Flood Damage Extent Detection Using Satellite Images and Meta Attributes

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1 Introduction

With the growth of the global population, urbanization in flood-prone areas, and the effects of climate change, the frequency and severity of floods, as well as their associated damage, are expected to continue to rise. Therefore, it is essential to have more efficient response measures in place. Traditional methods for identifying flooded areas rely on image segmentation, which can locate and flag buildings and roads affected by flooding, but may not provide a complete assessment of the extent of flood damage. Our method aims to address this issue by utilizing a set of images captured before and after the flood, as well as other meta attributes such as the elevation of the affected area, flood insurance claims, and soil imperviousness, to provide a more accurate and comprehensive assessment of flood damage extent.

The problem is challenging because traditional flood segmentation methods only focus on identifying flooded buildings by examining rooftops and neighboring pixels, without incorporating additional meta information or attributes that could provide a more accurate assessment of flood damage extent. This makes it difficult to provide a comprehensive evaluation of the damage caused by floods.

The input to our system are a pair of images (one captured before the flood and one captured after the flood) along with meta attributes. The output of the system is an assessment of the extent of flood damage, which is categorized as low, medium, or high levels of damage for each building in the affected area. This requires the system to analyze multiple factors such as elevation, flood insurance claims, and soil imperviousness.

Our contributions to this field include creating a new dataset that incorporates elevation and soil imperviousness meta attributes to improve the detection of flood damage extent. We have also designed and implemented a neural network called MetaSegNet, inspired by the UNet architecture, which achieved a significant improvement in accuracy for flood damage extent detection, as demonstrated by improved dice scores and tversky metric.

We compared the performance of multiple networks, including UNet, SENet, Siamese UNet, and MetaSegNet, for tasks such as building localization (segmentation) and flood damage extent detection, with and without the inclusion of meta attributes. By including these attributes along with satellite images, we observed a notable increase in accuracy for determining the extent of damage caused by floods, compared to traditional segmentation methods that can only identify whether a building is flooded or not.

2 Related Work

There are multiple datasets which can be used for detecting floods such as xBD [1], SpaceNet8 [2], FloodNet [3], which contain pre-disaster and post-disaster images with corresponding building masks which can be used to perform building segmentation.

The xBD dataset [1] is focused on classifying building damage levels caused by different natural disasters, ranging from - No Damage, Minor Damage, Major Damage and Destroyed, and was developed through several rounds of human verification. However, this dataset does not contain any meta attributes to determine flood damage extent. In contrast, our work includes the meta attribute of elevation in a region to improve flood damage extent detection. Additionally, we have developed a new baseline model using meta attribute injection, which considers additional information beyond the image data to enhance the accuracy of flood damage extent detection.

The SpaceNet8 dataset [2] includes images of flooded and non-flooded buildings and roads captured in Louisiana and Germany, which are used for flood segmentation. However, similar to the xBD dataset, SpaceNet8 does not contain any meta attributes for determining flood damage extent. Despite this limitation, we recognize the high quality and diversity of the densely labeled datasets of SpaceNet8 and xBD. Therefore, we adopted the baselines of these models to perform localization and segmentation, while integrating meta attribute data to enhance the accuracy of flood damage extent detection.

In addition to the xBD and SpaceNet8 datasets, we also curated an in-house dataset based on Hurricane Harvey in Harris County, Texas with the assistance of Airbus. This dataset includes geo-spatial coordinates of the region, as well as various meta attributes such as elevation, flood insurance claims, LiDAR scans, soil imperviousness, water inundation model, and flood risk factors. We utilized this dataset to construct our novel meta injection model, which incorporates meta attribute information to improve the accuracy of flood damage extent detection.

3 Proposed Methodology

We use xBD, SpaceNet8 and Harvey Dataset to perform flood damage extent detection. In order to perform robust building detection, we have used xBD and SpaceNet 8 datasets for building localization (Phase-1) and once a trained segmentation model is obtained, we then fine-tune it on the Harvey dataset ((Phase-2). The overall architecture is shown in Figure 1. The input to the network is highlighted (green color), the intermediate output of building localization (gray color), the trained segmentation model (blue color) and the final output (orange) are the flood damage extent detection classes.

