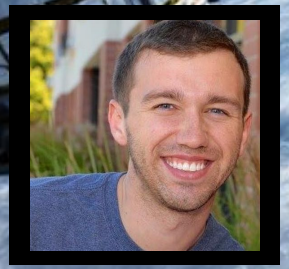
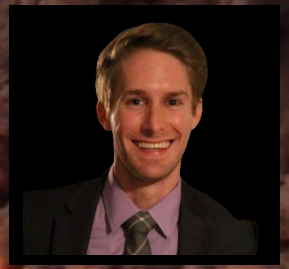
Natural Disaster Geospatial Damage Assessment

Team Disaster
DAEN 690 Project
Spring 2020
Sponsor: Accenture Federal Services

Team Members

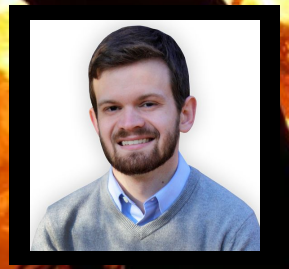


Billy Ermlick



Nick Newman
(Product Owner)

Devayani Pawar



Tyler Richardett
(Scrum Master)

Accenture Federal Services:
Marc Ruiz Bosch & Christian Conroy

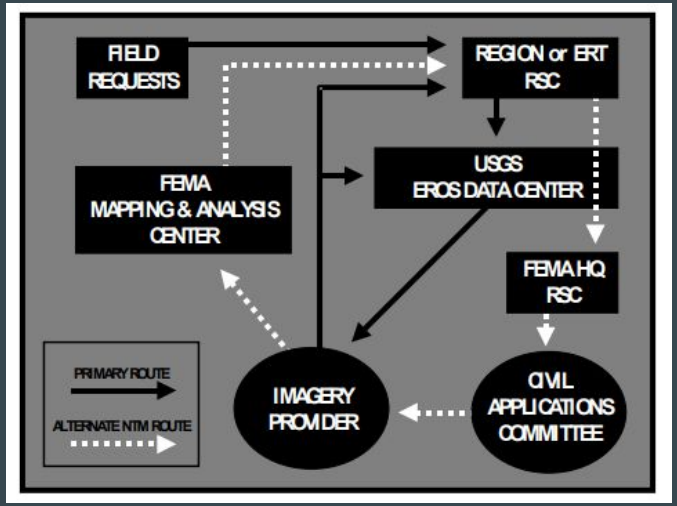
Problem Definition

- Relief efforts rely on damage assessments for identifying target areas, extent of damage, and required funding
- Typically a slow and dangerous “on-the-ground” assessment is performed
- Need a way to assess damage in a fast, accurate, and safe way

FEMA conventional damage assessments [1]

Problem Definition

- Satellite images provide fast information regarding damaged areas
- FEMA and others currently manually review images for building damage
- Provide assessments according to the United States National Grid
- Need to automate this review process



FEMA remote sensing procedure [2]

Project Definition

Objective

Create a proof-of-concept application which uses satellite images to automatically estimate building damage and visualize cost according to the United States National Grid coordinate system.

Agenda

1. Datasets
2. Financial Modeling
    - USNG Mapping
    - Financial Model & Visualization
3. Damage Estimate Modeling
    - U-net Architecture
    - Mask-RCNN
4. Application

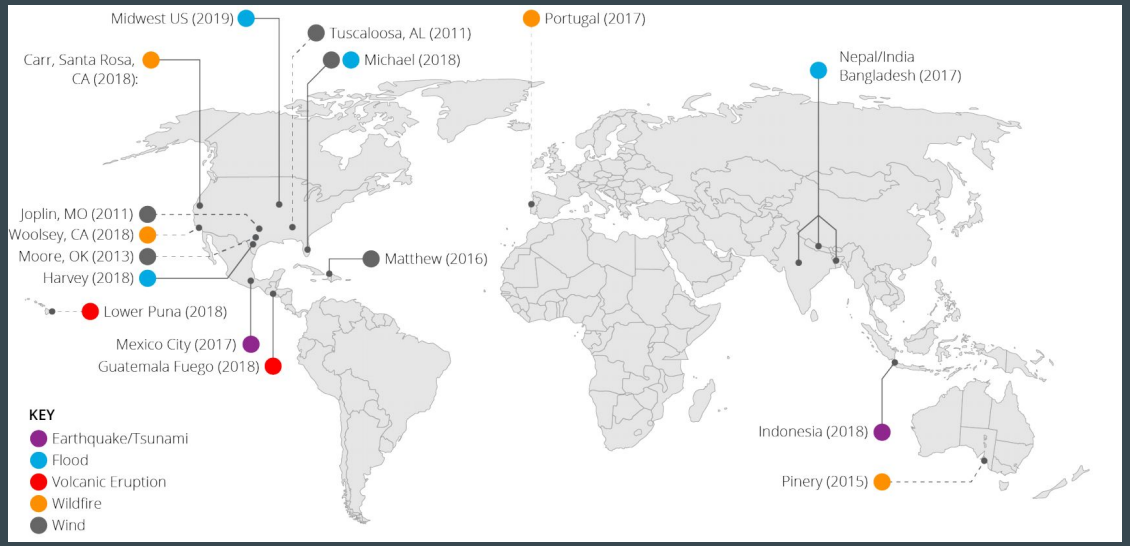
Datasets

Xview2

Xview2 Dataset

Overview

- Defense Innovation Unit & Maxar open competition ended January 2020
- Public dataset
- Images of 850k buildings before and after disasters from around the world from 2011-2018



Disaster events and locations [3]

Xview2 Dataset

Overview

- 6 types of disasters (hurricanes, wildfires, floods, earthquakes, etc.)
- Images of same location before/after disaster (nadir angles may vary)

Pre and post disaster image [3]

Xview2 Dataset

Annotations

- Unified labels for building locations and standardized damage level (0-4)
- Panel reviewed for consistency

Disaster Level	Structure Description
0 (No Damage)	Undisturbed. No sign of water, structural or shingle damage, or burn marks.
1 (Minor Damage)	Building partially burnt, water surrounding structure, volcanic flow nearby, roof elements missing, or visible cracks.
2 (Major Damage)	Partial wall or roof collapse, encroaching volcanic flow, or surrounded by water/mud.
3 (Destroyed)	Scorched, completely collapsed, partially/ completely covered with water/mud, or otherwise no longer present.

[3]

Annotated post-disaster image

Xview2 Dataset

Predictions & Evaluation

- Output two PNG image with pixel values representing
  - building locations (0/1)
  - damage level (0-4)
- Final f1 score is evaluated based on 30% location and 70% damage f1 values

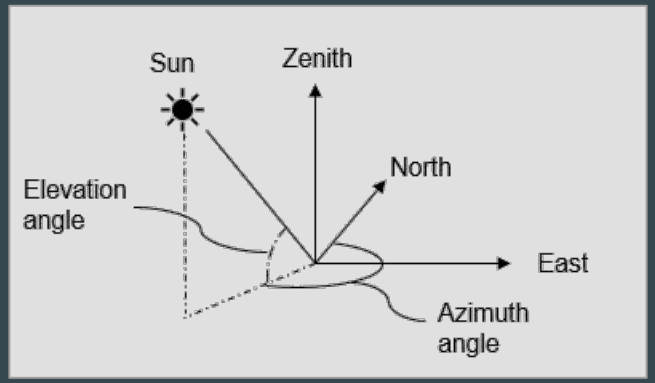
[3]

Annotated post-disaster image

Xview2 Dataset

Field Descriptions

Attribute	Type	Description
Image ID	STR	Unique ID identifying each image
Disaster ID	STR	Unique ID identifying each disaster
Image Name	STR	Pre/post and which disaster
Capture Date	Date	Date the image was captured
Height/Width	INT	All images are of size: (1024, 1024, 3)
Ground Sampling Distance	Float	Distance between pixel centers on the ground
Off_Nadir_Angle	Float	Image capture angle relative to ground plane
Pan_Resolution	Float	Resolution of single band image used for pan sharpening
Sun_Azimuth	Float	Angle of the sun from polar north
Sun_Elevation	Float	Angle of the sun from ground plane
Target Azimuth	Float	Angle of satellite from polar north
Provider_Asset_Type	STR	Satellite model image taken from
LAT/LON Polygon	Poly	Polygon lat/lon coordinates of each building
Damage-Classification	INT	Indication of level of damage for each building

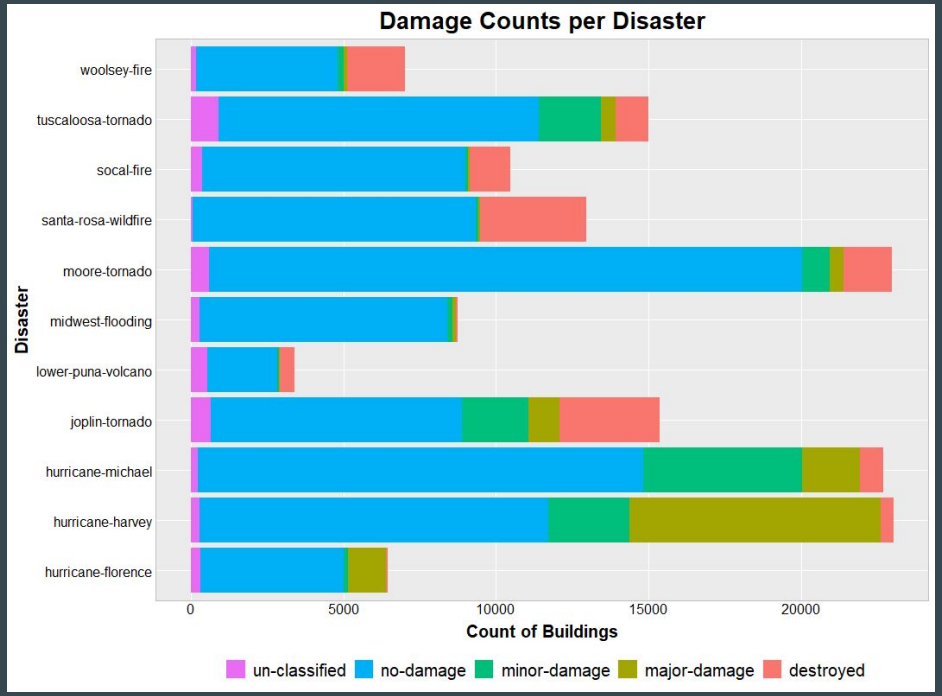


Sun azimuth and elevation angle [4]

Xview2 Dataset

Data Condition:

- Clean dataset
- No missing or incorrect values
- Buildings obsecured or newly built in an “after” image not counted
- Imbalanced by
  - disaster type
  - class - mainly un-damaged



Other Public Datasets

Zillow 2018 $/sqft:

- Dataset providing $/sqft for US zip codes
- Average cost used for missing zipcodes

US GeoID, County Tract, & Zipcode listings:

- Utilized to map building lat/lons to geoID -> countytract -> zipcode
- API & CSV files provided by US Census Bureau

NOAA Disaster Cost Evaluation Data:

- Ballpark cost of property damage for a few disasters by county

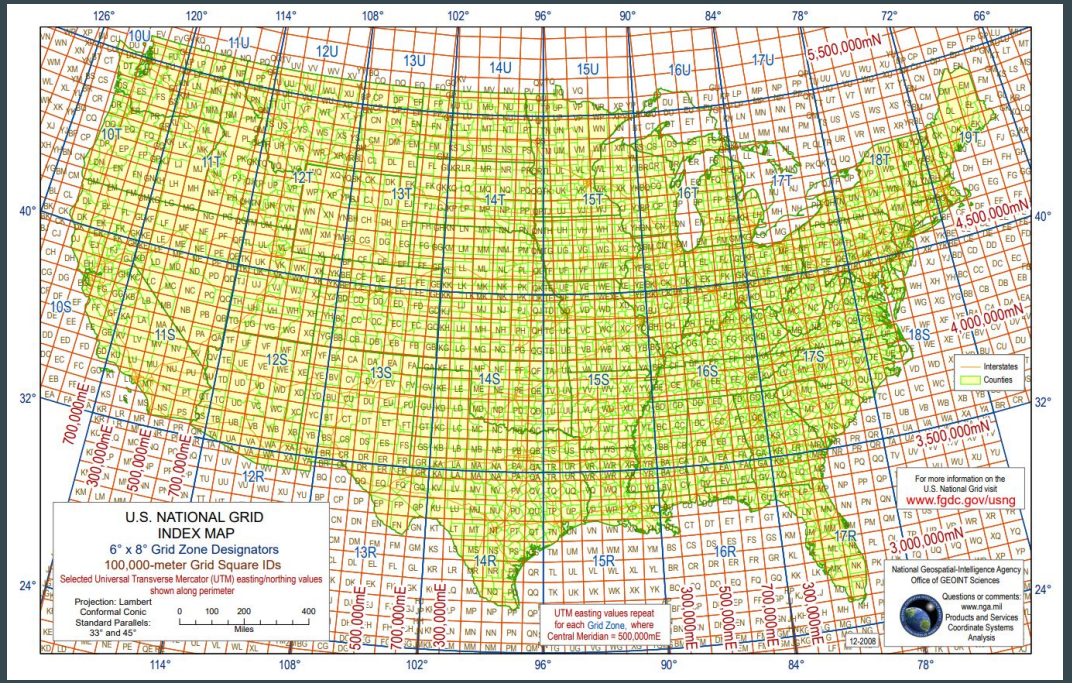
Financial Modeling

USNG Mapping Function

Financial Modeling - USNG Mapping

US National Grid Coordinates

- FEMA uses USNG coordinates for regional estimates
- Heierarchical rectuangular system which roughly follows lon/lat lines
  - 14 chars based on UTM and MGRS
- No available geocoding service for Python



[5]

