DisasterNet: Automatic Disaster Detection from Aerial Imagery

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Goal: Efficiently Find Badly Hit Areas After Disasters

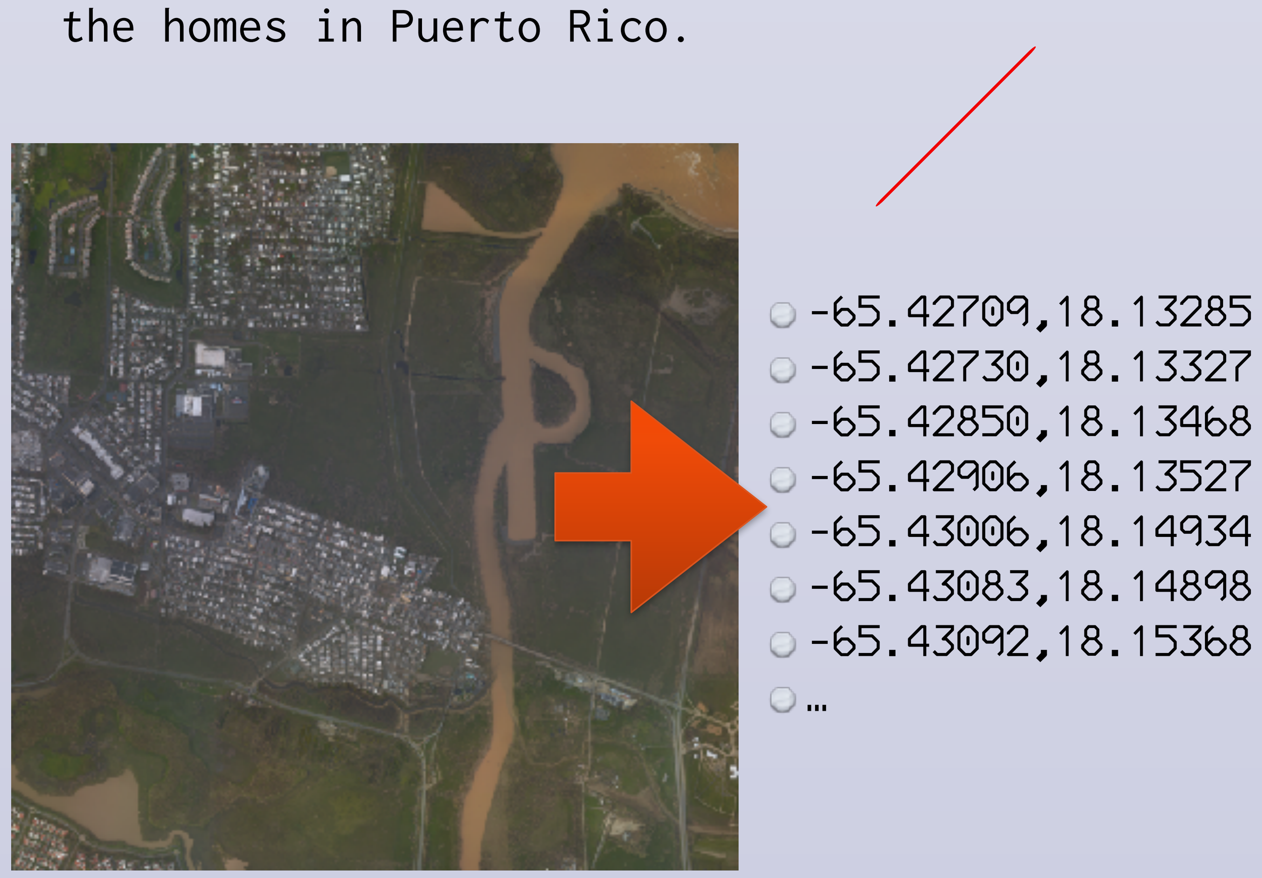
- First responders rely on disaster area windshield surveys and manual satellite image inspection, which is time consuming, error-prone, and oftentimes physically challenging.
- We train a Convolutional Neural Network (CNN) framework to identify areas hit by disasters.
- Emergency managers could run model in minutes and use results to prioritize rescue and resource allocation.