3.1 Dataset Preprocessing

In order to prepare the meta attribute dataset, we use the original Harvey dataset which contains buildings masks in the image domain which is then converted to the GIS domain to perform mapping with insurance claims. Polygons are created from masks which are then converted to GIS domain. The insurance claims obtained from FEMA has undergone data cleansing and then flood damage extent classes are generated based on claim amounts (based on box plots, the quartiles are categorized as low damage, medium damage and high damage). Finally, both the data are merged in the GIS

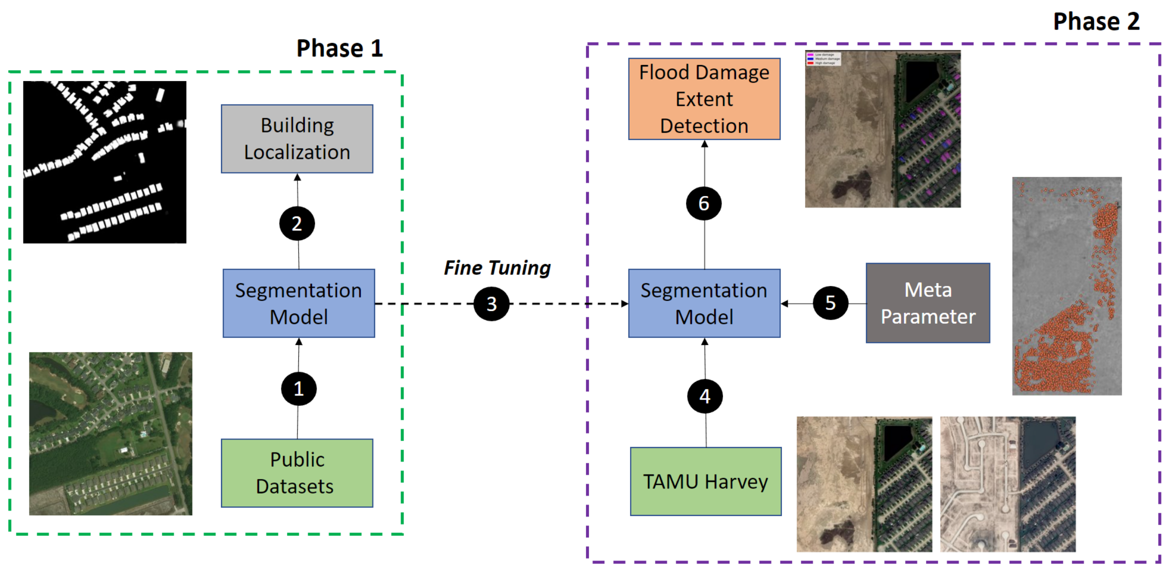

Figure 1: Overall architecture of our methodology

domain. In order to make this data viable for ML training, we convert the polygons from GIS domain to Image domain and finally create masks from these polygons, which are used for training.

3.2 MetaSegNet

The input to this network, as represented in Figure 3, comprises of the pre-flood images, post-flood images and meta attributes such as elevation and soil imperviousness. The proposed network, as described in Figure 2, uses a MLP-encoder to learn feature representations from multi-modal data of the meta attributes and then injects these features to the backbone of a UNet inspired SEResNeXt-50 network.

The output obtained from xBD and SpaceNet8 datasets on the task of building localization are shown in Figure 4. To better understand the process of meta attribute injection in our network, we drew inspiration from two previous works. The first, referenced as [4], utilizes a multi-encoder joint fusion process to incorporate meta attribute information into a decoder network. This is achieved through the use of mutual attention and multi-head cross attentions. The second, referenced as [5], employs MLP embeddings to fuse meta attribute information. In our MetaSegNet model, we have incorporated these approaches to enable the injection of meta attributes into the network,

