Flood Damage Extent Detection Using Satellite Images and Meta Attributes

CMPT 732 G200 Project Report

Amrit Paul
Simon Fraser University, Burnaby, BC
amrit_paul@sfu.ca

Karan Pathak
Simon Fraser University, Burnaby, BC
karan_pathak@sfu.ca

ABSTRACT

Climate change is one of the most serious issues confronting humanity today. Climate change has increased the frequency and severity of natural disasters in recent years, such as flooding. Floods cause significant socioeconomic damage and disrupt various ecosystems in agriculture, infrastructure, and other areas. In this work, we propose a solution to determine the extent of damage caused by floods by using a pair of pre and post flood images as well as various meta attributes such as elevation of the area, flood insurance claims of buildings, number of buildings, etc., to estimate flood damage extent. In the paper, we performed diverse tasks such as Building Localization, Flood Segmentation using only satellite images and Flood Segmentation with and without meta attributes. Our complete codebase can be found at - https://github.com/karanpathak/Flood-Damage-Extent-Detection

KEYWORDS

Flood Segmentation, Damage Extent, Siamese Neural Networks, UNet, Meta Attributes, Elevation, Rainfall, Building Localization

1 INTRODUCTION

Floods are one of the main natural disasters that cause fatalities, damage to buildings and infrastructure, exorbitant expenditures for replacing lost property, and other problems. Given the ever-increasing human population, the urbanisation of flood plains, and the impact of climate change, it is anticipated that the frequency and intensity of floods, as well as the damage they inflict, will increase. With the requirements for faster response times, traditional approaches to detect flooded zones rely on semantically segmenting images to identify and detect flooded building and roads.

There are multiple datasets which can be used for detecting floods such as xBD [1], SpaceNet8 [2], FloodNet [3], etc., which contain pre-disaster and post-disaster images with corresponding building masks which can be used to perform semantic segmentation. However, these datasets lack the meta information to determine flood damage extent and can be used to only detect flooded or non-flooded buildings/roads.

Research Problem. Current approaches mostly consider the building roof tops and neighbourhood pixels around the flooded buildings to perform flood segmentation, with no supporting meta information/attributes. The proposed approach uses meta attributes such as elevation of the area, flood insurance claims of buildings, etc., along with satellite images to determine extent of damage caused due to floods, based on 3 categories such as low damage, medium damage and high damage.

Contribution Summary. The following are the contributions of this project:

- We built a novel dataset containing elevation meta attribute for flood damage extent detection
- We implement *MetaSegNet* using the meta attibute dataset inspired from the UNet architecture and obtain considerable improvements in accuracy based on dice scores and tversky metric.
- We evaluate our implementation on multiple networks such as UNet, SENet, Siamese UNet and MetaSegNet for various tasks such as building localization, Flood segmentation using only satellite images and Flood segmentation with meta attributes.

2 RELATED WORKS

Throughout the evolution of various flood datasets, we come accross multiple datasets such as xBD, SpaceNet8, FloodNet, SpaceNet-1/2, Sentinet-1/2, SEN12-Flood, etc., which have their limitations as dicussed below.

The dataset of xBD [1] comprises of four-levels of building damage classification from different natural calamities such as - No Damage, Minor Damage, Major Damage and Destroyed. These labels were created based on multiple rounds of human verifications, however, do not contain any meta attributes to determine flood damage extent. Our work in contrast,use the meta attribute of elevation of an area in a region and also a new baseline model using meta injection of attributes.

The dataset of SpaceNet8 [2] comprises of flooded and non-flooded buildings and roads captured from Louisiana and Germany which is used for flood segmentation, however, also does not contain any meta attribute to determine flood damage extent. Although, we find the densely labelled datasets of SpaceNet8 and xBD to be superior in quality and diversity, hence, we adopt the baselines of this model to perform localization and segmentation.

We have curated an in-house dataset of Harris county, Texas, based on Hurricane Harvey with the help of Airbus to determine geo-spatial coordinates of the region as well as obtain various meta attributes such as elevation of an area, insurance claims, LiDAR scans, soil types, water inundation model, flood risk factors. We use this dataset to construct our novel meta injection model and

Figure 1: Snapshot of xBD dataset which shows pre-disaster, post-disaster and building damage masks

obtain improvements in accuracy.

In order to understand the process of meta injection of attributes in the network, we draw inspiration from [4], which uses a multi-encoder joint fusion process to inject the parameter along with a decoder using mutual attention and multi-head cross attentions. We also draw inspiration from [5], which uses MLP embeddings for fusion of meta attributes, which we have incorporated in *MetaSegNet* model.

