Design Document - ETCI Flood Detection

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This project consists of training a model to detect floods from Synthetic Aperture Radar (SAR) images. To do this, we have a dataset that consists of around 30 thousand tiles for each of which we have a VV and a VH polarised image (the model combines the information from these two images into one RGB image; see more info on polarisation below) as well as two sets of mask tiles: one for water (all water, flood or permanent) and one for flooded areas (all water minus permanent water).

The goal is to train the model to detect water masses, not exclusively flooded areas, as that would be an impossible task without geographical data of permanent water masses. Those are later subtracted manually to determine flooded areas.

The broader goal of this project is to assess the status of areas affected by a disaster for decisions related to deployment of personnel and rescue missions. The goal is not, however, to create a prediction model for floods. The scope is limited to detection

We identify some limitations in the data and resources. Firstly, the data used in this document does not include HH images, the polarisation most useful to detect buildings, vegetation and inundated vegetation. Secondly, the dataset is highly unbalanced with 98% of the data not belonging to the class of interest, even after resampling (cutting out tiles without any water pixels). Thirdly, the dataset contains images from only three territories – Bangladesh, Nebraska, and North Alabama.

These limitations can, on the one hand, affect the efficiency of the model by difficulting the training process and biasing the model towards detecting a negative class. On the other hand, they can really limit its external validity as the data might not be diverse enough in terms of types of natural and urban features, and climate conditions. Nonetheless, this means there is also a very significant opportunity for improvement in the refinement/ expansion of the dataset.

Moreover, we have a major material limitation due to the large demand for computational resources required to process a deep learning model on this dataset. This prevents us from training it on more than a few epochs and from doing multiple runs to make improvements.

We test our model on the data before and after resampling and, in the second case, we test a non-weighted and a weighted loss function. Essentially, our goal is to compare these methods. We evaluate the results by looking at IntersectionOverUnion, precision, recall, and F1-score, in order to be able to better compare the three instances of our model according to different standards.

On SAR data

SAR (Synthetic Aperture Radar) images are composed by the signal obtained from bouncing a signal off the Earth surface. Meaning, the radar sends a signal, it bounces off, and the radar captures the returned signal, which changes according to the surface it is bouncing off (depending on its texture and other characteristics such as moisture).

Polarisation refers to the direction/angle of the plane in which the signal (wave) oscillates. Radar images generally use two directions, vertical and horizontal (V and H). A signal's polarisation is labeled by two letters, the sending signal's direction and the receiving's one, respectively – so we have VV, VH, HH, HV.

Optimal polarisation for certain types of surface, meaning which signal they are most sensitive to:

- VV - Rough surface scattering, such as that caused by bare soil or water
- VH or HV - Volume scattering caused by the leaves and branches in a forest canopy
- HH (we don't have it in this project) - double bounce scattering caused by buildings, tree trunks, or inundated vegetation