Framework Input & Output

Input: Post-disaster satellite and flight/ aerial images covering large areas (RGB images)

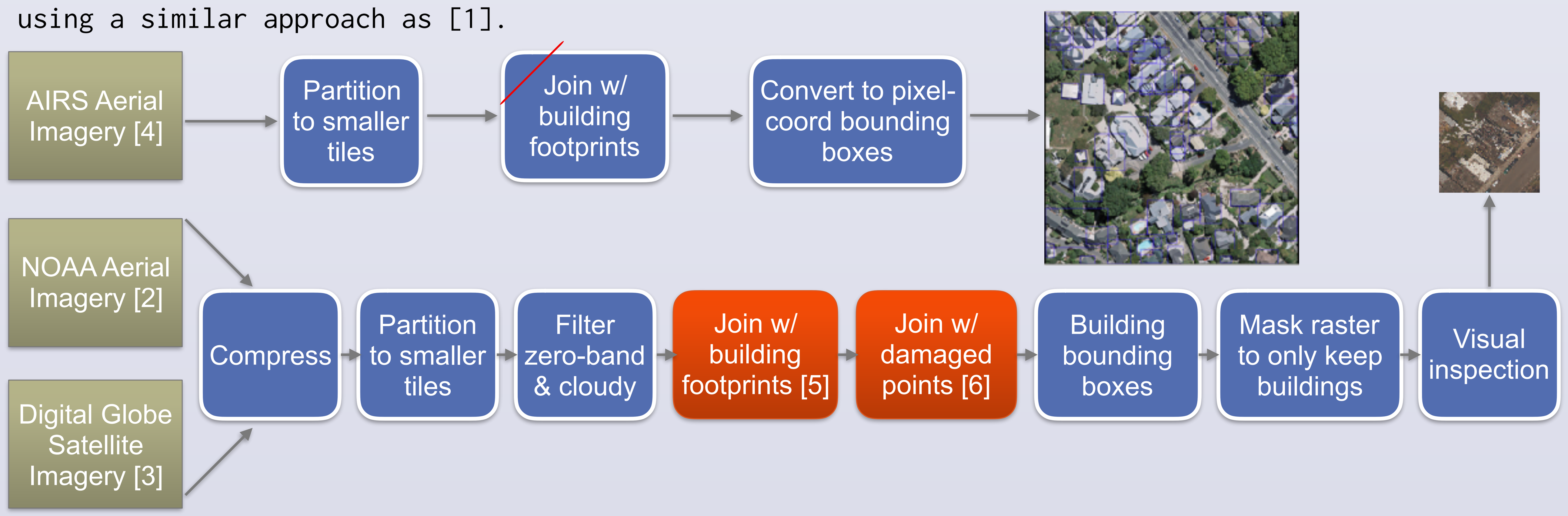
Output: Vector with damaged or not-damaged label for individual buildings detected in the original imagery (1D vector)

- Damage labels can be joined back to the building's coordinates, to finally return a vector of locations where damage was detected by the framework.
- We apply this to Hurricane Maria, which damaged or destroyed more than one third of the homes in Puerto Rico.



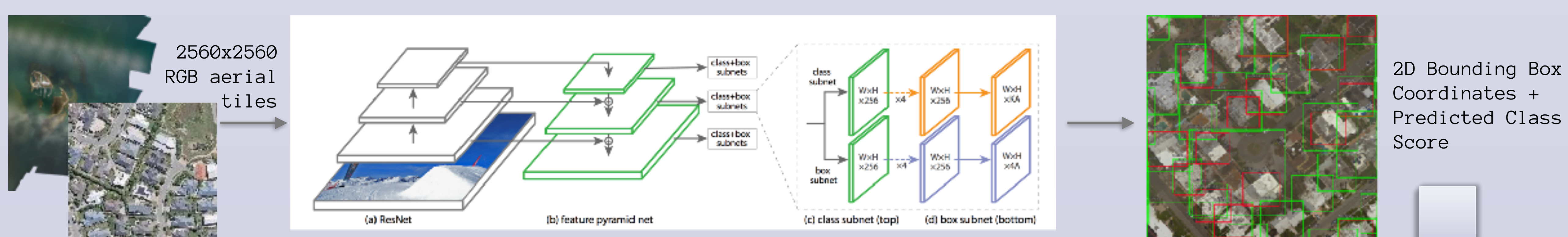
Training Data

- **Buildings in photographs of the Earth are unlabeled!** Bonus: original imagery is too large to process at once (~35,000x35,000px).
- Images can be cloudy, blurry, or include empty-band (black) sections on the edges that can throw the models off.
- No single source for all the data we need: aerial imagery, building footprints, and ground truth for damaged buildings. **We gathered them separately and combined it all to create our datasets**, using a similar approach as [1].