3 DATASETS

We have described multiple datasets such as SEN12-Flood, SpaceNet-1/2, Sentinel-1/2 & FloodNet which cannot be used for our usecase as they contain low resolution SAR images and also, FloodNet has been captured using an UAV, which is not the same resolution as captured from a satellite. Alternatively, we use xBD, SpaceNet8 and TAMU Harvey Datasets as described below.

3.0.1 ***xBD Dataset****.* This dataset comprises on 4 classes namely - No Damage, Minor Damage, Major Damage and Destroyed. A snapshot of the dataset is shown in Figure 1.

3.0.2 ***SpaceNet8 Dataset****.* This dataset comprises on 4 classes namely - Flooded Buildings, Non-Flooded Buildings, Flooded Roads and Non-Flooded Roads. A snapshot of the dataset is shown in Figure 2.

3.0.3 ***TAMU Harvey Dataset****.* This dataset comprises of 4 classes namely - Background, Water/Flood, Flooded Buildings and Non-Flooded Buildings. A snapshot of the dataset is shown in Figure 3.

3.0.4 ***TAMU Harvey Dataset with Meta Attributes****.* This dataset comprises of 4 classes namely - Background, Low Damage, Medium Damage and High Damage due to floods using insurance claims. A snapshot of the dataset is shown in Figure 4.

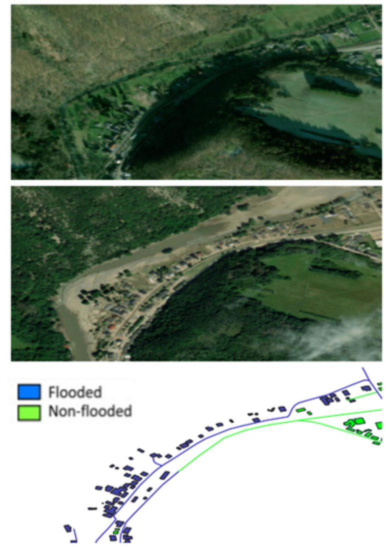

Figure 2: Snapshot of SpaceNet8 dataset which shows pre-disaster, post-disaster and building/road damage masks

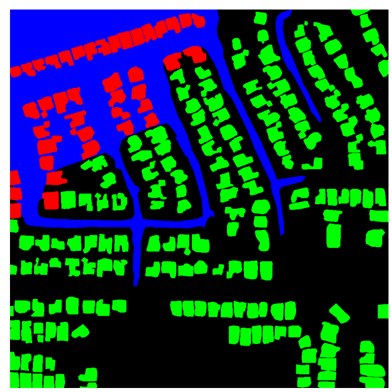

Figure 3: Snapshot of TAMU Harvey dataset without meta attribute, using only satellite images (Non-Flooded Buildings (Green), Water (Blue), Flooded Buildings (Red))

3.1 Dataset Preprocessing

In order to prepare the meta attribute dataset, we use the originial TAMU 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 domain. In order to make this data viable for ML training, we convert the polygons from GIS domain to GIS domain and finally create masks from these polygons. The architecture diagram of this process can be found in Figure 5. Snapshot of the ground truth can be found in Figure 6.

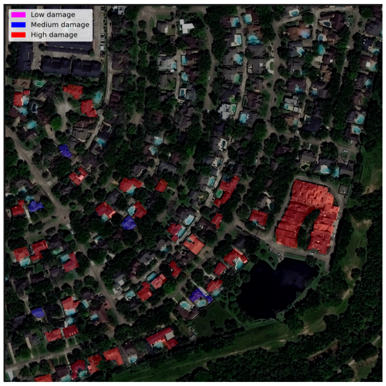

Figure 4: Snapshot of TAMU Harvey dataset with elevation meta attribute which shows low damage, medium damage and high damage masks of buildings

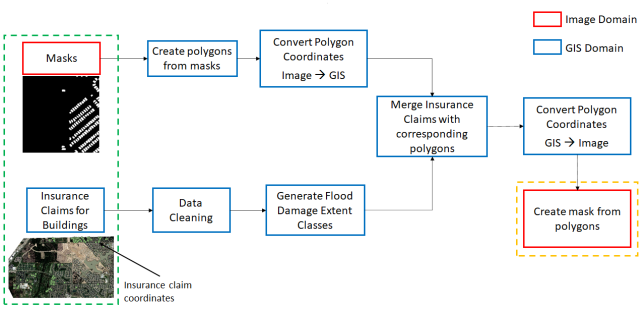

Figure 5: Architecture Diagram: Dataset Pre-processing to create ground truth meta attribute dataset

