can be used to highlight areas of significant change. Ideally, this could be applied at a granular level down to the structure or parcel level, though given the currently available aerial photography, it is more likely that a spatial unit such as a census block or tract may need to be chosen as the unit of analysis for the output data.

ArcGIS Pro provides a relatively straightforward and accessible product in the geoprocessing suite which makes this workflow readily available to GIS analysts. The Change Detection Wizard via the Image Analyst extension enables users to compare continuous raster datasets with Band Difference. Typically, when selecting a difference type, Absolute is the default. This analyzes the mathematical difference between the pixel values in the pre-event raster image and post-disaster event image. The Band Index, Cell Size Type, and Extent Type will all need to be applied based on the output the analyst is aiming to achieve. The Change Detection Wizard output is a computation of the band index, computing the difference between raster images, and a histogram visualizing the difference values.



Image 3.14: Change detection can be used in this image to identify change after a disaster.

RESOURCES

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AERIAL IMAGERY: DEEP LEARNING FOR DAMAGE DETECTION

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.