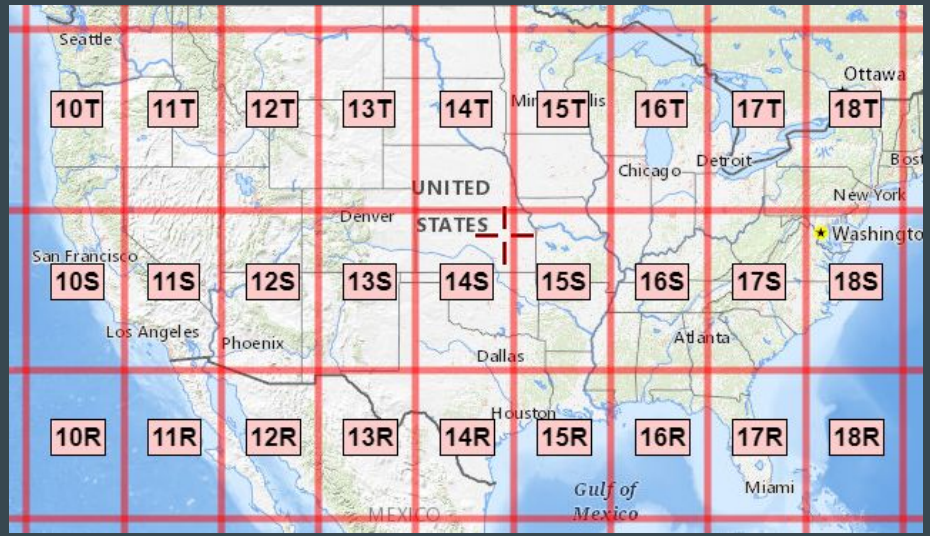
USNG coordiantes

Financial Modeling - USNG Mapping

US National Grid Coordinates

- 15S .....precision level 6° × 8°
- 15S WV .....precision level 100 km
- 15S WV 8 6 .....precision level 10 km
- 15S WV 83 68 .....precision level 1 km
- 15S WV 832 683.....precision level 100m
- 15S WV 8320 6830.....precision level 10m
- 15S WV 83200 68300 .....precision level 1m

UTM zone group main easting northing



[6]

USNG coordiantes

Financial Modeling - USNG Mapping

US National Grid Coordinates

- 15S .....precision level 6° × 8°
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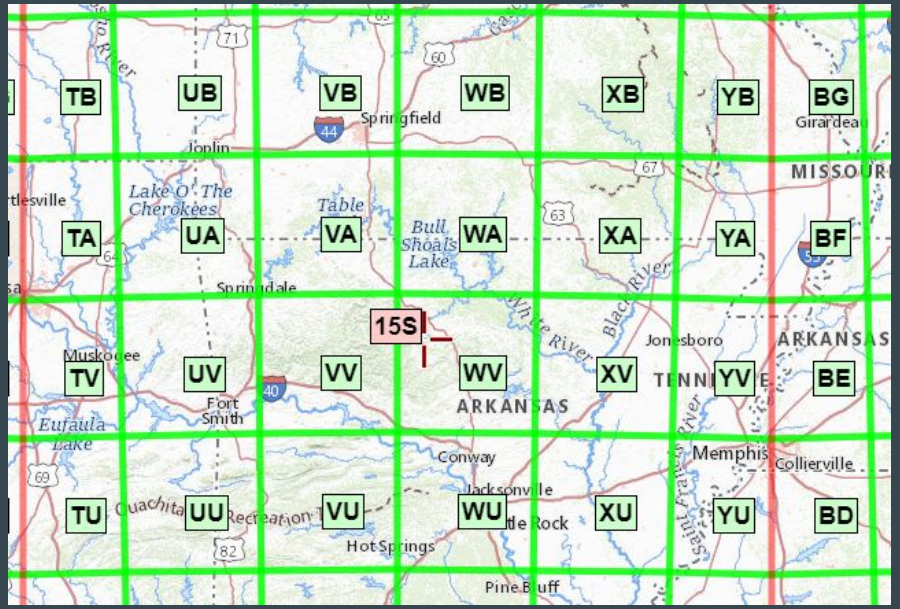
UTM zone main group easting northing



[6]

USNG coordiantes

Financial Modeling - USNG Mapping

US National Grid Coordinates

- 15S .....precision level 6° × 8°
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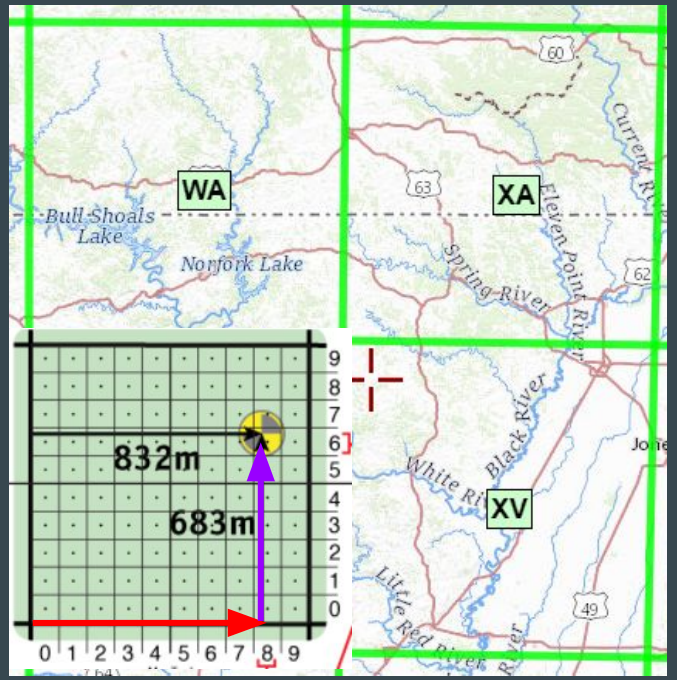
- 15S WV 832 683.....precision level 100m
- 15S WV 8320 6830.....precision level 10m
- 15S WV 83200 68300 .....precision level 1m

GZD main group easting northing

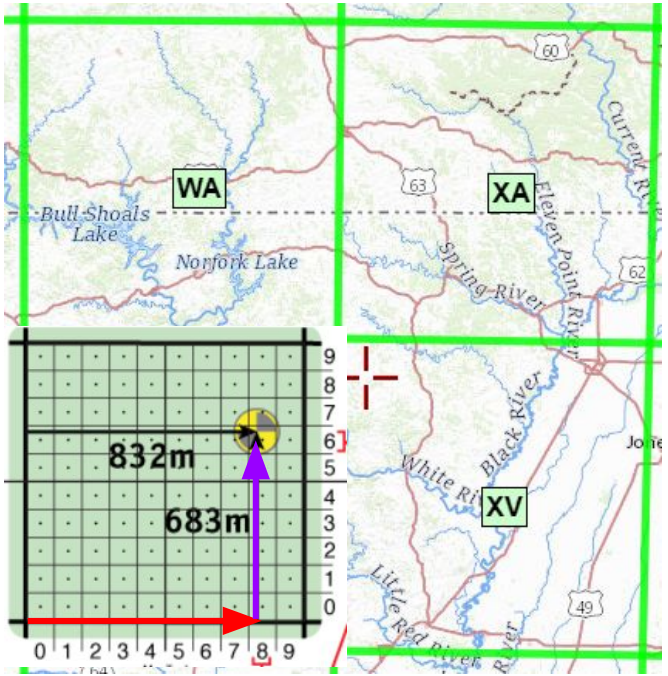


USNG coordiantes

[6]

US National Grid Coordinates

- 15S .....precision level 6° × 8°
- 15S WV .....precision level 100 km
- 15S WV 8 6 .....precision level 10 km
- 15S WV 83 68 .....precision level 1 km
- 15S WV 832 683.....precision level 100m
- 15S WV 8320 6830.....precision level 10m
- 15S WV 83200 68300
  GZD main easting northing
  group



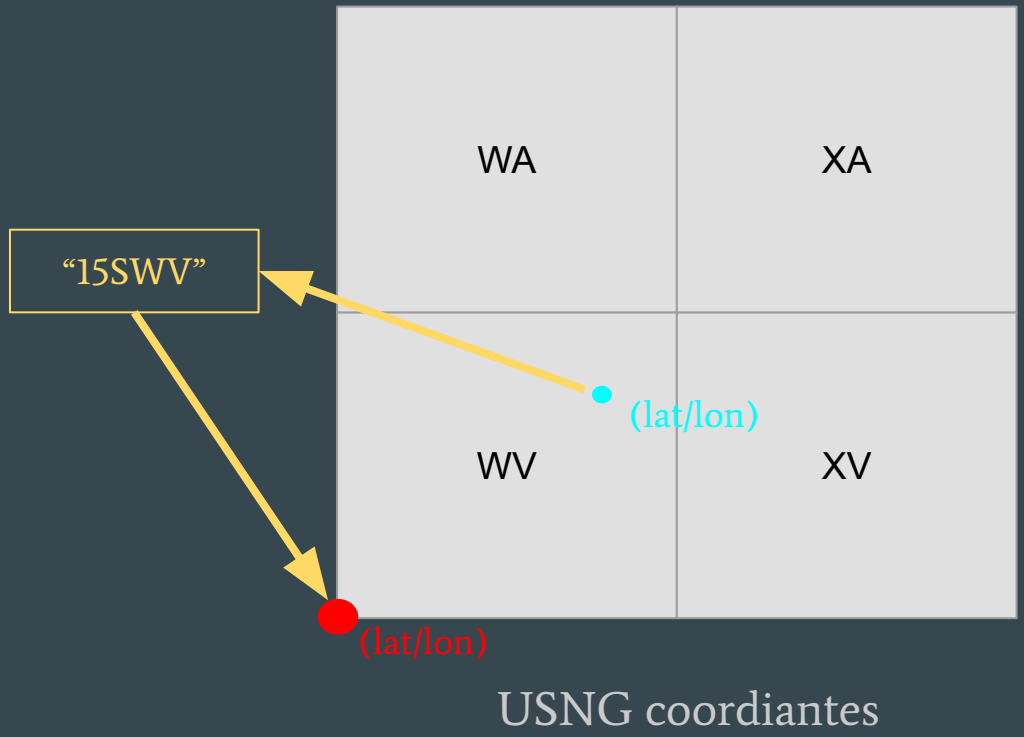
USNG coordiantes

[6]

Financial Modeling - USNG Mapping

USNG Mapping Function

- Python package mgrs to convert lat/lon to cell and vice versa
- Backwards gives cell SW corner lat/lon
- Need polygons for each grid of any precision...

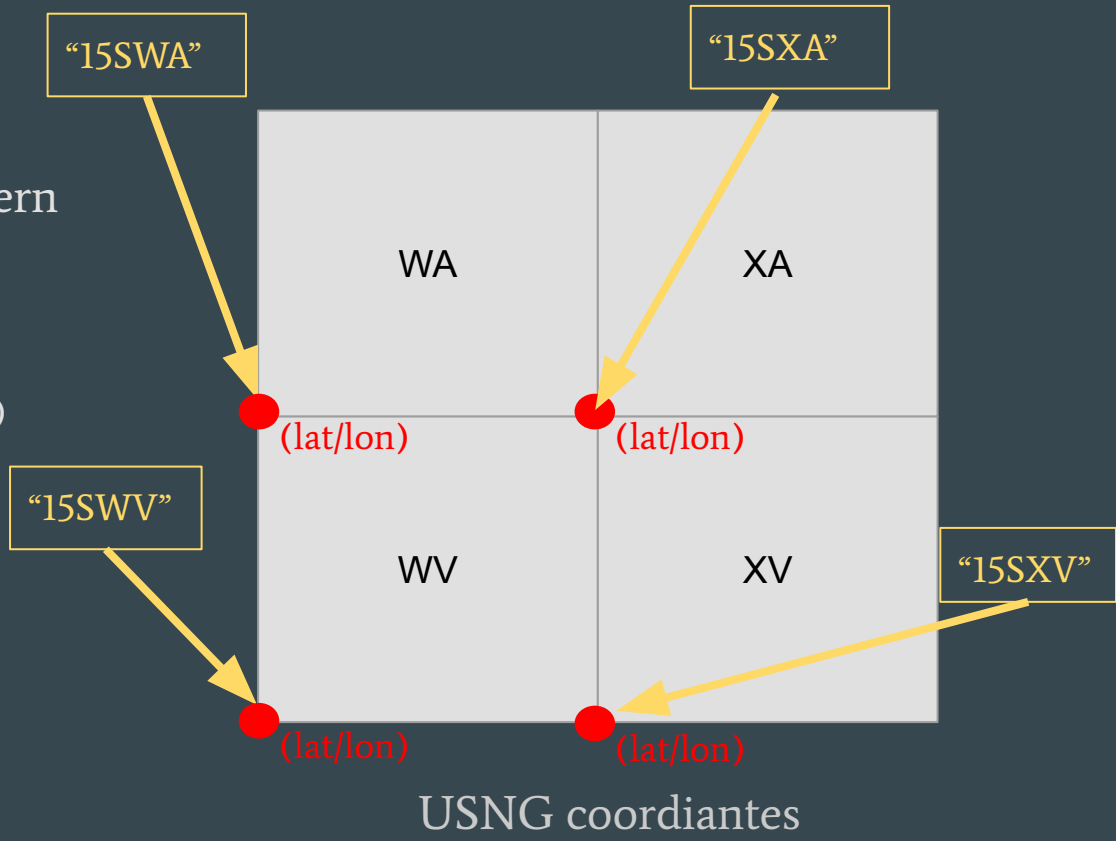


USNG coordiantes

Financial Modeling - USNG Mapping

USNG Mapping Function

- Main groups have a general pattern
  - first letter A-Z (without I and O) west-east
  - second letter A-V (without I and O) south-north
- Use 4 adjacent cells to get full polygon



