

ABSTRACT

We present research to detect flooding changes in NASA’s Uninhabited Aerial Vehicle Synthetic Aperture Radar (UAVSAR) imagery using deep learning, and to classify the land cover types affected by these floods. First, a binary change detection model is used to identify flooded areas by comparing pre-event optical data and post-event UAVSAR data. Next, the regions are classified by land cover category to determine what types of terrain experienced the most inundation. The outcome is an integrated flood mapping and land cover analysis tool, which is important for decisions regarding where priority disaster response is dispatched and for land use analysis. This tool provides timely flood extent maps regardless of weather or daylight conditions and helps to understand which land covers and communities are impacted by flooding to aid in recovery efforts, where to develop preventative infrastructure, and future urban planning. The work builds on state-of-the-art deep learning methods for image segmentation and leverage geospatial data platforms to efficiently handle large remote sensing datasets. We train and test the models on UAVSAR data, and the models achieve 90.0%, pixel accuracy for change detection and 86.1% pixel accuracy for land cover classification. The code can be found at: <https://github.com/kevintang6142/flood-detection>.

FRAMEWORK OVERVIEW

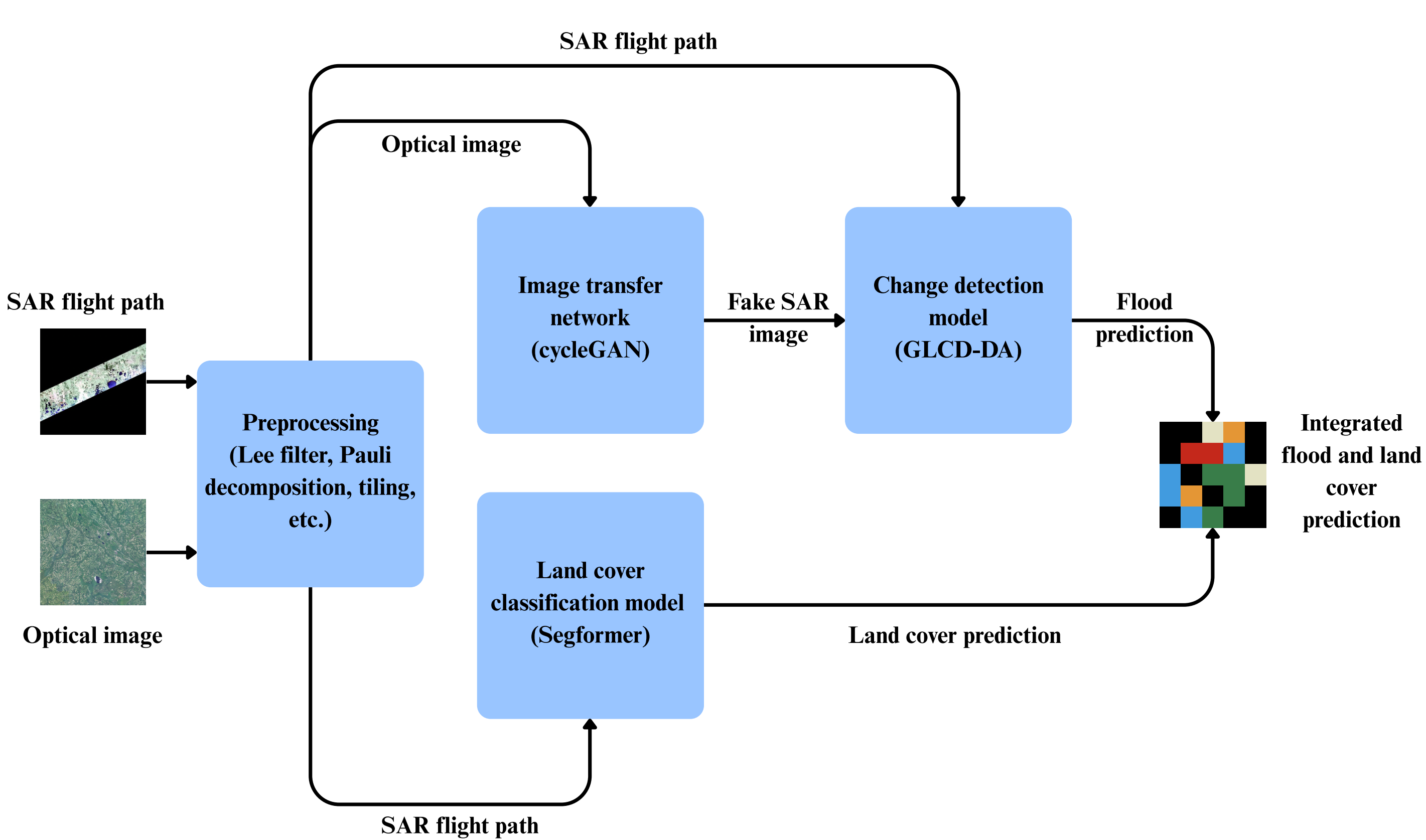


Figure: Overview of data pipeline and model structure for combined change detection and land cover classification.

PREPROCESSING

We used the National Agriculture Imagery Program (NAIP) dataset, filtering for cloud-free imagery from before Hurricane Florence in 2017, as our source of pre-flood high-resolution optical images [1]. Leveraging synthetic aperture radar imaging’s ability to penetrate clouds and operate day and night, we obtained Pauli decomposed L-band SAR data from NASA JPL’s airborne UAVSAR image platform, specifically from flight lines recorded in the days immediately following Hurricane Florence’s flooding [2]. We applied an Enhanced Lee filter, which reduces speckle noise [3]. We use a high-resolution flood extent dataset for Hurricane Florence from NC OneMap [4] as the ground truth target for our change detection model and the ESRI 10 m Land Cover Dataset-filtered for data from the year 2017-as the ground truth for land cover (pre-flood) [5]. We created consistent sized tiles with 20 meter resolution over all four datasets, converted from a GeoTIFF format to PNG, and discarded tiles that consisted entirely of no-data values.