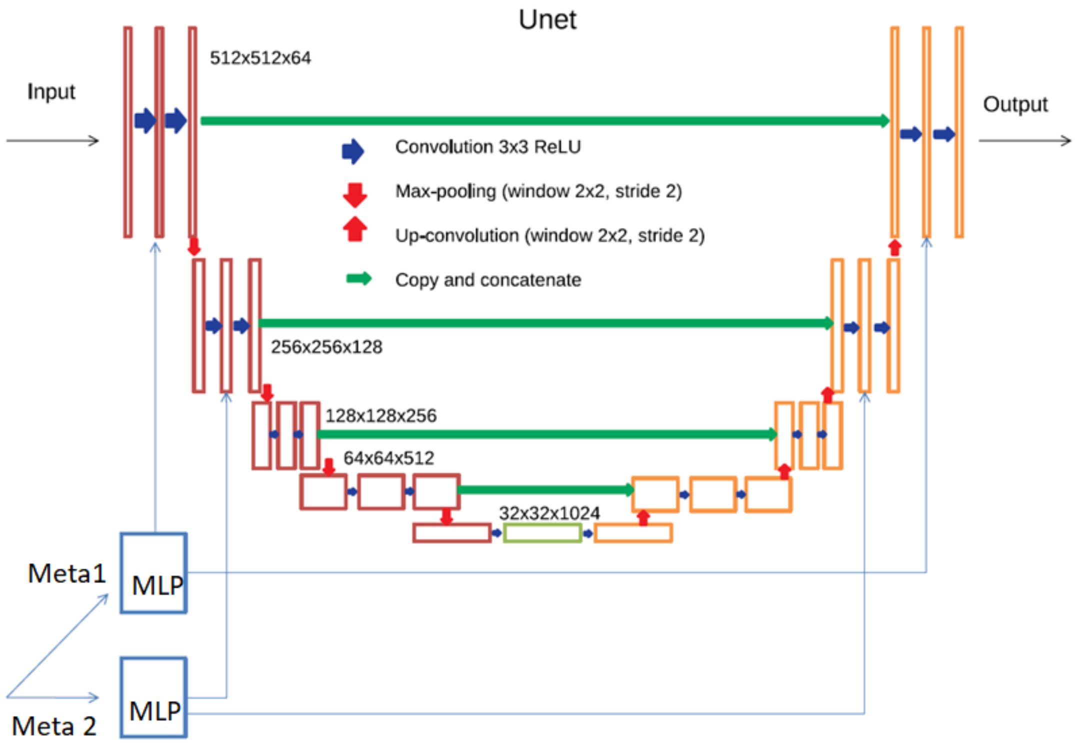

Figure 2: Architecture Diagram of MetaSegNet

allowing for a more comprehensive assessment of flood damage extent.

3.3 Metrics

The metrics used to evaluate our work are Dice score and Tversky score. Dice score is a metric used to measure the similarity between two sets of data. It is commonly used in image segmentation tasks to evaluate the accuracy of a segmentation algorithm. Higher Dice scores indicate a better segmentation performance.

$$DiceScore = 2 * |X \cap Y|/(|X| + |Y|)$$

The Tversky score is a generalization of the Dice coefficient and Jaccard index, which are used to measure the similarity between two sets. In the context of binary segmentation, the Tversky score is often used to evaluate the performance of segmentation algorithms in segmenting images into foreground and background regions.