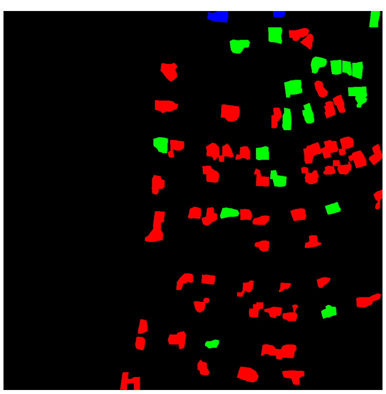

Figure 6: Snapshot of ground truth meta attribute dataset [High Damage(Red), Medium Damage(Green), Low Damage(Blue)]

3.2 Dataset Limitations

Based on the statistics of meta attributes obtained from insurance claims, we find that the number of viable buildings which contain different damage categories are only 258, out of which, 114 buildings have high flood damage, 75 have medium flood damage and the remaining 69 have low flood damage. It is quite inevitable that there is a need for more amount of data to truly generalize the hypothesis of meta attributes improving the accuracy of flood segmentation models. However, in our limited experimentation setup, we have been able to showcase that elevation meta attribute has increased the dice score and tversky metric for extremely unbalanced dataset using class weights and penalty. Number of pixels per class is as follows - Background (115,324,383), Low Damage(289,326), Medium Damage(297,753), High Damage(480,474).

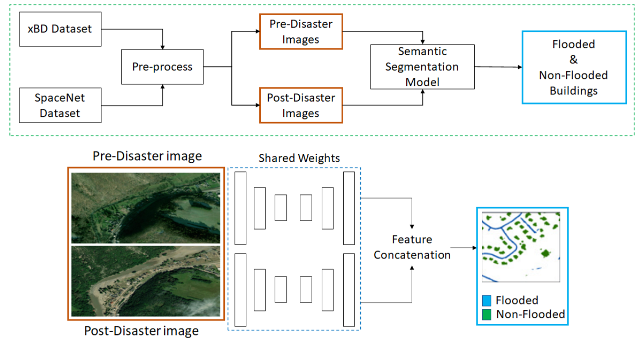

Figure 7: Architecture Diagram of training of public dataset for flooded and non-flooded building detection

4 EXPERIMENTATION AND RESULTS

We evaluate our implementation on multiple networks such as UNet, SENet, Siamese UNet, MetaSegNet for various tasks such as Building Localization, Flood Segmentation with and without meta attribute and Flood Segmentation with only satellite images.

4.1 Experimentation on xBD and SpaceNet8 baselines

In order to check the traditional methods on the task of building localization as well as on semantic segmentation using satellite images, we trained the baselines of xBD and SpaceNet models on Siamese UNet Network and the architecture is shown in Figure 7, while a snapshot of the output is given in Figure 8 (SpaceNet Results) and Figure 9 (xBD Results) respectively.

4.2 Experimentation on TAMU Harvey Dataset

In order to test the hypothesis of meta attributes with semantic segmentation on the TAMU Harvey dataset, we build the following architecture, where meta attribute is injected, which we refer to a MetaSegNet model. The overall pipeline of meta injection is shown in Figure 10.

4.2.1 Building Localization. We train building localization on the dataset using UNet architecture as well as on SENet architecture.

4.2.2 Flood Segmentation using Satellite Images. We train flood segmentation on the dataset using UNet architecture using the post image and masks as well as Siamese UNet architecture using pair