CHANGE DETECTION METHODOLOGY

The first component of our framework is a flood change detection model defined by a double-neural-network structure. It has an image transfer network, a cycle generative adversarial network (cycleGAN) that translates an optical image into an SAR image. It consists of an encoder-decoder architecture with nine residual blocks for the generators. The discriminator follows a pathGAN design which classifies local sections of the image as real or fake. The loss function we used for the generator is a summation of adversarial, identity, and cycle loss calculated for every backwards pass. This model was trained using a batch size of one and a learning rate of 0.0005 for 200 epochs. This step allows us to input a pre and post-flood pair of SAR images into the model, Global-Local Change Detection with Diversified Attention (GLCD-DA) [6]. The GLCD-DA change detection network uses the Siamese ResNet18 as a backbone with three modules: an edge injected fusion module to preserve spatial details, a global-local interaction module that captures long and short range dependencies, and a feature fusion module that creates the final change probability map. The dataset is augmented using vertical and horizontal flips. We trained this model with various batch sizes, learning rates, gamma rates, optimizers, and loss functions to find optimal hyperparameters.

CHANGE DETECTION RESULTS

Using GAN generated SAR images and post-flood SAR images, we trained the GLCD-DA change detection model. We found that the optimal parameters were a batch size of 16, an Adam optimizer, a learning rate of 0.001, a gamma value of 99, 70 decay iterations, and a cross-entropy loss function. We selected the best model based on the intersection over union score. This model achieved a pixel accuracy of 90.0% and a mean Dice coefficient of 0.771. The recall score for non-flooded areas was 93.7%, and the recall score with respect to flooded areas was 76.7%. The differing recall scores show us that the model predicts the non-flooded regions with more accuracy than it predicts flooded regions, likely due to a class imbalance. The figure shows an example of original optical and SAR inputs, the output of the image transfer network (GAN generated SAR), the predicted flood mask, and the ground truth.