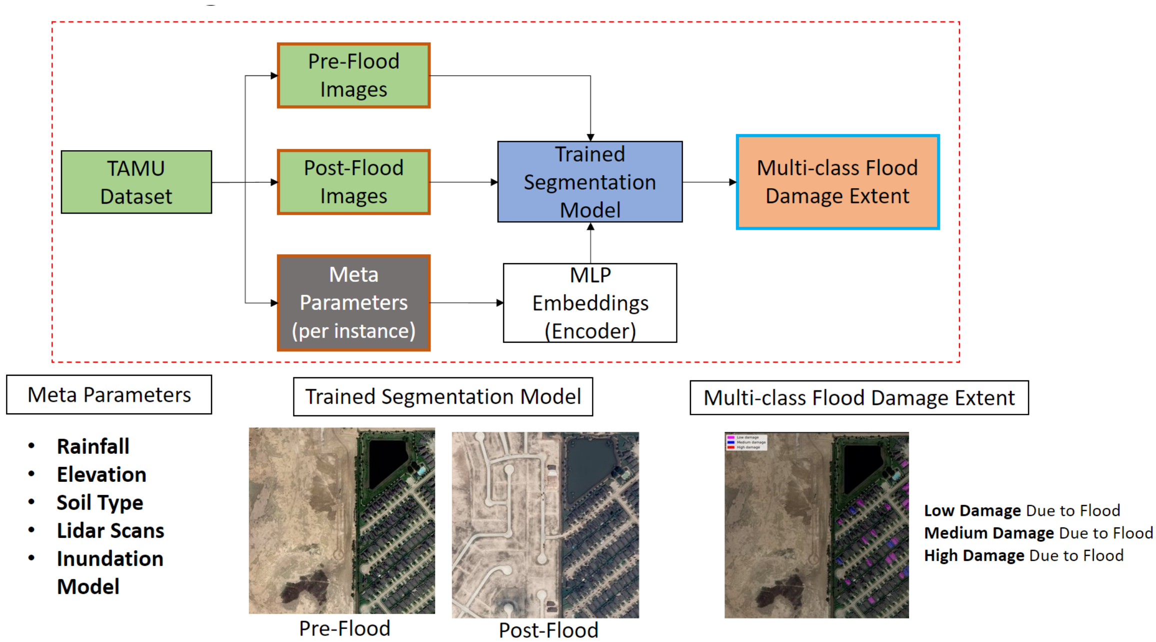

Figure 3: Architecture Diagram of TAMU Harvey training with meta injection of attribute

$$Tversky(\alpha, \beta) = TP/(TP + \alpha * FP + \beta * FN)$$

4 Results and Discussion

We evaluate our implementation on multiple networks such as UNet, SENet, Siamese UNet, MetaSegNet for various tasks such as Building Localization and Flood Damage Extent with and without meta attributes.

4.1 Results from xBD and SpaceNet8 datasets

The results obtained from xBD dataset is described in Figure 4 and the results obtained from SpaceNet8 dataset is described in Figure 5.

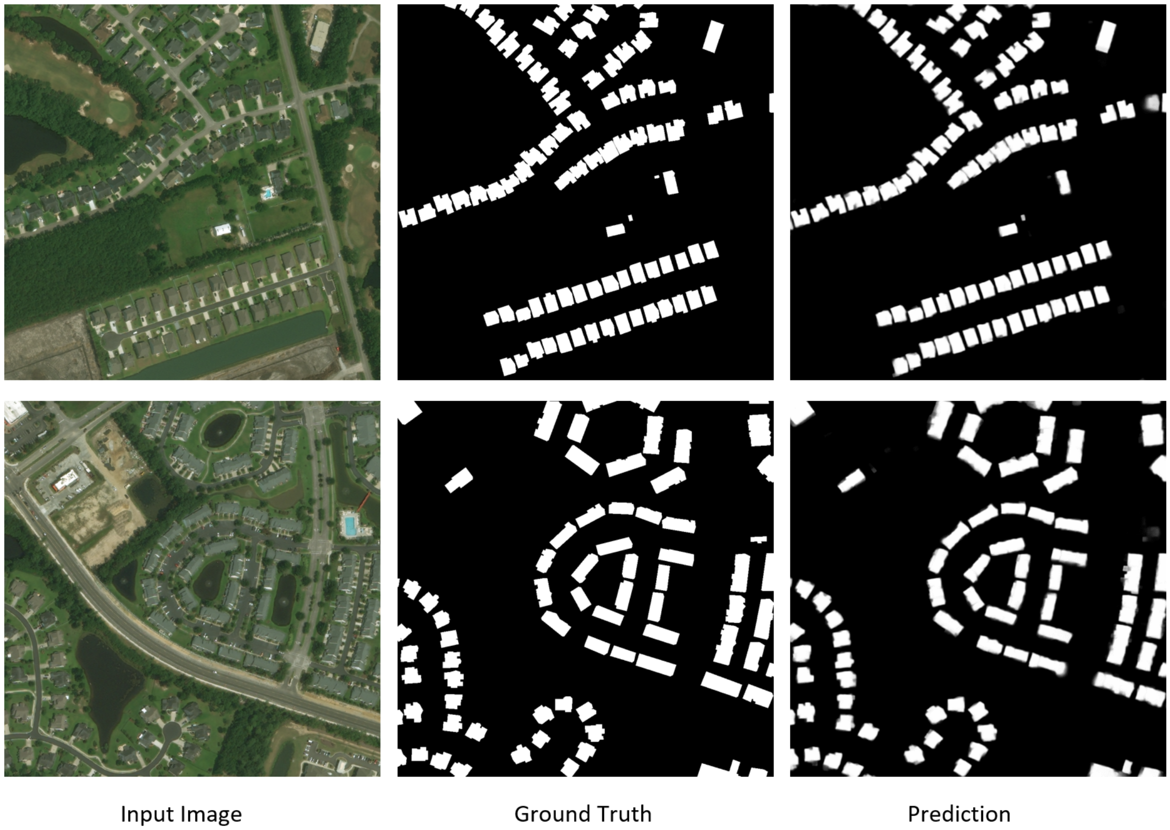

Figure 4: Network predictions on xBD dataset

4.2 Results from Harvey dataset

The results obtained from Harvey dataset is described in Figure 6. We have used elevation meta attribute on this dataset, however the results portray dataset imbalance, due to fluctuations in the amount of damaged buildings in the ground truths.