USNG coordiantes

Financial Modeling - USNG Mapping

USNG Mapping Function

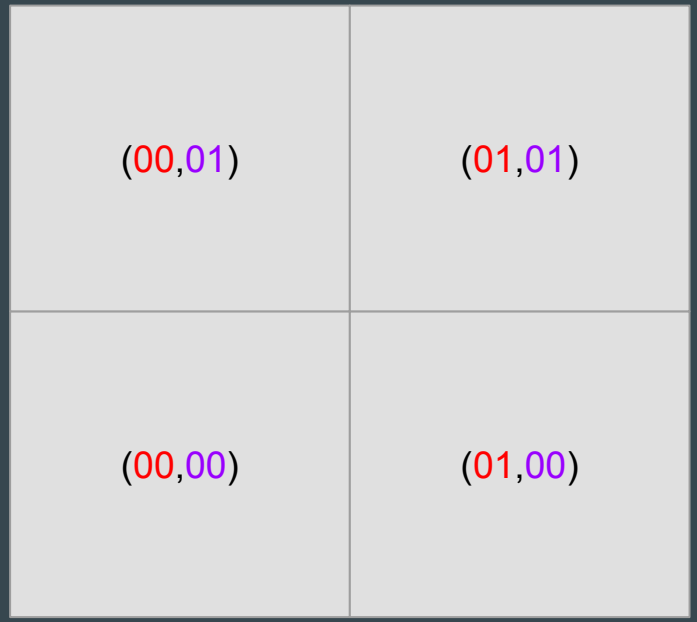
- Number are easier:
  - Add 1 to easting/northing

Ex: 15SWV 83200 50000

-> SE - 15SWV 83201 50000

-> NW - 15SWV 83200 50001

-> NE - 15SWV 83201 50001



USNG coordiantes

Financial Modeling - USNG Mapping

USNG Mapping Function

- Few edge cases:
- Ex: 15SWV 83200 99999

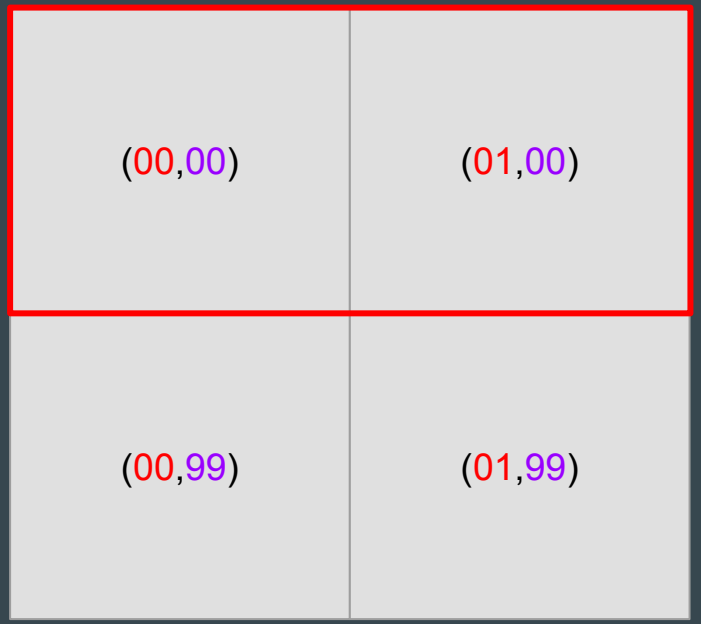
-> SE - 15SWV 83201 99999 (normal)

-> NW - 15SWA 83200 00000 (edge)

- UTM zone changes:

-> main group easting break pattern every 6° lon

-> some main groups only within certain latitudes



USNG coordiantes

Financial Modeling

Xview2 USNG Visualization

Financial Modeling - Xview2 Mapping

Financial Model

- Mapped zip-code for all xview2 data based on buildings lat/lon centroids
- Pulled Zillow data for a price/sqft for each zipcode from 2018 and averaged missing data
- Validated model against county level data obtained from NOAA for a few trusted counties (same order of magnitude accuracy)
- Proof of concept

Financial Cost Model:

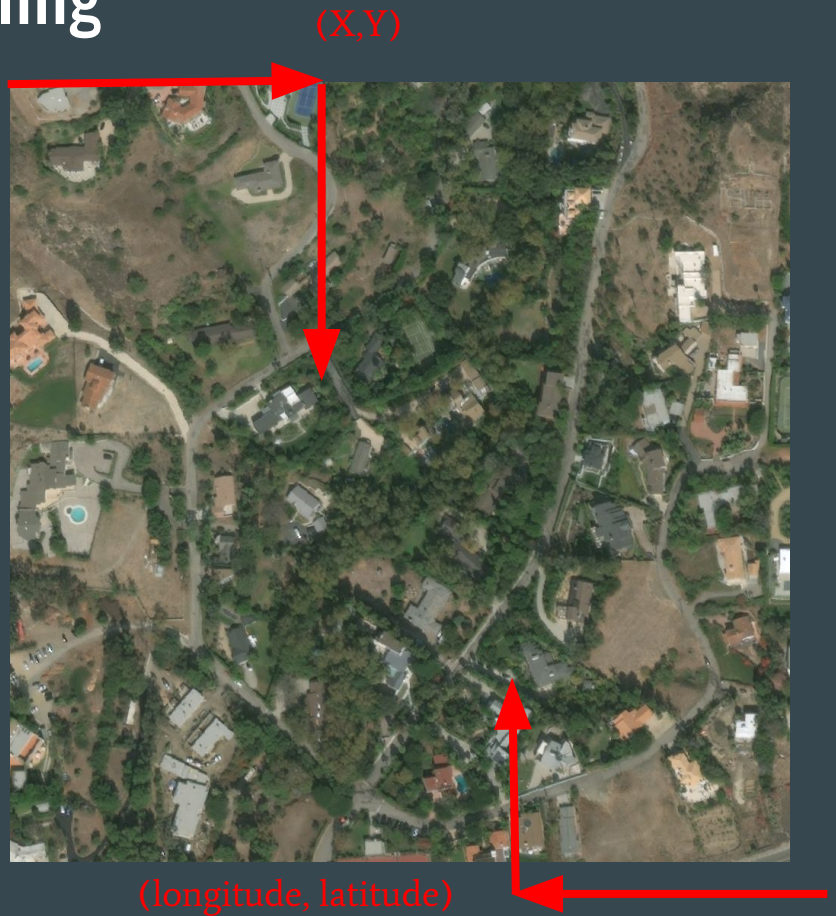
$/sqft/zipcode * sqft * 2floors * damage level factor

damage level factor	
0	no damage
0.5	minor
0.8	major
1	destroyed

Solution Models - Financial Modeling

Xview-2 Image Lat/Lon

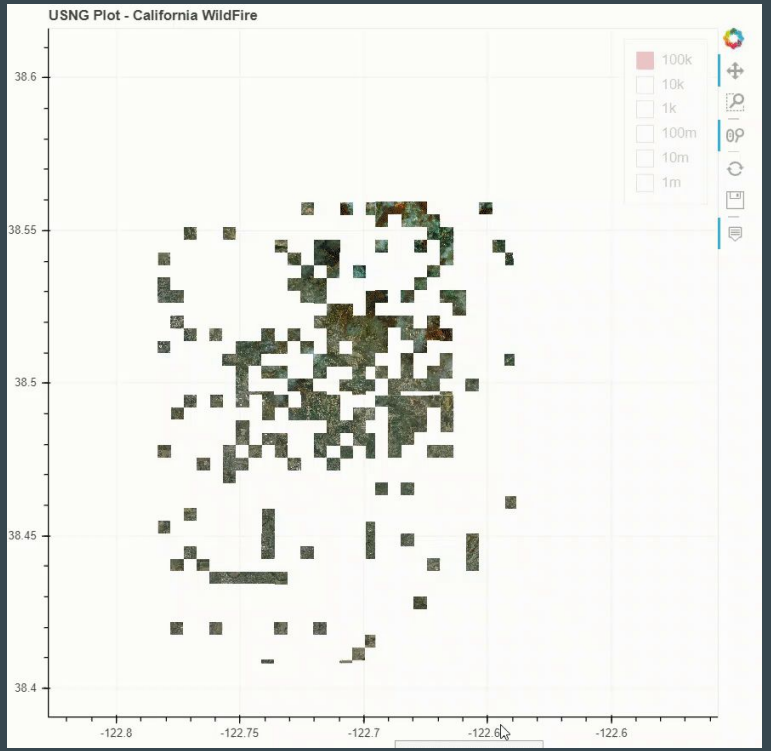
- Xview2 data provides only lon/lat for each building - not image as a whole
- lat/lon position is needed for conversion from model -> lat/lon -> USNG coords
- All xview2 (x,y) are w.r.t. NW corner
- Used building lat/lons to get
    - Δlatitude/pixel
    - Δlongitude/pixel
    - corner lon/lat



Financial Modeling - Xview2 Mapping

USNG Large Scale Visualization

- https://ermlickw.github.io/
- Uses centroids, areas, and damage labels of each xview2 building
- Financial cost summed over each UNSG grid over all precisions
- Methods used in application



Financial cost estimation using USNG coordinates

Xview2 Modeling

Connected UNets

Solution Models - Final Report

Keras Model Pipeline

- Image masks are created
  - Use polygons from json files to draw building outlines in an array
  - Result is a (1024, 1024) shaped array where each pixel is a class
  - 0: No Building, 1: No Damage, 2: Minor Damage, 3: Major Damage, 4: Destroyed
- Keras data loader is created
  - At each iteration, pre image, post image, and mask are loaded from the training data
  - Prevents all images from being loaded into memory at once
- Model is trained on these images

Solution Models - Final Report

Keras Model Pipeline continued

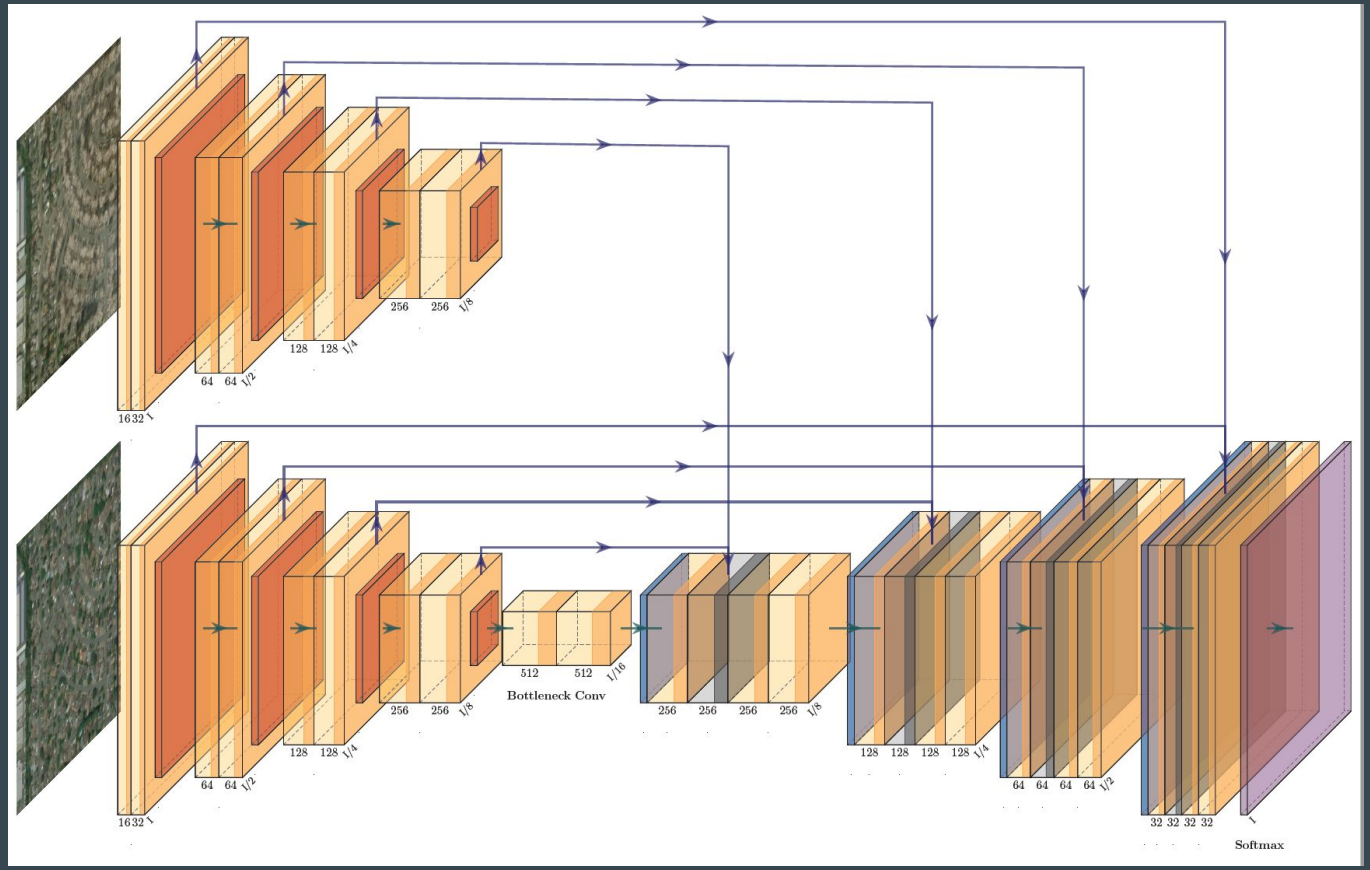
- The model is validated
  - At each epoch, a random subset of the training data was used for validation
  - Due to the limited training data, being able to use all for training was key
- Best model weights are saved
- Inference is performed
  - Iterate over test images and return pixel-by-pixel predictions for each class
  - Output is a softmax function and each array is shape (1024, 1024, num_classes)
  - Take the argmax over the classes to reshape to (1024, 1024)
  - This is fed into the metrics script, and F1 scores are returned