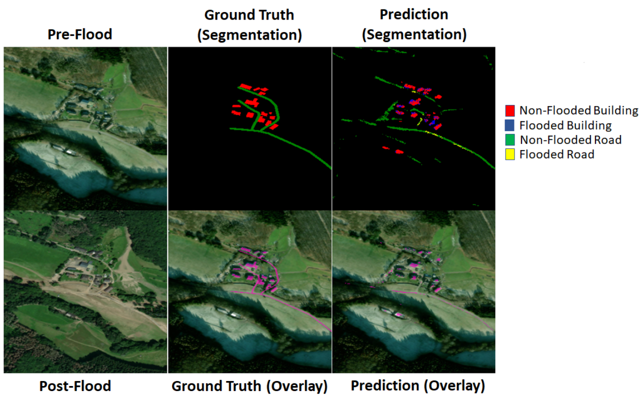

Figure 8: SpaceNet 8 baseline results

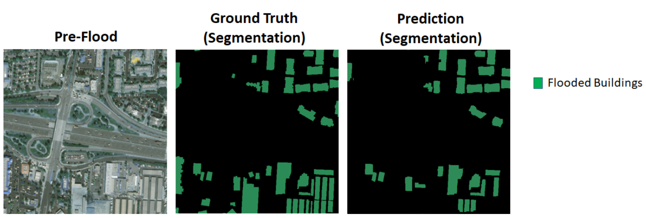

Figure 9: xBD baseline results

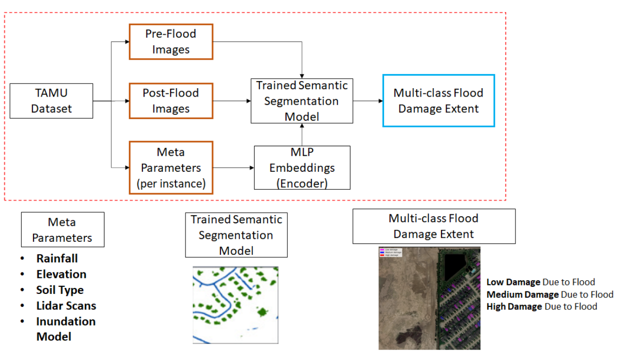

Figure 10: Architecture Diagram of TAMU Harvey training with meta injection of attribute

of pre and post images and well as masks. Based on experiments, we observe better results with the Siamese architecture.

4.2.3 Flood Segmentation using Meta Attributes. We train flood segmentation with meta attribute on the dataset using MetaSegNet architecture using the pre image, meta attribute and masks generated from insurance claims and compared that with UNet architecture using only pre image and masks generated from insurance claims. Based on experiments, we observe better results with the MetaSegNet architecture due to the addition of meta attribute. The architecure of the MetaSegNet network is shown in Figure 11.

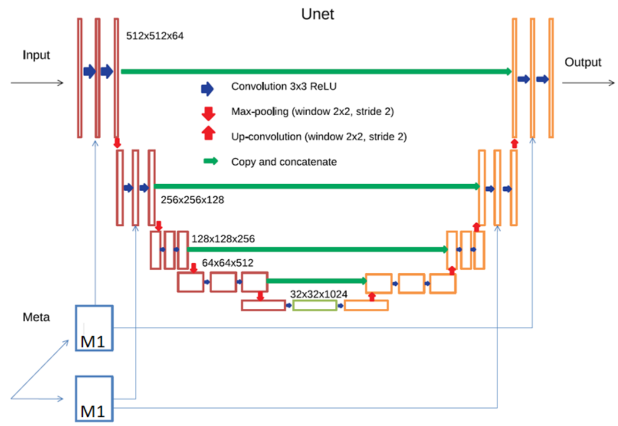

Figure 11: Architecture of MetaSegNet network, where M1 is the elevation meta attribute

Figure 12: Output of Building Localization using SENet with mIoU of 69%

4.3 Results on TAMU Harvey Dataset

4.3.1 Results on Building Localization Task. The output of SENet is shown in Figure 12.

4.3.2 Results on Flood Segmentation using Satellite Images. The output of UNet using 4 classes (Background, Water/Flood, Non-Flooded Buildings, Flooded Buildings) is shown in Figure 13 and the output using the same data using Siamese UNet is shown in Figure 14.

4.3.3 Results on Flood Segmentation using Meta Attributes. The output of UNet using 4 classes (Background, Low Damage, Medium Damage and High Damage) is shown in Figure 15 and the output using the same data using MetaSegNet with elevation meta attribute injected is shown in Figure 16.

The experimentation results on different models for the task of Building Localization and Flooded-Building Localization are 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.

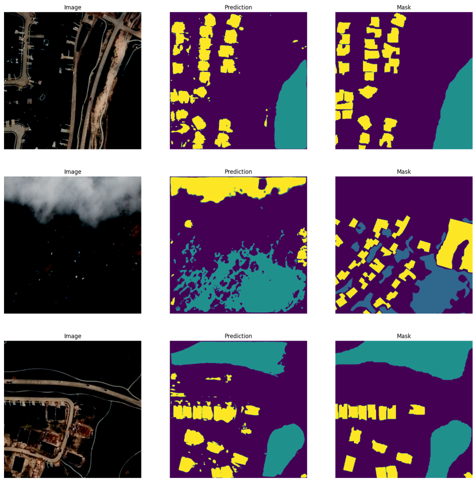

Figure 13: Output of Flood Segmentation using Satellite Images using UNet with accuracy of 70%