4.3 Metrics

The experimentation results on different models for the task of Building Localization is shown in Table 1.

The experimentation results on different models for the task of Flood Damage Extent on TAMU Harvey dataset are shown in Table 2.

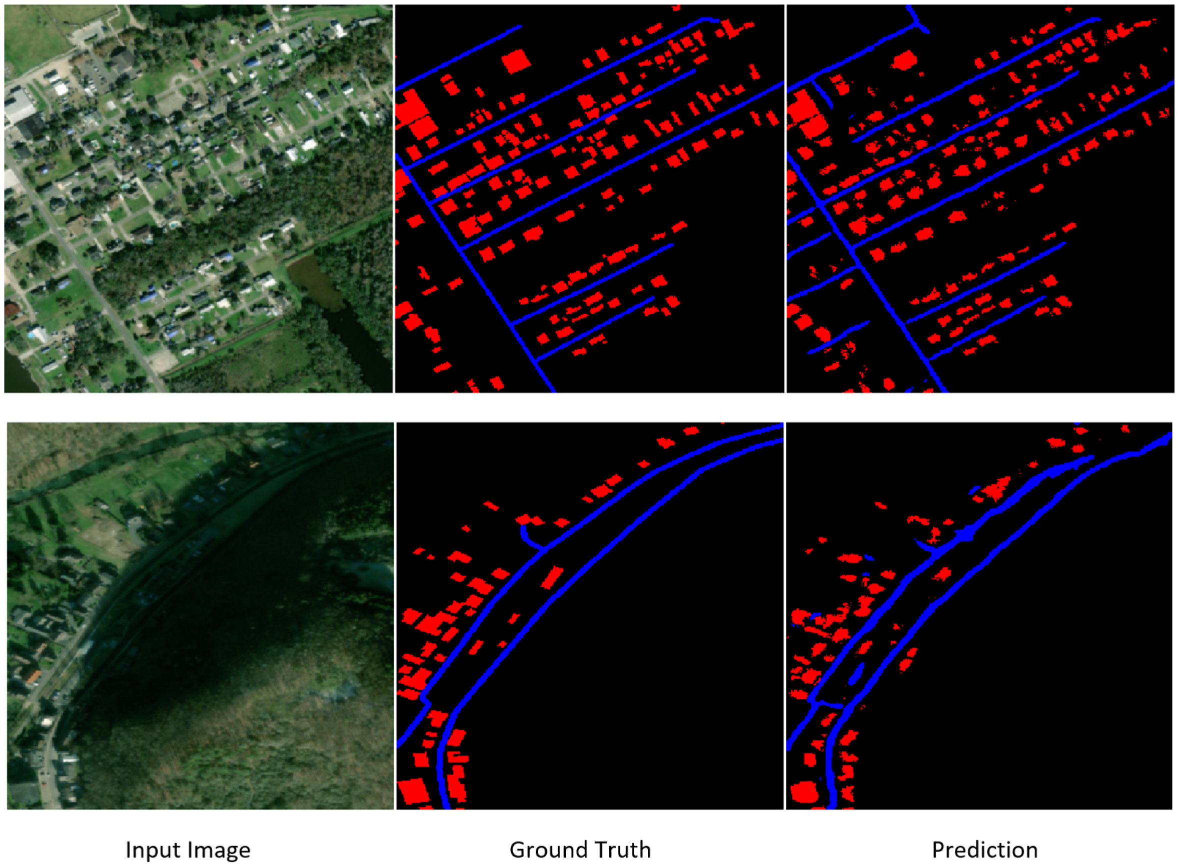

Figure 5: Network predictions on SpaceNet8 dataset

5 Conclusion

The study reviewed existing datasets for flood segmentation using satellite images, such as xBD and SpaceNet8, which is used to build a robust building segmentation network, to compensate for data limitation found in the Harvey dataset. A novel dataset was created using insurance claims and injecting meta attributes like elevation of a region and soil imperviousness. The extremely imbalanced dataset was handled with Focal Loss and class weights, leading to improved Dice scores and Tversky metrics when using meta attributes in combination with satellite images. The results show that incorporating meta attributes with satellite images increases accuracy in determining flood damage extent compared to traditional flood segmentation methods.