Solution Models - Final Report

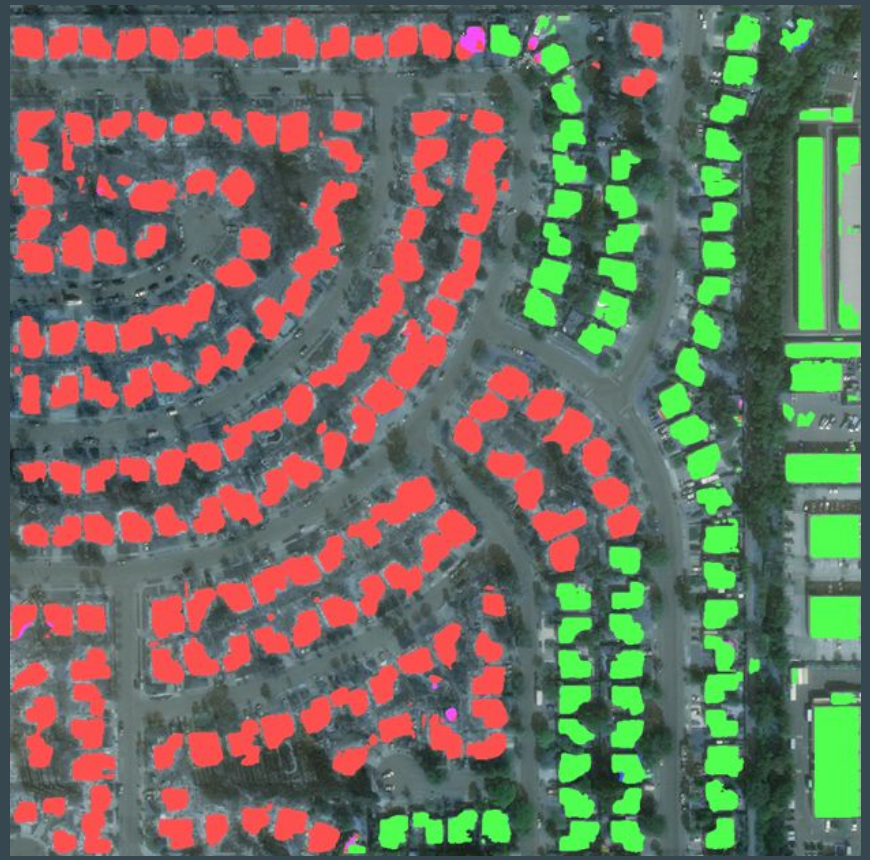
U-Net Model

- U-Net models have had success in image segmentation problems
- Created a dual-input U-Net model using Keras and TensorFlow
  - Needed a way to use both pre and post disaster images
  - Images are encoded differently, but share the same weights
  - The image differences are taken into account during the decoder stage
- Used a combination of Weighted Cross Entropy and Dice Loss
  - RMSProp loss function
  - Adjusted class weights and learning rate throughout training
  - augmentations were not effective

Solution Models - Final Report



Santa Rosa Wildfire - Post Disaster



Xview2 Modeling

Mask RCNN

Analytics & Algorithms -Localization&Damage Assessment

- Here we have used open-source library that implements Mask RCNN on top of TensorFlow/Keras.

- It is a simple model that combines two extremely powerful existing models together - Faster R-CNN and semantic segmentation. Two Main components of this model are RPN and RoIAlign Layer

    1. Region Proposal Network (RPN)is able to look at the feature map and get a set of bounding boxes that would essentially have an object of relevance by using selective search
    2. RoIAlign Layer helps with pixel-level segmentation and uses bilinear interpolation to avoid mis alignments

Analytics & Algorithms- Damage Assessment

- Mask RCNN approach for Damage Detection in keras.

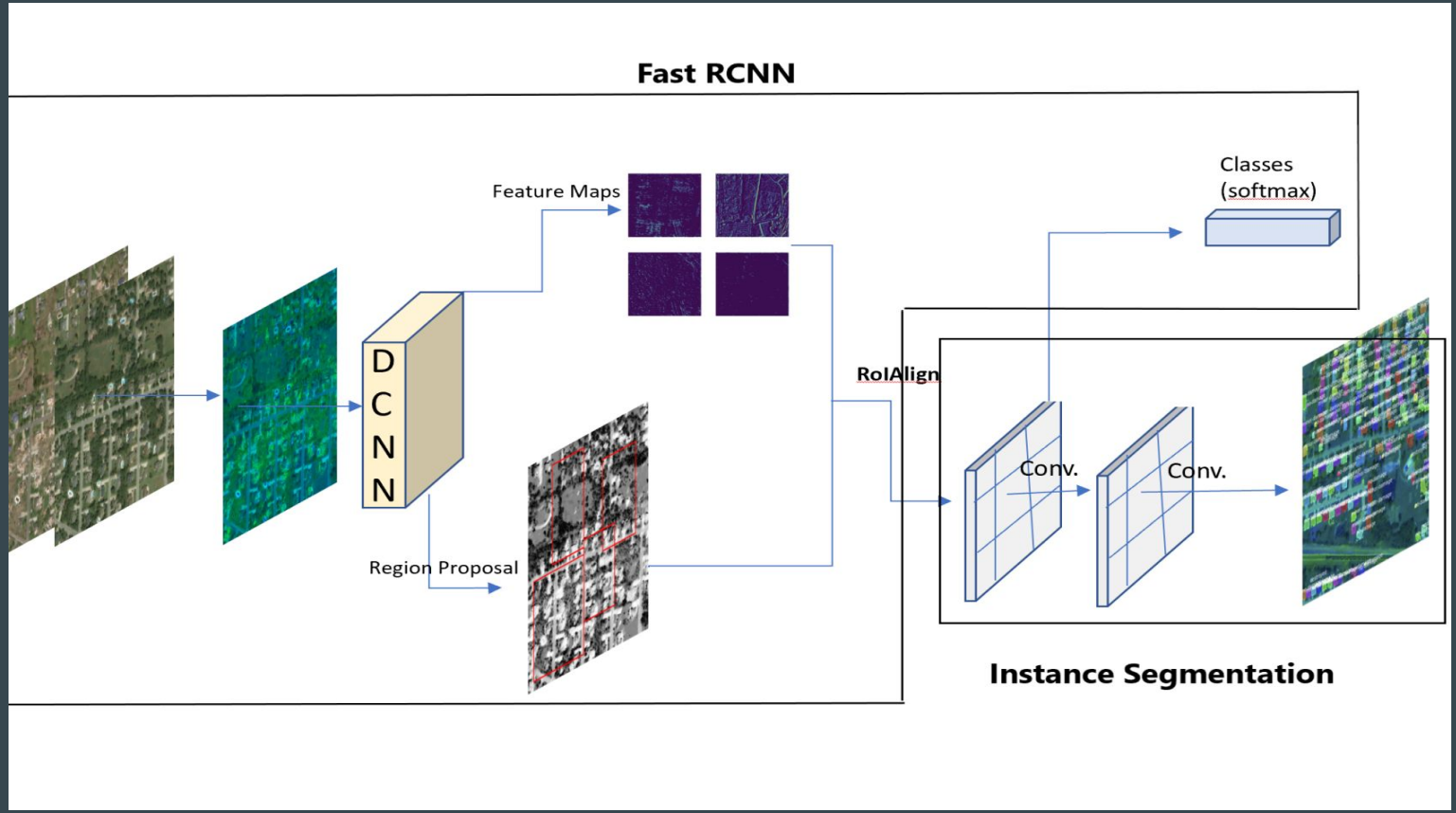
1. Combine pre - post images to get 6-channel input image.
2. Use Pretrained weights from the localization model.
3. Update Classes to - 0 : No-damage 1: Minor-damage 2: Major-damage 3: Destroyed and BG

   Supercategory: Building

3 Architecture remains same with **Hyper - Parameter Tuning**.

- Learning rate
- RPN anchor scale : This adjusts pixel level for detection of Region proposals.
- Detection threshold: This adjusts the detection threshold to give room to false positives when the objects detected are much smaller
- non-maximum suppression : It groups highly overlapped detection into one class to avoid duplication