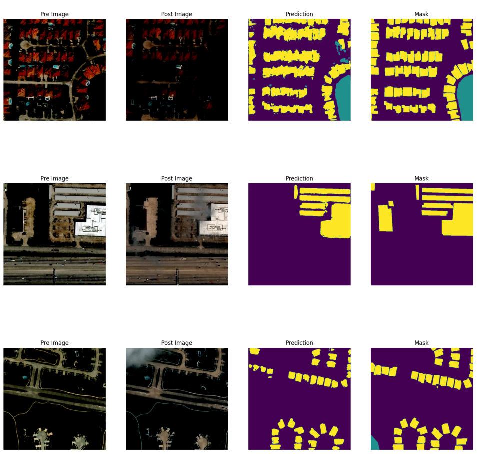

Figure 14: Output of Flood Segmentation using Satellite Images using Siamese UNet with accuracy of 85%

5 CONCLUSION

We reviewed multiple datasets which perform flood segmentation using satellite images such as xBD, SpaceNet8, etc., but lack the meta information to determine damage extent due to floods on the buildings. Furthermore, due to such shortcomings, we created a novel dataset by using insurance claims of the buildings and then performing meta injection of attributes (such as elevation of a region) on an extremely unbalanced dataset with a very few viable images. Using Focal Loss and class weights for this imbalanced dataset, we were able to conclude that the Dice score and Tversky metric using meta attributes is better as compared to using only satellite images, as shown in our results.

Therefore, the experimentation of injecting meta attributes along with satellite images to determine damage extent due to floods has increased accuracy as compared to traditional semantic segmentation methods which only determines flooded or non-flooded buildings.

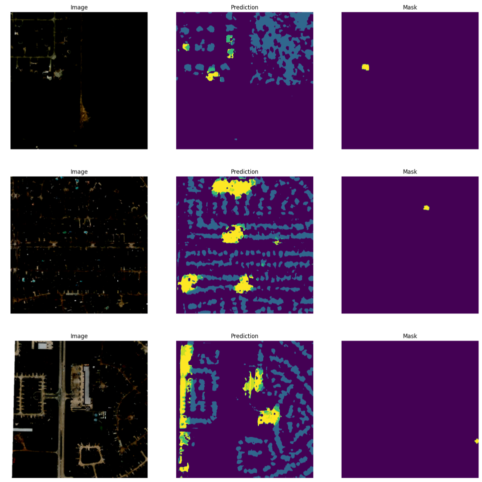

Figure 15: Output of Flood Segmentation using meta attributes without insurance claims (Dice Score-0.17, Tversky Metric-0.03)

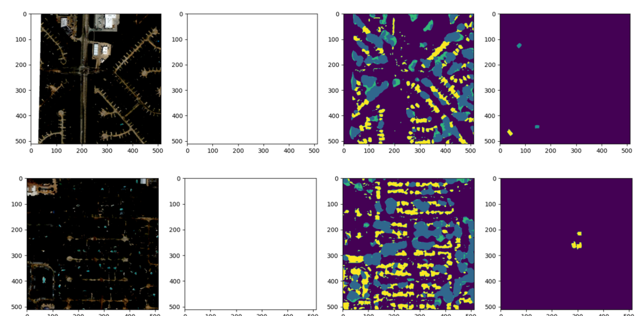

Figure 16: Output of Flood Segmentation using meta attributes with insurance claims (Dice Score-0.42, Tversky Metric-0.04), (Pre Image, Elevation Data, Prediction, Ground Truth)

Building and Flooded-Building Localization			
Dataset	**Task**	**Network**	**Metric**
xBD	Building Localization	ResNet34 Siamese	0.6 IoU
SpaceNet8	Building Localization	Siamese UNet	0.63 IoU
SpaceNet8	Flooded Building Localization	Siamese UNet	0.22 IoU
TAMU Harvey	Building Localization	SENet	0.69 IoU
TAMU Harvey	Flood Segmentation	UNet	70% Acc.
TAMU Harvey	Flood Segmentation	Siamese UNet	85% Acc.

Table 1: Localization Results

Flood Damage Extent on TAMU Harvey			
Dataset	**Task**	**Network**	**Metric**
TAMU Harvey	Flood Segmentation without meta attributes	UNet	Dice Score-0.17, Tversky - 0.03
TAMU Harvey	Flood Segmentation with meta attributes	MetaSegNet	***Dice Score-0.42, Tversky - 0.04***

Table 2: Flood Damage Extent Results

6 FUTURE SCOPE

The future scope of this project is to improve the baseline algorithms of xBD dataset and SpaceNet8 datasets and then fine tune on TAMU Harvey dataset along with need for more training and viable data from the TAMU Harvey dataset. Also, currently this project only uses elevation meta attribute as meta injection strategy, however, other meta attributes such as inundation model, flood risks, soil types can be used to improve the accuracy and result in more hierarchical understanding of flood building damage extent.

7 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