Building Localization			
Dataset	**Task**	**Network**	**Metric**
xBD	Building Localization	Unet (SE-ResNeXt-50)	0.72 IoU
xBD	Building Localization	Unet (ResNet34)	0.65 IoU
xBD	Building Localization	Unet(EfficientNet-B2)	0.54 IoU

Table 1: Building Localization Results

Building Localization				
Dataset	**Task**	**Network**	**Dice Score**	**Tversky Score**
TAMU Harvey, NFIP	Flood building damage extent without meta	Unet (Vanilla)	0.17	0.03
TAMU Harvey, NFIP	Flood building damage extent with Elevation meta parameter	Unet (Vanilla)	0.32	0.04
xBD, TAMU Harvey, IA	Flood building damage extent with Elevation meta parameter	Unet (SE-ResNeXt-50)	0.48	0.09
xBD, TAMU Harvey, IA	Flood building damage extent with Imperviousness meta parameter	Unet (SE-ResNeXt-50)	In progress	In progress

Table 2: Flood Damage Extent Results

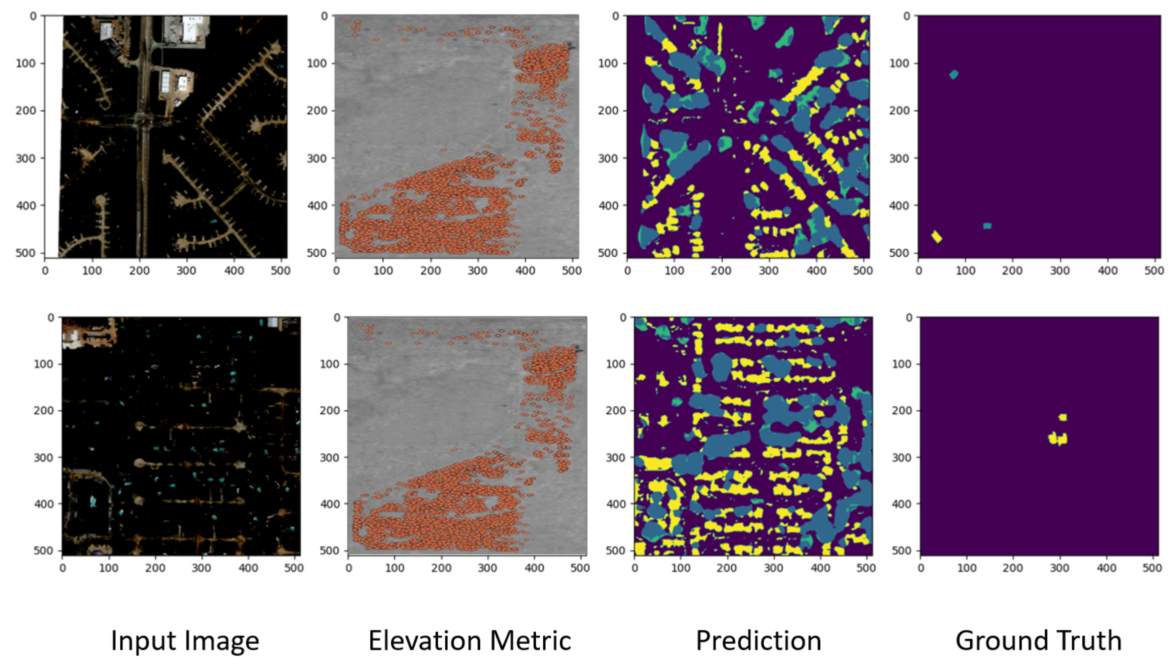

Figure 6: Network predictions of MetaSegNet on Harvey dataset with elevation meta-parameter

References

[1] xBD: A Dataset for Assessing Building Damage from Satellite Imagery

[2] SpaceNet 8 - The Detection of Flooded Roads and Buildings

[3] FloodNet: A High Resolution Aerial Imagery Dataset for Post Flood Scene Understanding

[4] A multimodal transformer to fuse images and metadata for skin disease classification

[5] Incorporating Metadata for Semantic Segmentation