Analytics & Algorithms -Damage Assessment



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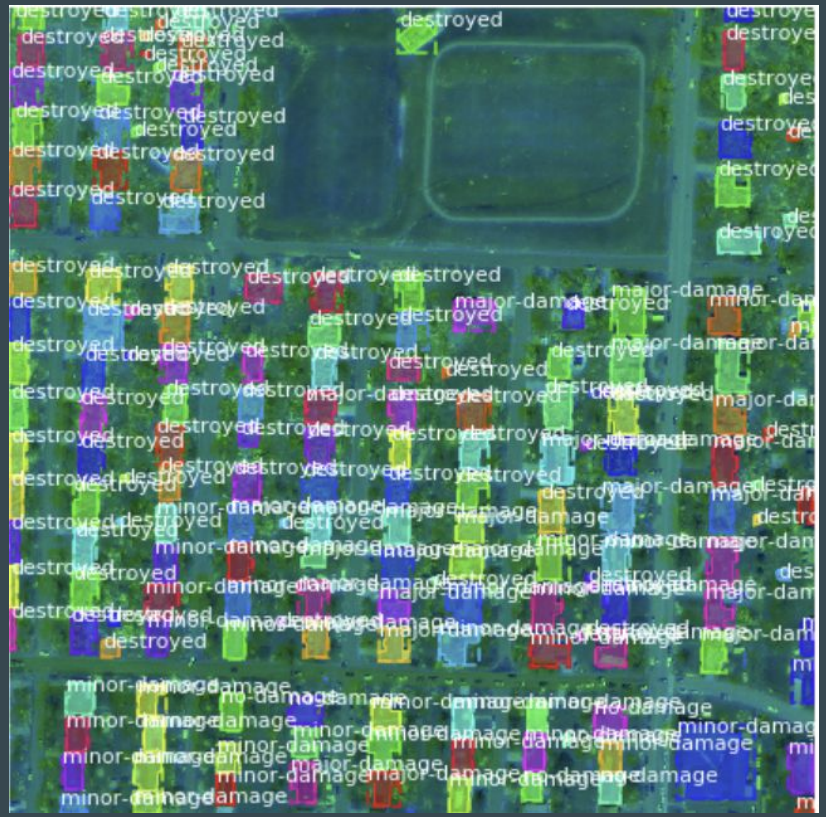
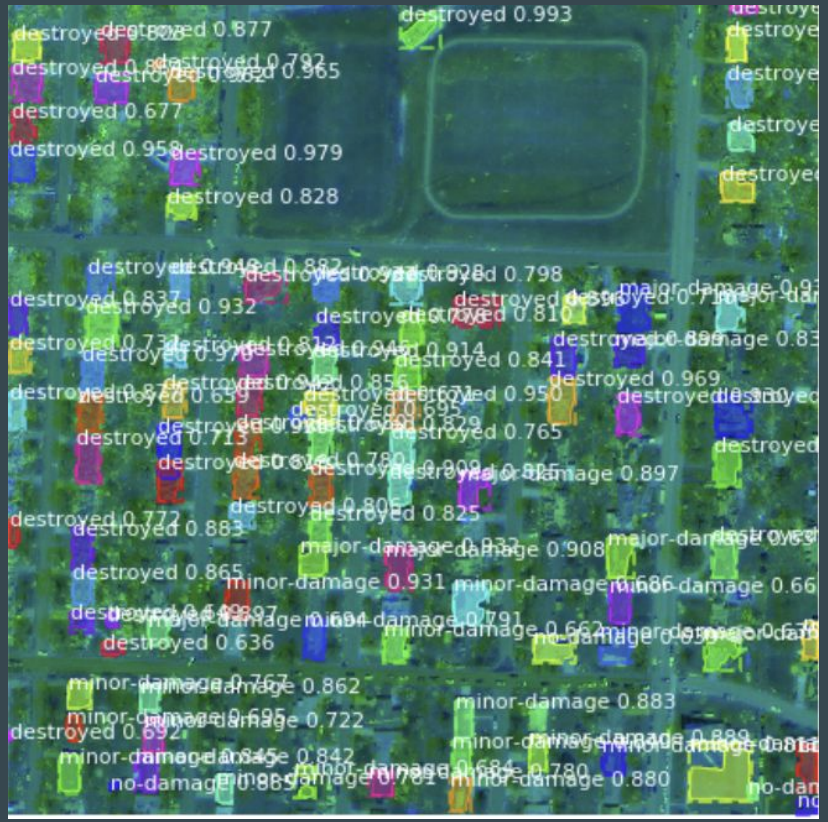
F1:  0.588235294117647 1
```

Ground Truth



After Detection

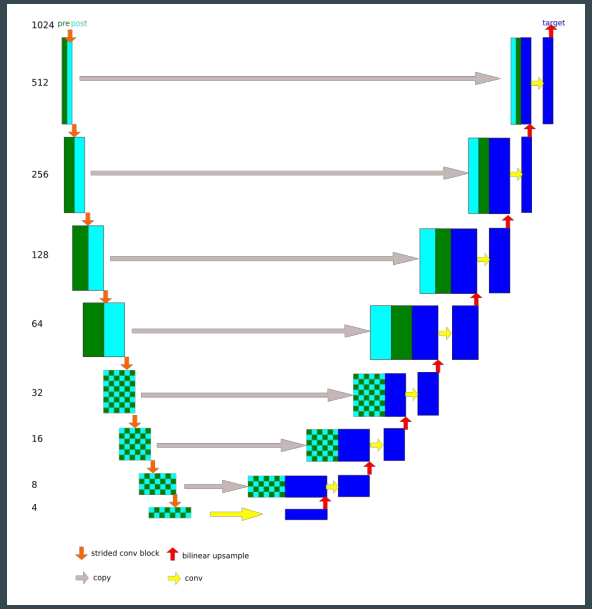


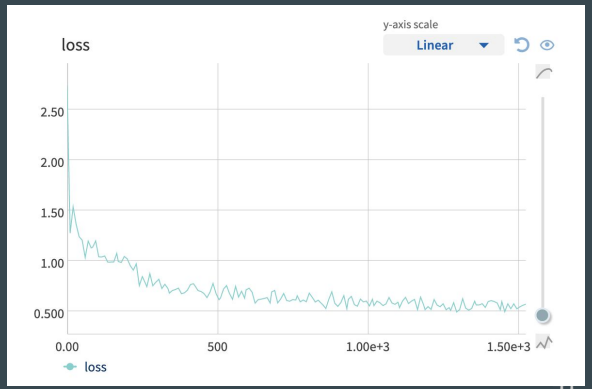
Application

Application

Modified U-Net with Paired Image Inputs

- To establish an MVP — and use inference outputs to validate the financial modeling approach — we applied two, relatively simple, open source U-Nets with near-top-50 weighted score (0.68)
  - 6–8 GPUs leveraged, both models trained overnight
  - Modified U-Nets with EfficientNet encoder blocks
- ~5 seconds for inference per image
  - Damage classification is done at the pixel level (as opposed to the building level) with the localization applied as a “mask”



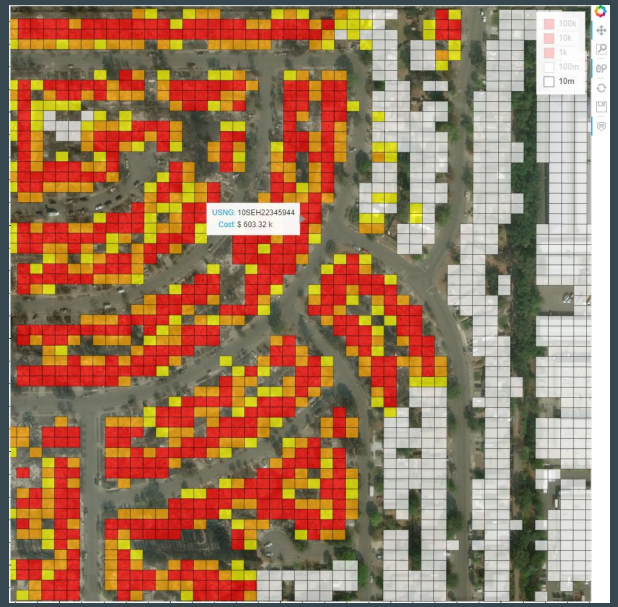


Application

Overview

- User inputs
  - before and after image
  - lat/lon of NW and SE corners

Model



Application

Workflow

inputs

- Before and after image
- NE and SW corner lat/lons

methods (should be ~15 seconds)

- run building localization and damage assessment and output pixel map (5~sec)
- convert building masks to polygons
- divide polygons into smaller polygons (to ensure all USNG grids are represented)
- find centroids of polygons in lat/lon
- find MGRS grids coords for each centroid lat/lon using our in-house function
- convert MGRS grid coords to image coordiantes
- sum pixel values within each MGRS grid multiplied by sqft/pixel and $/sqft based on zip code

outputs

- display image with USNG overlaid with aggregate cost

Application

Methods

- User inputs
  - before and after image
  - lat/lon of NW and SE corners

Damage Classification Model

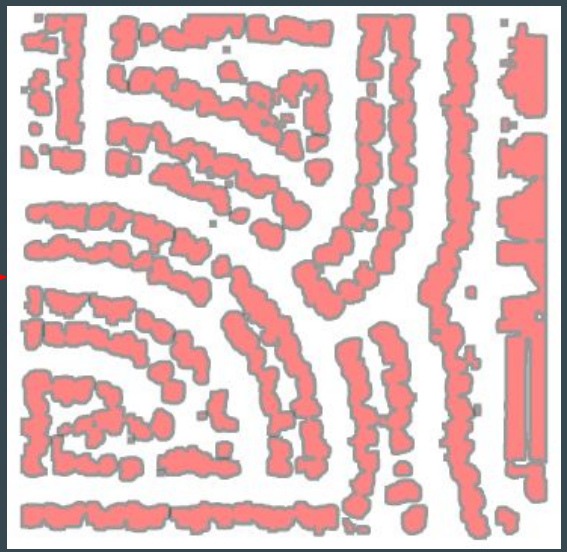
Application

Polygon Conversion and Image lat/lon Transform

- Determine building polygons using contour function
- Convert pixel coordiantes to lat/lon
  - Δlat/pix and Δlon/pix

translate
&
scale

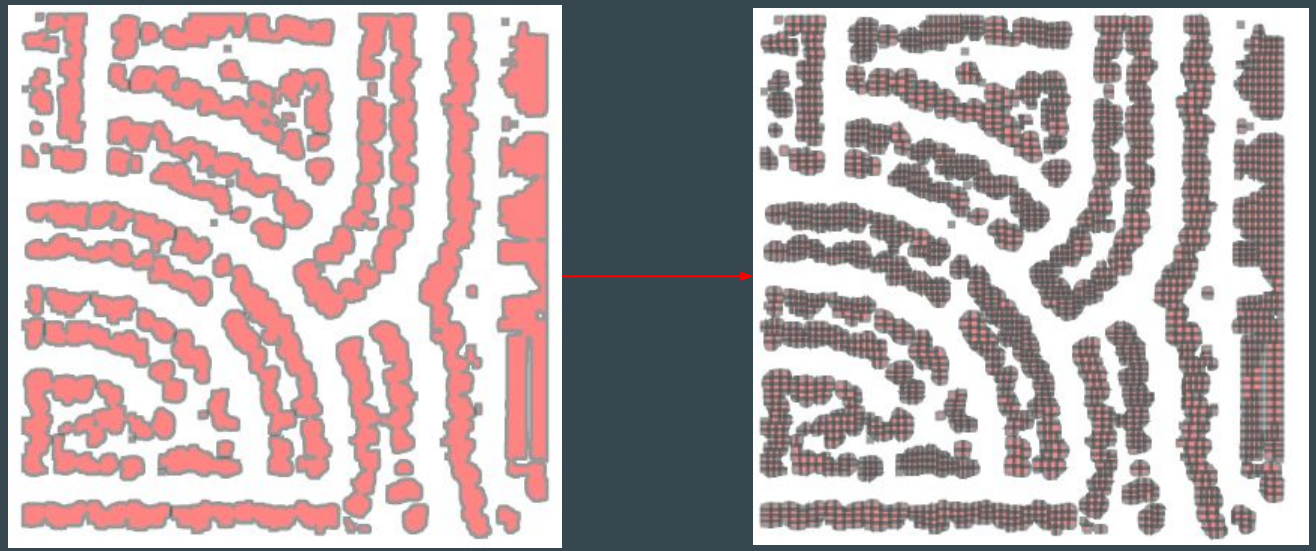
Damage Classification Model



Application

Polygon Division

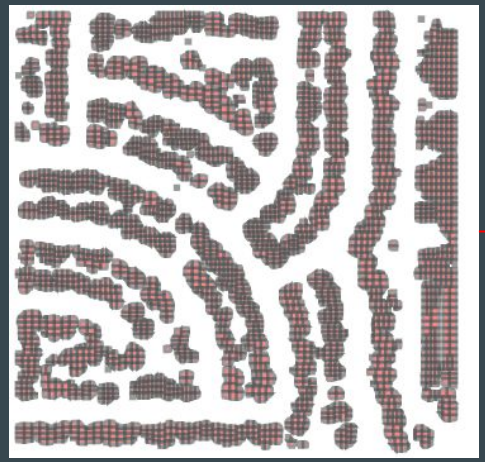
- Divide large polygons (model incorrectly combines buildings)
- Determine centroid of each polygon (USNG all accounted for)

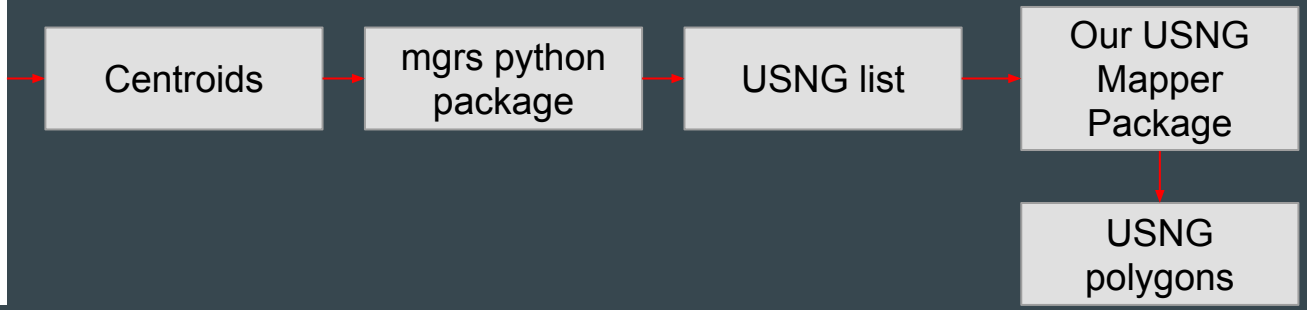


Application

Get USNG polygons

- Determine list of unique USNG grids from centroids
- Get polygons of USNG grids using our in house function (all precisions)

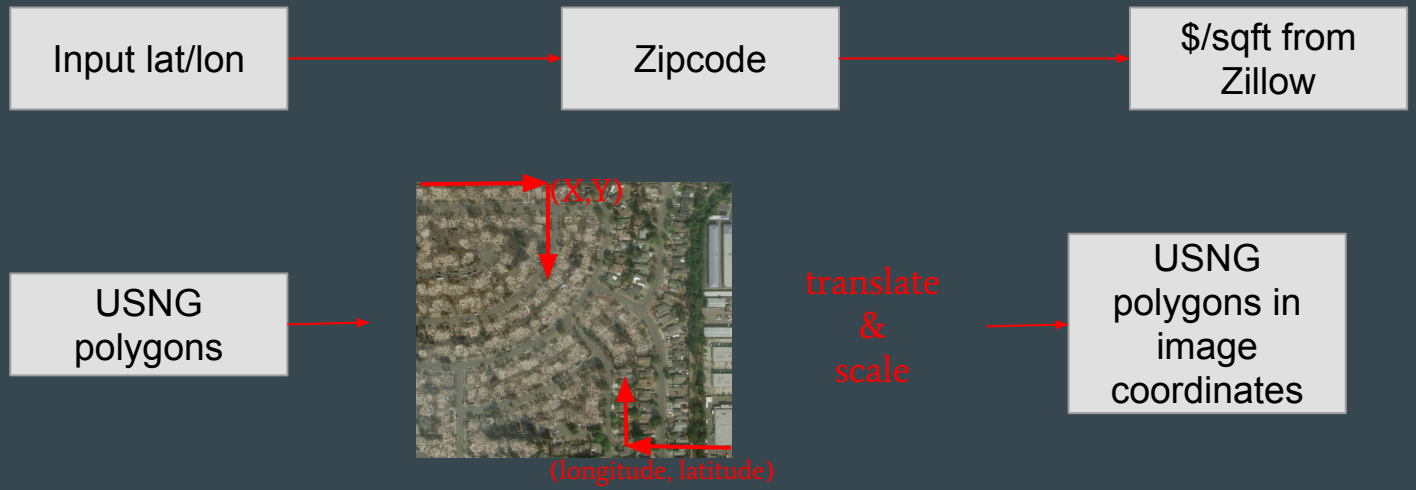




Application

Get cost for each USNG

- Get zipcode from lat/lon and $/sqft from Zillow data
- Backconvert USNG lat/lons to image (x,y) coordinates

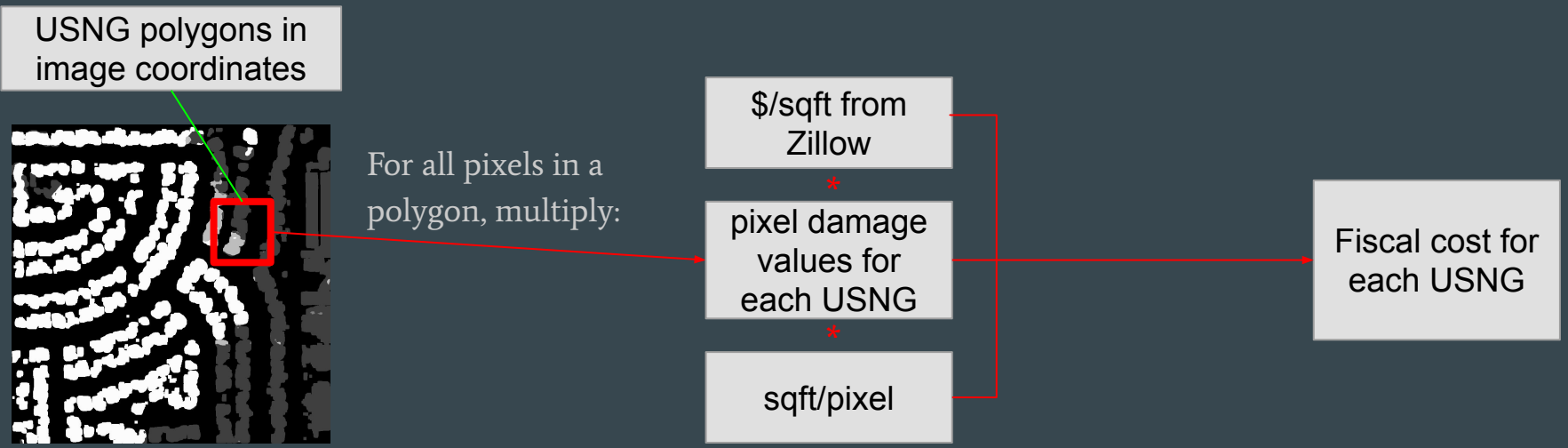


Application

Get cost for each USNG

- Find sqft per pixel - area of image / resolution
- Change pixel values to financial model damage levels

damage level factor	
0	no damage
0.5	minor
0.8	major
1	destroyed



Application

Financial Model -- Flask Application Pipeline

- Around 5 seconds for pixel level building localization & damage classificaiton
- Less than 15 seconds for financial analysis
- Accurate financial estimates to 10 meter precision (1m is possible but computationally expensive and GSD is >1m)

Contibutions

- ✔ USNG Mapping Function
- ✔ Connected U-Net Model
- ✔ Mask R-CNN Model
- ✔ Proof of Concept Application http://test-env.eba-6qua3x4j.us-east-1.elasticbeanstalk.com/

Lessons Learned

- Large images and dense networks are not a good combination
  - The computation power needed to run models was significant
  - Multiprocessing on GPUs didn't always offer significant speed gains
  - Used vectorization where possible, to improve performance
- The U-Net struggled on classifying minor and major damage
  - There is not a clear delineation between the classes
  - The classes are significantly imbalanced
  - Oversampled minor and major damage
  - Gave these classes more weight with the loss function
- Mask RCNN is not a ideal model for satellite images due to the sheer detailed objects in the images