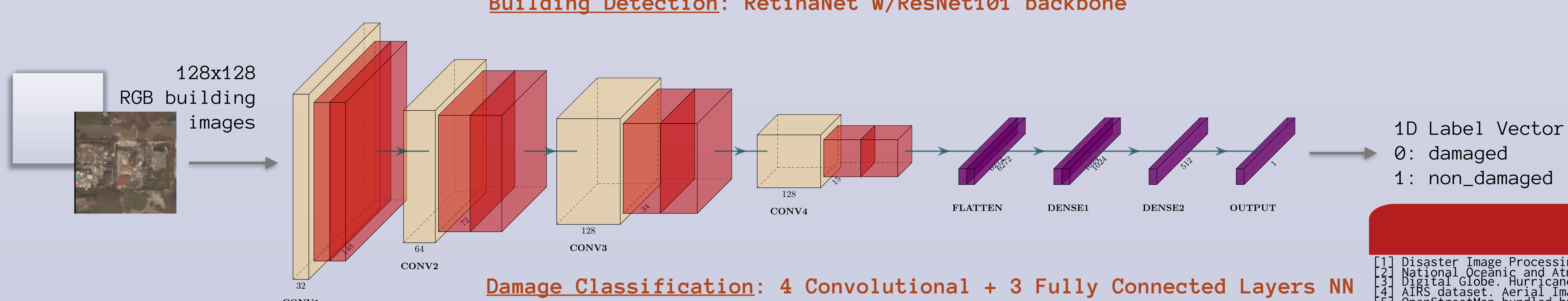


Framework Architecture

- Framework consists of two CNNs: one for **building detection**[7] and another for **damaged building classification**[8].



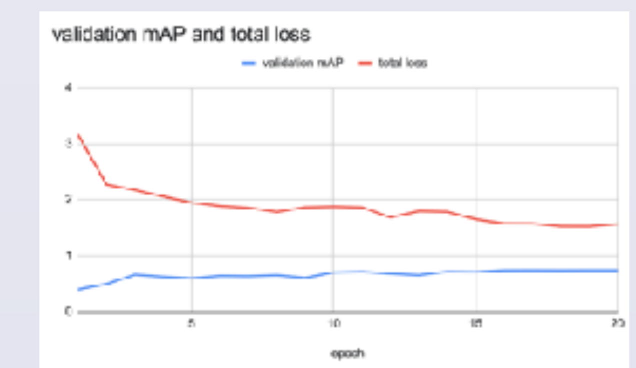
Building Detection: RetinaNet w/ResNet101 backbone



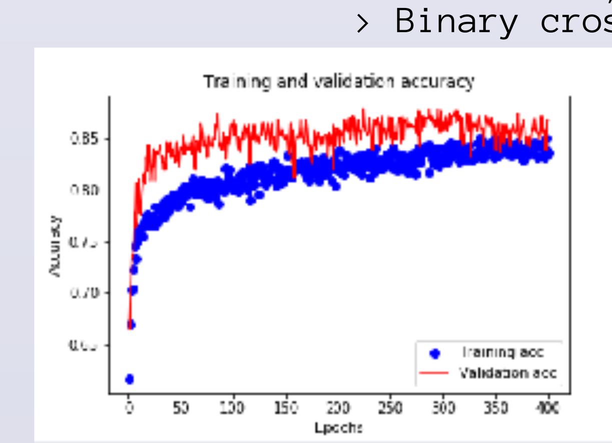
Damage Classification: 4 Convolutional + 3 Fully Connected Layers NN