  - It is still a good model for experimenting with dataset and with minor tweaks in the architecture can get better at detecting satellite image objects due to its simplicity.

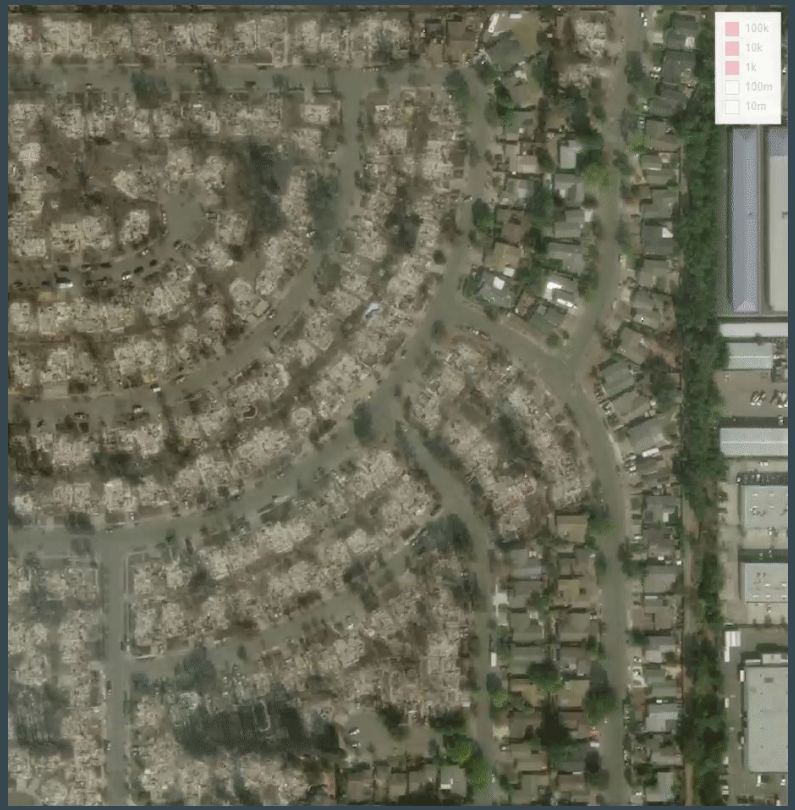
Example Flooding Image

- Some of the flooded buildings are classified as major damage and some are classified as minor damage
  - Green = No Damage
  - Blue = Minor
  - Purple = Major
- Hard for humans to tell the difference

Future Work

- More accurate pixel-based financial model if claims data can be obtained
- Flooding around buildings was difficult to classify
  - Hard to see on the images for humans
  - Model had the most trouble classifying these instances
- Experiment with different U-Net encoder blocks
  - VGG, Inception, ResNet, etc.
- Use Quadratic Weighted Kappa as a loss function
  - The model blends together some predicitons (i.e. no damage and major)
  - Places higher penalty on classes that are further away from the actual
- Improve Mask RCNN further by combining pre post images during segmentation phase and implement weighted cross entropy loss.

Questions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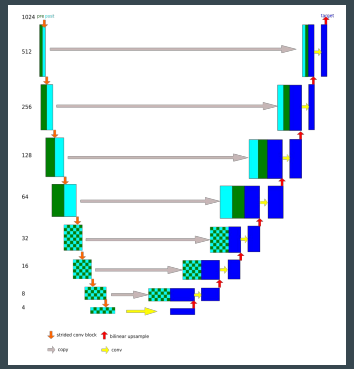
10k
1k
100m
10m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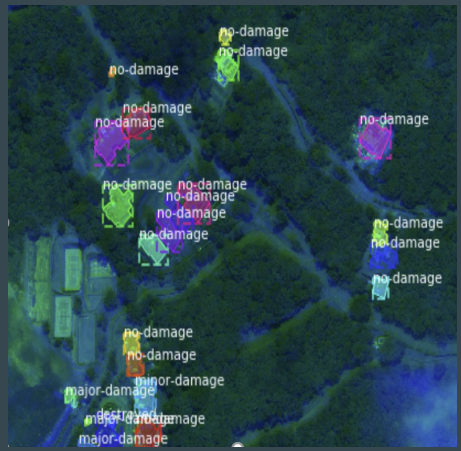
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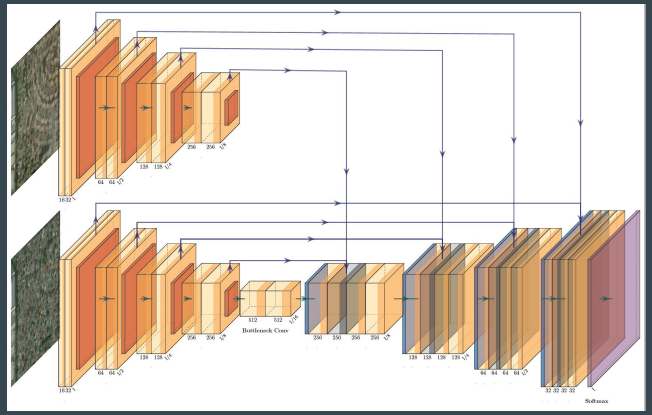
major-damage



References

1) https://www.fema.gov/news-release/2017/09/07/fact-sheet-what-expect-when-you-register-fema-disaster-assistance
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3) https://xview2.org/ & https://arxiv.org/pdf/1911.09296.pdf
4) https://keisan.casio.com/exec/system/1224682277
5) https://legallandconverter.com/p50.html
6) https://mappingsupport.com/p2/coordinates-usng-gissurfer-maps.html

APPENDIX SLIDES

APPENDIX SLIDES

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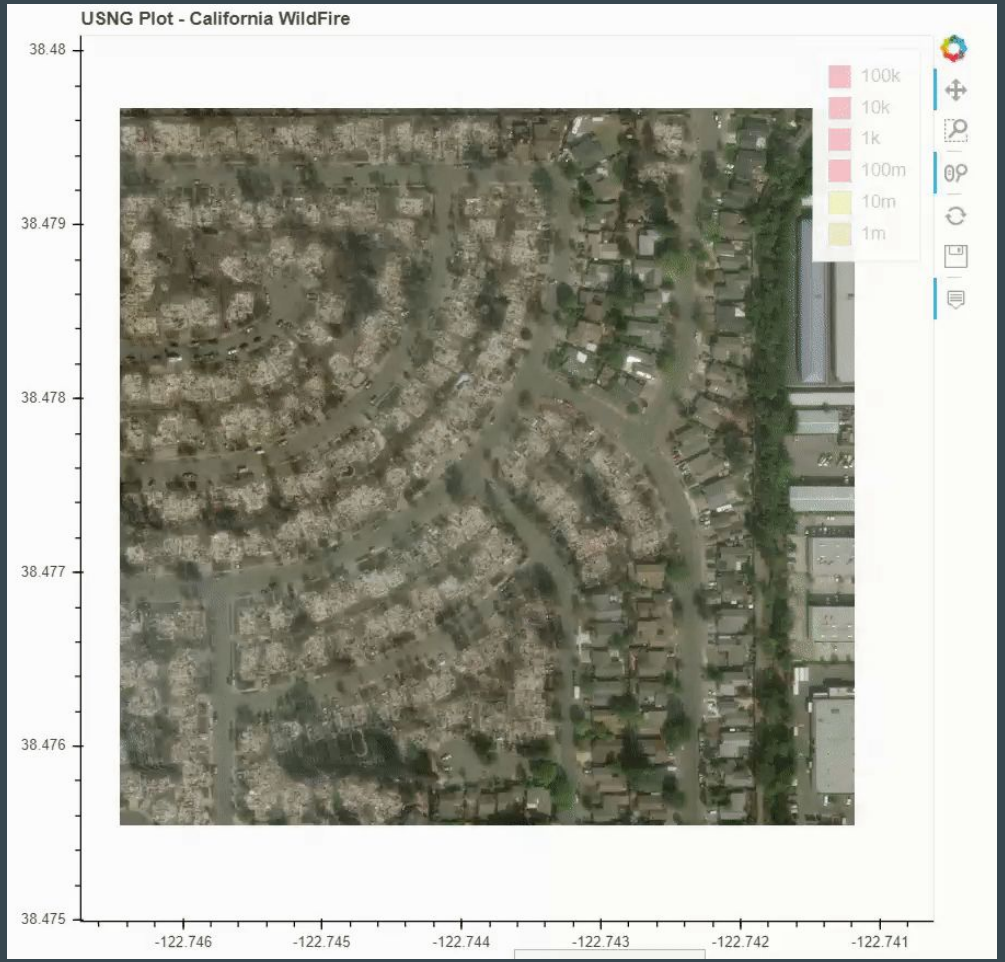
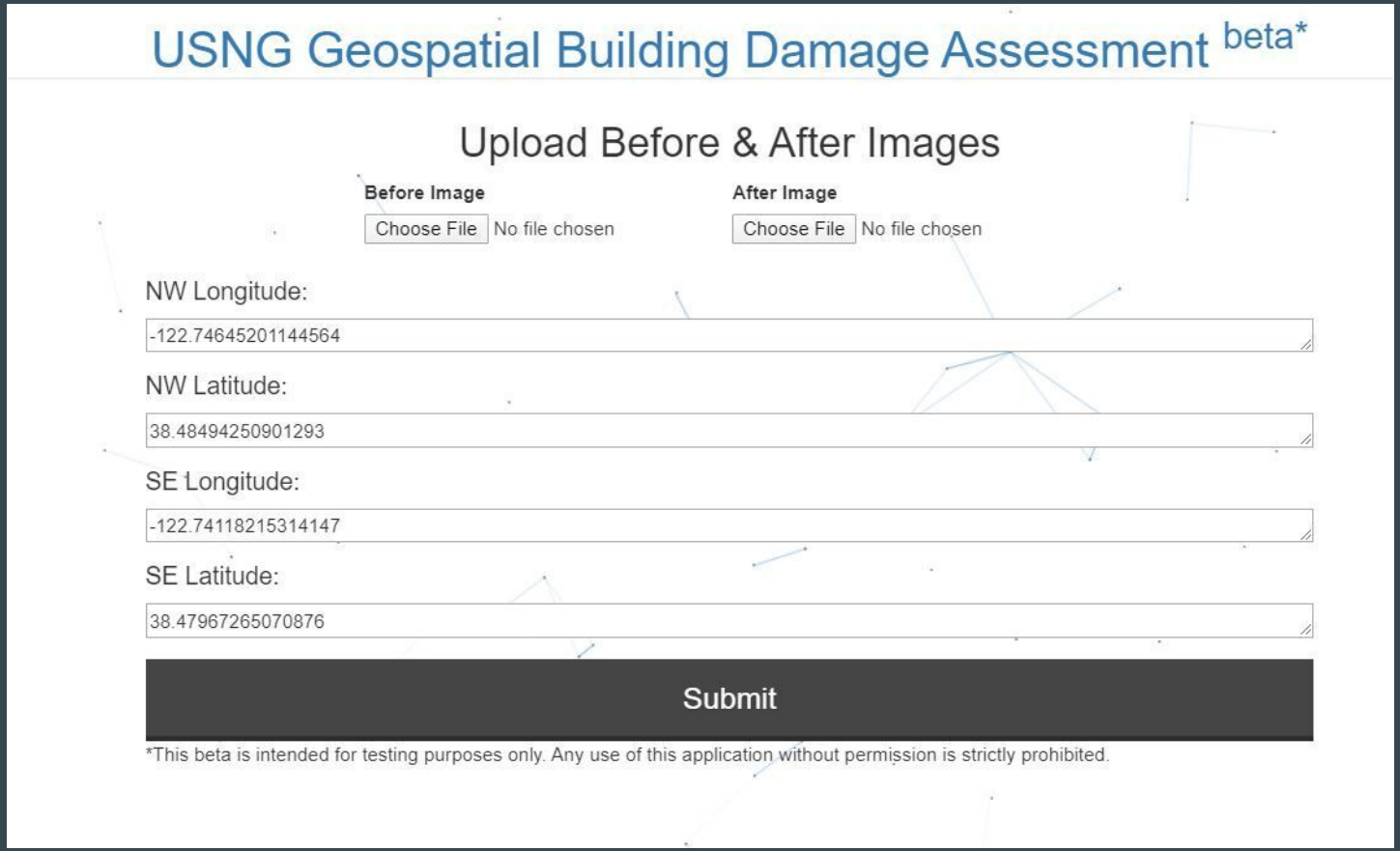
Application

Financial Model -- Flask Application Pipeline

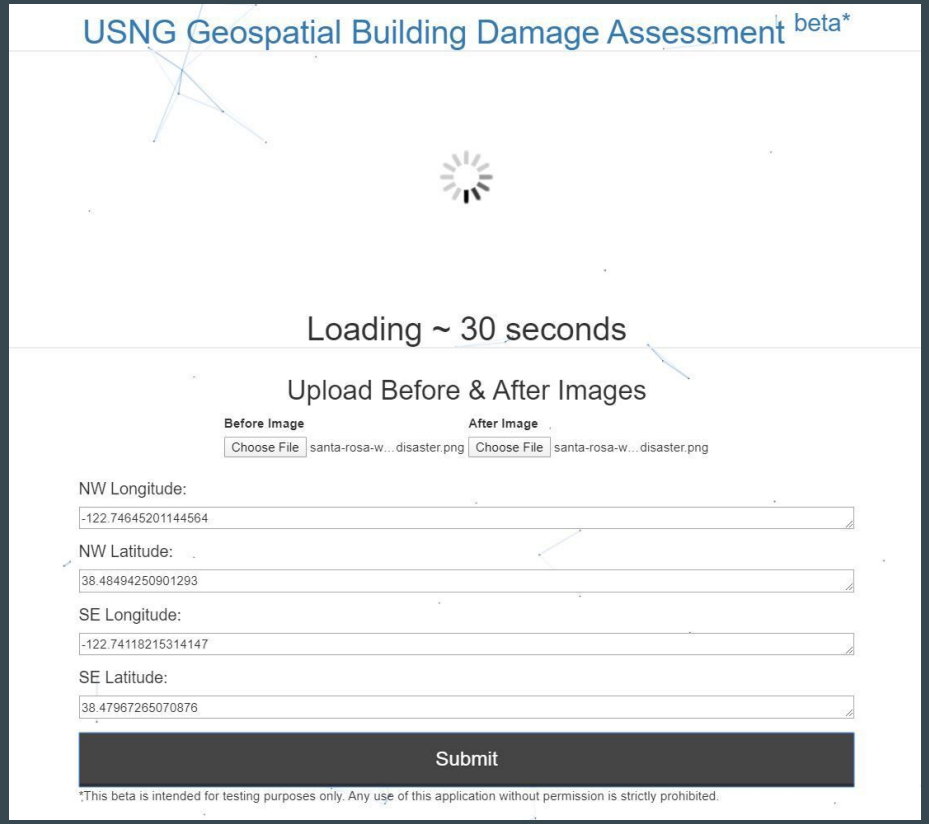
- Around 5 seconds for pixel level building localization & damage classificaiton
- ~7 seconds for financial analysis
- Accurate financial estimates to 10 meter precision (1m is possible but computationally expensive and GSD is >1m)
- http://test-env.eba-6qua3x4j.us-east-1.elasticbeanstalk.com/



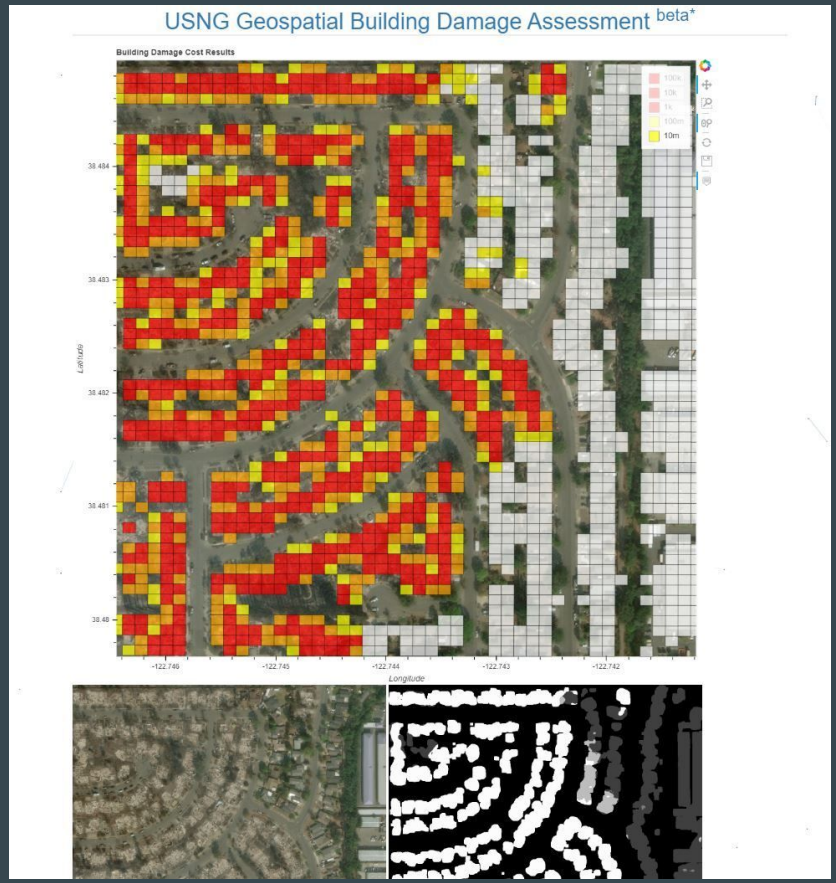
Application



Application



Application



Solution Models - Final Report

Keras Model Pipeline

- Image masks are created
  - Use polygons from json files to draw building outlines in an array
  - Result is a (1024, 1024) shaped array where each pixel is a class
  - 0: No Building, 1: No Damage, 2: Minor Damage, 3: Major Damage, 4: Destroyed
- Keras data loader is created
  - At each iteration, pre image, post image, and mask are loaded from the training data
  - Prevents all images from being loaded into memory at once
- Model is trained on these images

Solution Models - Final Report

Keras Model Pipeline continued

- The model is validated
  - At each epoch, a random subset of the training data was used for validation
  - Due to the limited training data, being able to use all for training was key
- Best model weights are saved
- Inference is performed
  - Iterate over test images and return pixel-by-pixel predictions for each class
  - Output is a softmax function and each array is shape (1024, 1024, num_classes)
  - Take the argmax over the classes to reshape to (1024, 1024z0
  - This is fed into the metrics script, and F1 scores are returned

Solution Models - Final Report

Baseline Model

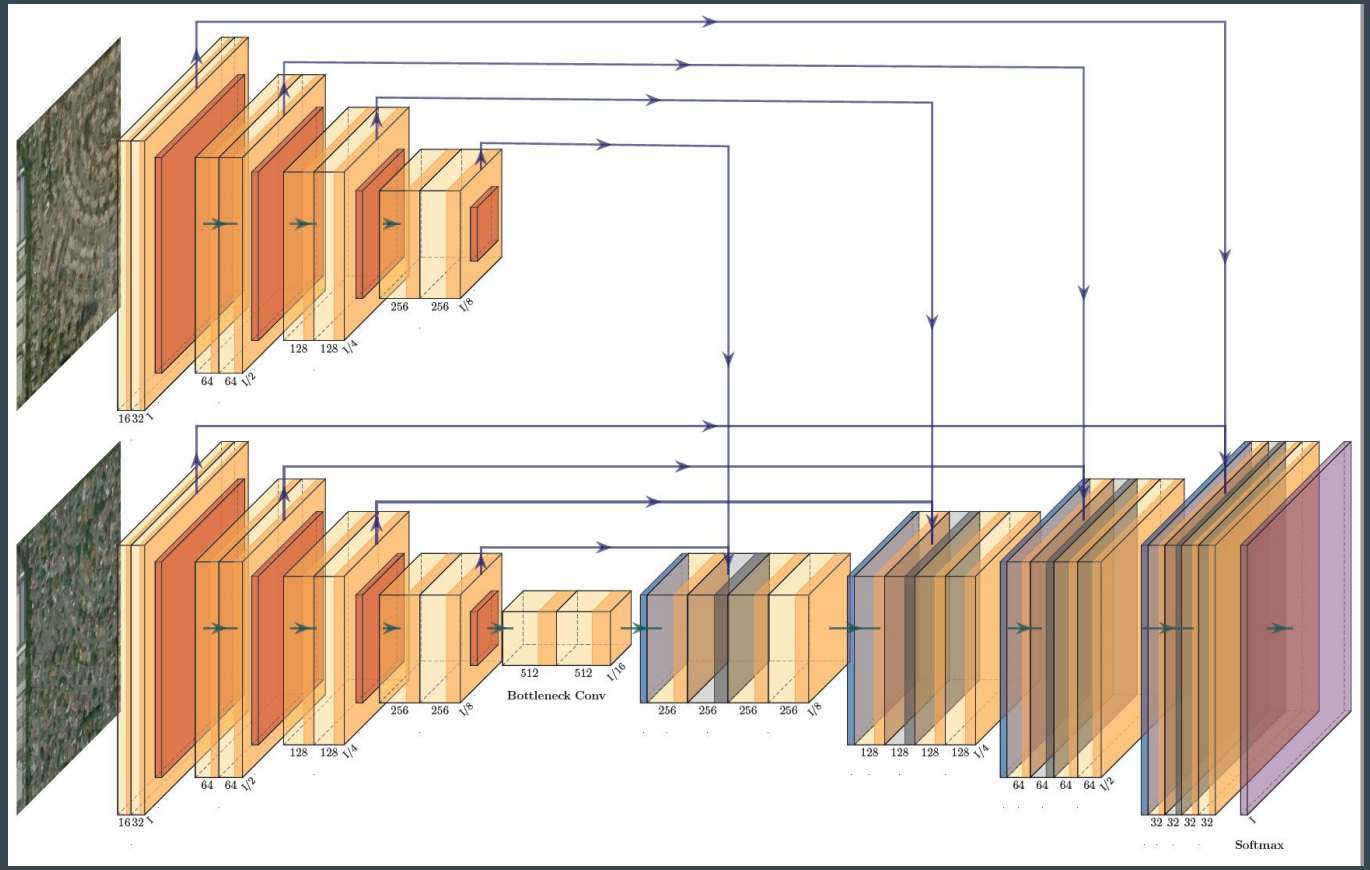
- Used a baseline model provided with the competition
  - Localization: spacenet building segmentation model
  - Classification: simple CNN architecture
- Results were effective for localization, but poor for classification
  - Method was also too slow to implement in an application
- Needed a model that simulataneously performs classification and prediction

Solution Models - Final Report

U-Net Model

- U-Net models have had success in image segmentation problems
- Created a dual-input U-Net model
  - Needed a way to use both pre and post disaster images
  - Images are encoded differently, but share the same weights
  - The image differences are taken into account during the decoder stage
- Used a combination of Weighted Cross Entropy and Dice Loss
  - RMSProp loss function
  - Adjusted class weights and learning rate throughout training
  - augmentations were not effective

Solution Models - Final Report



Lessons Learned

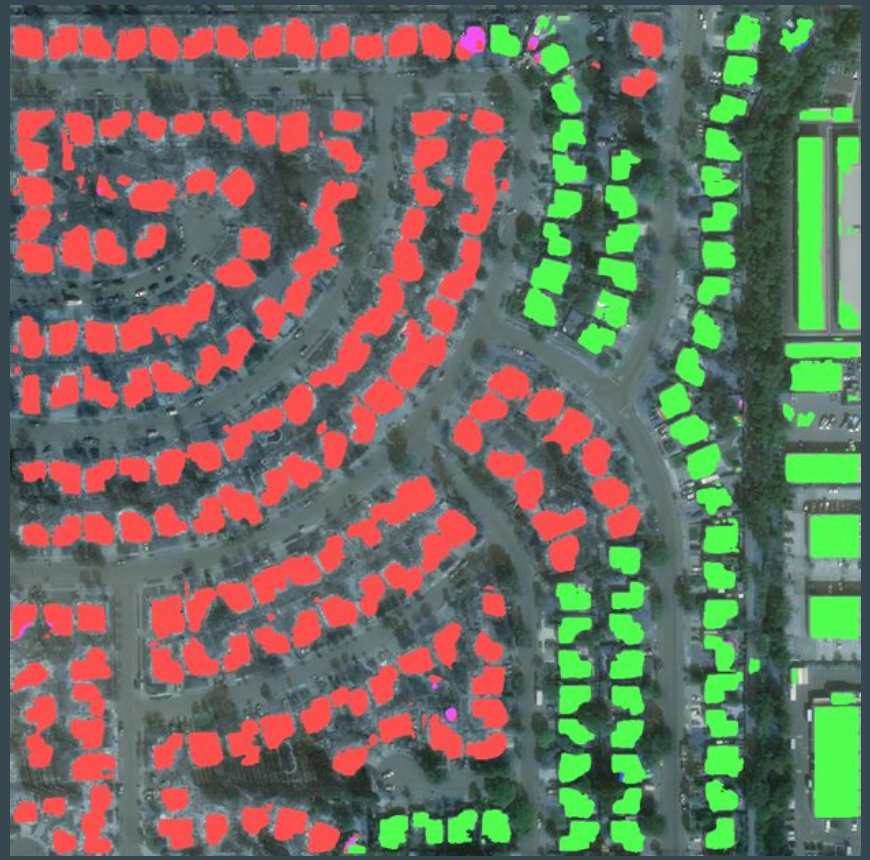
- Large images and dense networks are not a good combination
  - The computation power needed to run models was significant
  - Multiprocessing on GPUs didn't always offer significant speed gains
  - Used vectorization where possible, to improve performance
- The model struggled on classifying minor and major damage
  - There is not a clear delineation between the classes
  - The classes are significantly imbalanaced
  - Oversampled minor and major damage
  - Gave these classes more weight with the loss function

Disaster Level	Structure Description
0 (No Damage)	Undisturbed. No sign of water, structural or shingle damage, or burn marks.
1 (Minor Damage)	Building partially burnt, water surrounding structure, volcanic flow nearby, roof elements missing, or visible cracks.
2 (Major Damage)	Partial wall or roof collapse, encroaching volcanic flow, or surrounded by water/mud.
3 (Destroyed)	Scorched, completely collapsed, partially/ completely covered with water/mud, or otherwise no longer present.

Future Work

- Flooding around buildings was difficult to classify
  - Hard to see on the images for humans
  - Model had the most trouble classifying these instances
- Experiment with different U-Net encoder blocks
  - VGG, Inception, ResNet, etc.
- Use Quadratic Weighted Kappa as a loss function
  - The model blends together some predicitons (i.e. no damage and major)
  - Places higher penalty on classes that are further away from the actual

Santa Rosa Wildfire - Post Disaster



Solution Models - Final Report

Problem areas that were solved

- Large images and dense networks are not a good combination
  - The computation power needed to run models was significant
  - Multiprocessing on GPUs didn't always offer significant speed gains
  - Used vectorization where possible, to improve performance
- The model struggled on classifying minor and major damage
  - There is not a clear delineation between the classes
  - The classes are significantly imbalanaced
  - Oversampled minor and major damage
  - Gave these classes more weight with the loss function

Score	Label	Visual Description of the Structure
0	No damage	Undisturbed. No sign of water, structural damage, shingle damage, or burn marks.
1	Minor damage	Building partially burnt, water surrounding the structure, volcanic flow nearby, roof elements missing, or visible cracks.
2	Major damage	Partial wall or roof collapse, encroaching volcanic flow, or the structure is surrounded by water or mud.
3	Destroyed	Structure is scorched, completely collapsed, partially or completely covered with water or mud, or no longer present.

Solution Models - Final Report

Areas to focus on - if given more time

- Flooding around buildings was difficult to classify
  - Hard to see on the images for humans
  - Inconsistency in classification, minor or major
  - Model had the most trouble classifying these instances
- Experiment with different U-Net encoder blocks
  - VGG, Inception, ResNet, etc.
- Use Quadratic Weighted Kappa as a loss function
  - The model blends together some predicitons (i.e. no damage and major)
  - Places higher penalty on classes that are further away from the actual

Solution Models - Updates

Financial Model

- Will need to integrate model output into financial model
  - identify buildings as polygons
  - squarefootage
  - centroids
  - lat/lon conversion