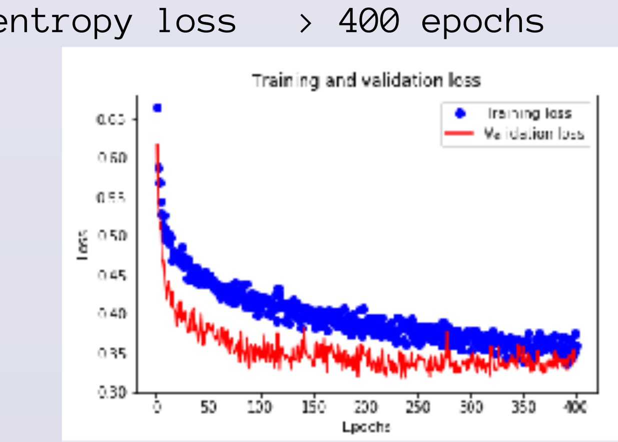
Results

Building Detection
- Adam, 0.0001 learn rate
- 15216 train, 2000 validation
- Focal loss function
- **0.743 mAP** (validation)
- 0.25 IoU thresh
- 20 epochs



Damage Classification
- Adam, 0.001 learn rate
- Dropout, 0.5
- 2406 train, 428 validation
- Binary cross entropy loss
- **384 test samples**
- **84.1% acc**
- **86.8% F1**
- 400 epochs





Hyperparameter Tuning

Learn Rate	Loss
0.001	2.35 (no convergence)
0.0001	1.5685
0.00001	1.9322
0.000001	2.2 (too slow)

< Building Detection

Loss	ResNet101	ResNet50
Total	1.5277	1.6626
Reg.	1.2484	1.3483
Class.	0.2793	0.3143

Damage Classification >

Data Aug	Dropout	Building box zoom	# FC Layers	# Frozen Conv Layers	# Epochs	Accuracy
No	0.5	0.00016	2	4	100	53.9%
Yes	0.5	0.00016	2	4	100	52.7%
Yes	0.5 (2 FC)	0.00024	3	2	100	83.9%
Yes	0.5 (2 FC)	0.00024	3	3	100	83.3%
Yes	0.5 (2 FC)	0.00024	3	3	400	84.1%
B	A	S	E			61.4%

Discussion

- Combining two CNN models for two tasks to ultimately perform one objective works! However, performance would likely have been better with more training data. Raw satellite imagery requires a non-trivial amount of preprocessing and visual inspection.
- We chose Hurricane Maria to test current literature performance on a different environment (climate and infrastructure) than those previously evaluated (mainland US). Damage classification base model performance was poor in spite of similarity of the task; however, transfer learning on images from new environment proved effective. A greater diversity of disaster types and environments would make the model more robust.
- This deep learning technique can have a big impact in helping first responders identify first-pass, worst-hit areas immediately following a disaster.

Future Work

- Labeling more aerial/satellite post-disaster images, for Hurricane Maria and other disasters, would likely increase performance and make the framework more robust.
- With more data, we could also explore an end-to-end model that can detect damaged buildings without a two-model framework with separate tasks.

References

[1] Disaster Image Processing. Utils for satellite image processing. https://github.com/DDS-Lab/disaster-image-processing.
[2] National Oceanic and Atmospheric Administration. Hurricane Maria aerial imagery. https://storms.ngs.noaa.gov/storms/maria/index.html.
[3] Digital Globe. Hurricane Maria satellite images. https://www.digitalglobe.com/opendata/hurricane-maria/post-event.
[4] AIRS dataset. Aerial Imagery for Roof Segmentation. https://www.airs-dataset.com/.
[5] OpenStreetMap bundled by GeoFabrik. Puerto Rico building footprints. http://download.geofabrik.de/.
[6] FEMA. Hurricane Maria damage assessments. https://data.femadata.com/NationalDisasters/HurricaneMaria/.
[7] Tsung-Yi Lin, Priyal Goyal, Ross Girshick, Kaiming He, and Piotr Dollar. Focal loss for dense object detection. IEEE Transactions on Pattern Analysis and Machine Intelligence, PP:1-1, 07 2018.
[8] Cao and Choe. Deep Learning based damage detection on post-hurricane satellite imagery. CoRR, abs/1807.01688, 2018.