  - MGRS grids cost summation - could be building level summation or pixel level

Solution Models - Updates

Financial Data

- validated results with county level data

updated model is more accurate (same order of magnitude as approximations)

$/sqft/zipcode * sqft * 2floors * damage level factor

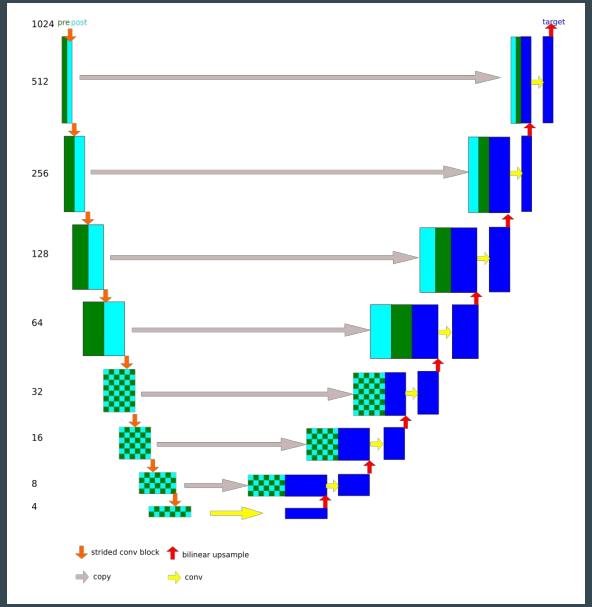
where damage level factor

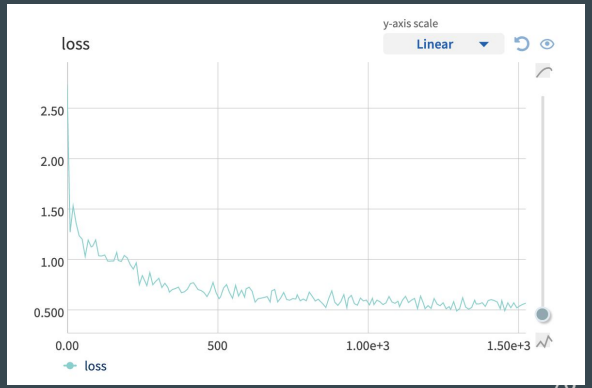
= 0 for no damage, 0.5 minor, 0.8 major, 1 destroyed

Solution Models - Updates

Modified U-Net with Paired Image Inputs

- To establish an MVP — and use inference outputs to validate the financial modeling approach — we applied two, relatively simple, open source U-Nets with near-top-50 weighted score (0.68)
  - 6–8 GPUs leveraged, both models trained overnight
  - Modified U-Nets with EfficientNet encoder blocks
- ~5 seconds for inference per image
  - Damage classification is done at the pixel level (as opposed to the building level) with the localization applied as a “mask”





Solution Models - Updates

Financial Data - next steps

- Will compare these values with our obtained county level values and see how accurate they are and what needs to be adjusted

Solution Models - Updates

Xview-2 lat/lon mapping

- Xview2 data provides lon/lat for each building but not image as a whole
- This lat/lon position is needed for mapping and also for conversion from model -> lat/lon -> USNG coords
- We found an algorithm to determine lat/lon of each xview2 image for mapping
- We will use this for final flask app as well

Solution Models - Updates

Financial Data

- Mapped zip-code for all xview2 data
- Pulled zillow data for a price/sqft for each zipcode

financial cost model is currently

$/sqft/zipcode * sqft * damage level factor

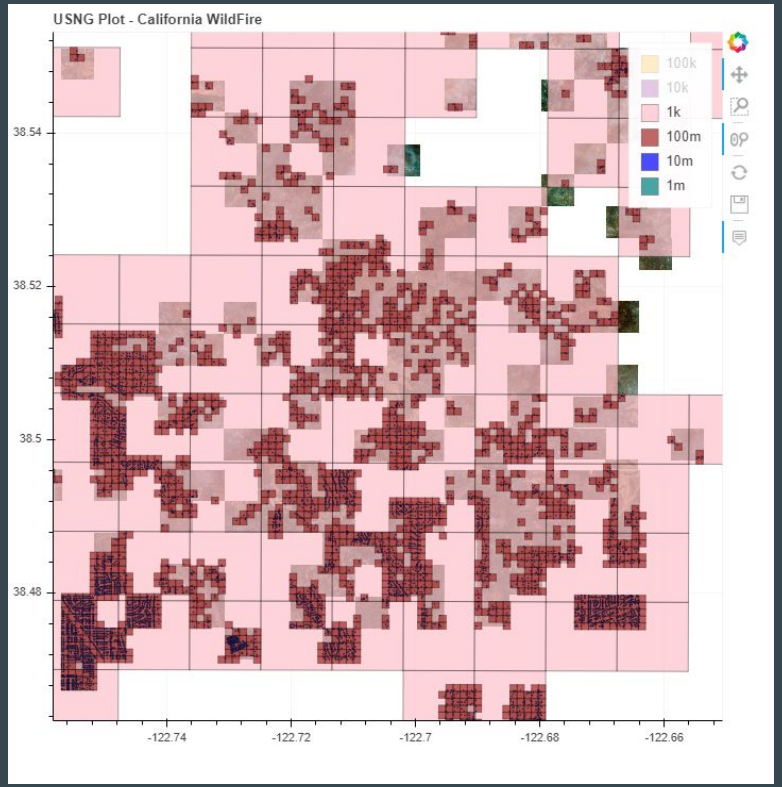
where damage level factor

= 0 for no damage, 0.25 minor, 0.75 major, 1 destroyed

Solution Models - Updates

US National Grid Coordinates Viz

- Added xview2 images to Bokeh plot
- Color scaled each precision layer by financial cost
- Precision layers are hideable

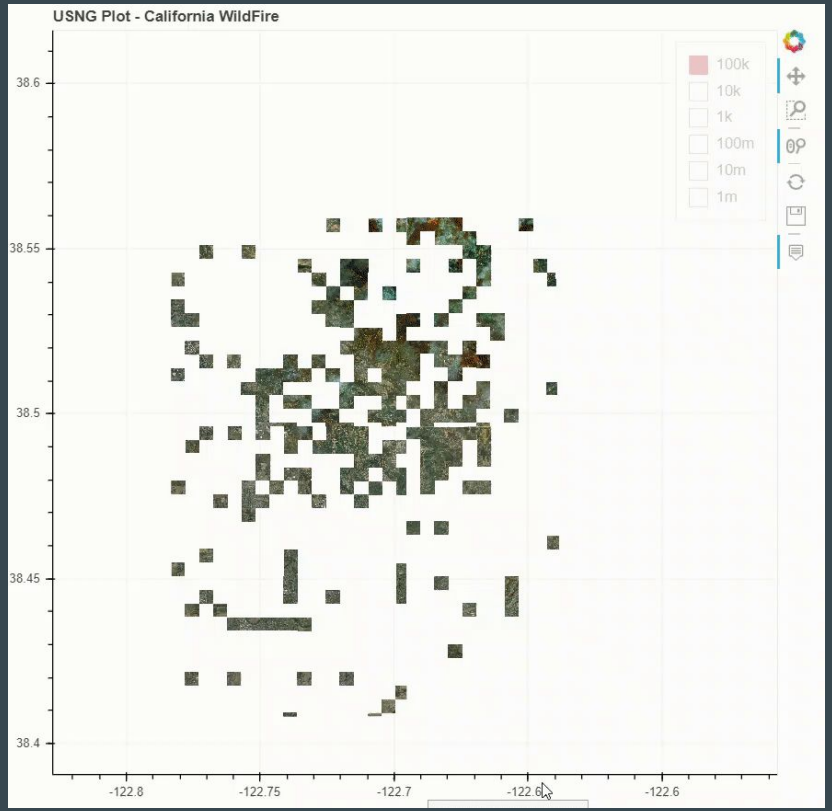


Financial cost estimation using USNG coordinates

Solution Models - Updates

US National Grid Coordinates Viz - next steps

- Will need these processes to display images received in app
- https://ermlickw.github.io/

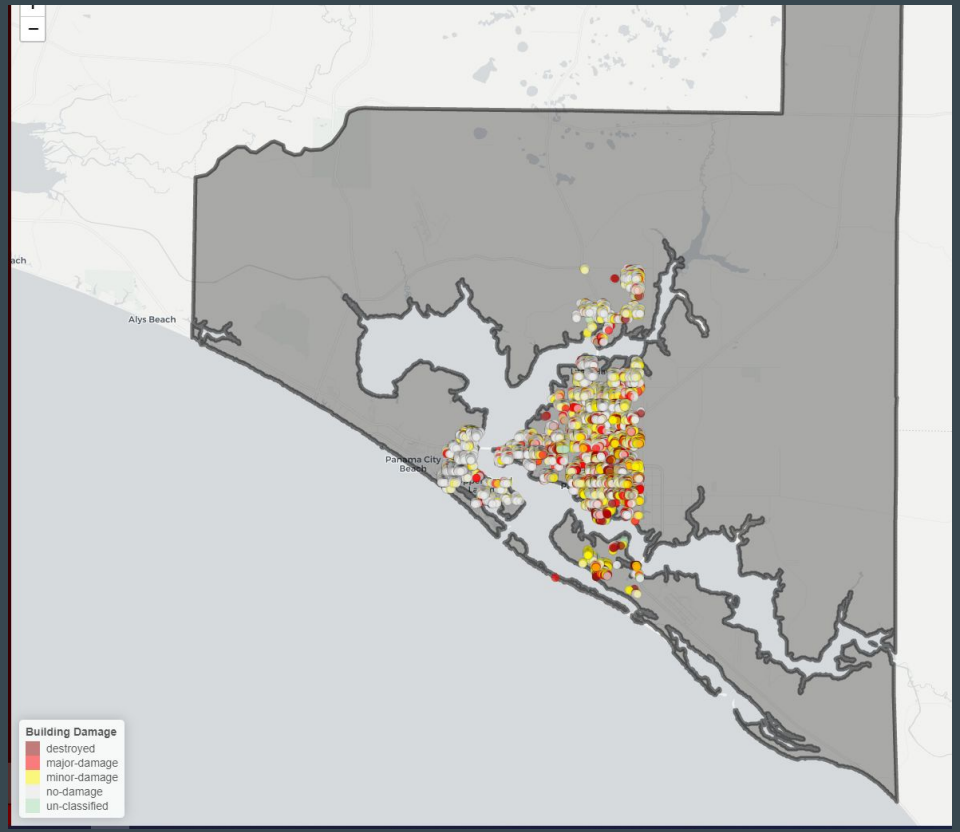


Financial cost estimation using USNG coordinates

Analytics & Algorithms -Updates

County level visualizations

- Noticed damage area is much smaller than county area
- Will result in poor estimations
- Some disasters in Xview2 (moore, tuscaloosa, joplin tornadoes and Hawaii eruption) may have captured all affected buildings
- Focus on these for financial modeling checking only



Hurricane Michael Bay County Xview2

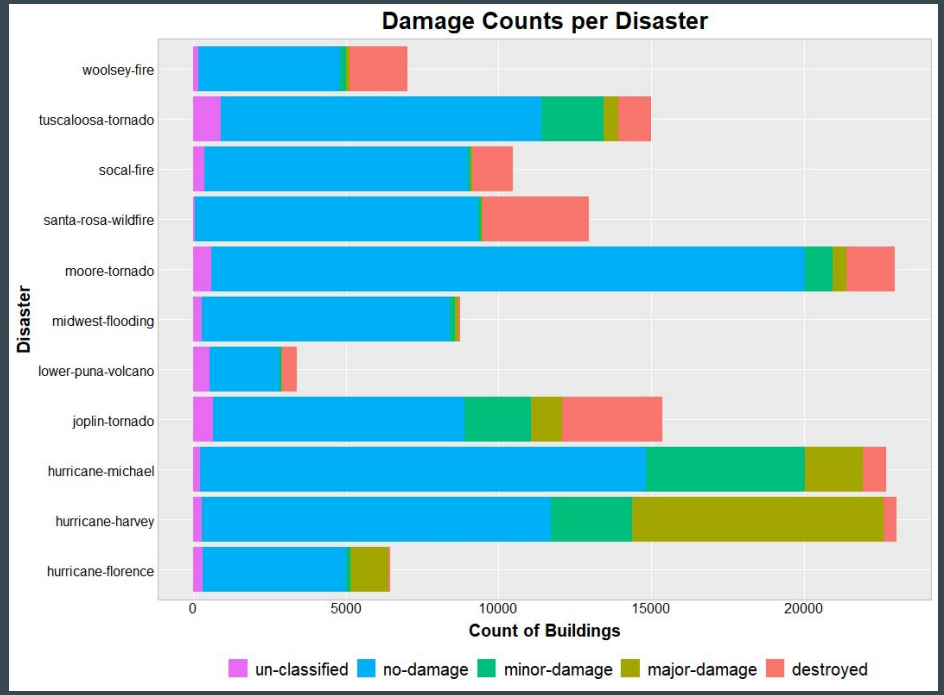
DAEN 690 Schedule

Sprint	Milestone Goals		Presentation
Problem Definition and Project Plans	• Problem (decision) defined • Understanding of complexity • Potential data source identified • Potential analytics identified	• Project schedule defined • Participant roles assigned • Risks identified and mitigation plan	Mid-Sprint 28 May; Full Sprint 4 Jun
Data Sets	• Data located and accessed • Initial processing underway	• Risks identified and mitigated	Mid-sprint 11 Jun; Full Sprint 18 Jun
Analytics/algorithms	• Algorithms defined and coded • Initial applications completed	• Risks identified and mitigated	Mid-sprint 25 Jun & 2 Jul; Full Sprint 9 Jul
Visualizations	• Visualization concepts defined • Visualization implemented	• Risks identified and mitigated	Mid-sprint 16 Jul; Full Sprint 23 Jul
Final Presentations	• Project components completed • Project components integrated	• Project supports final decision • Presentation made	Mid-Sprint 30 July; Full Sprint 6 Aug

Analytics & Algorithms -Updates

Dataset imbalance & resampling

- Imbalanced classes will need to be upsampled or downsampled for each disaster type
- Critical for training



Hurricane Michael Bay County and Xview2 Image Data