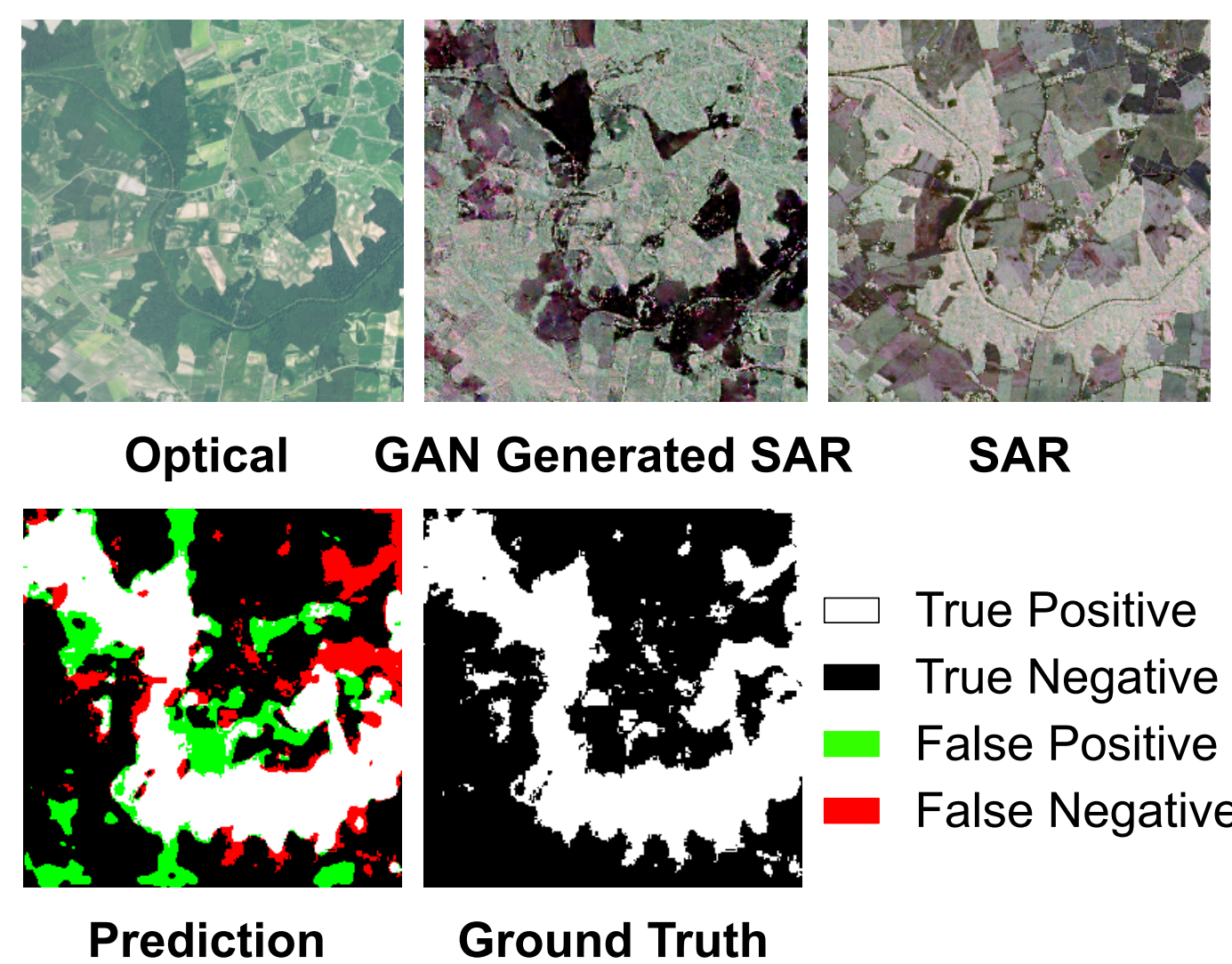


Figure: Example inputs, GAN generated image, prediction, and ground truth for GLCD-DA change detection model.

LAND COVER CLASSES

Value	Color	Label
1		Water
2		Trees
4		Flooded Vegetation
5		Crops
7		Built Area
8		Bare Ground
9		Snow/Ice
10		Clouds
11		Rangeland

Figure: Land Cover Classes and Colors

LAND COVER CLASSIFICATION METHODOLOGY

The second component of our framework is a semantic segmentation model which assigns each pixel of post-flood SAR images to one of seven land cover class labels corresponding to the land cover pre- flood. For this, we utilize encoder-decoder models. Their encoders compress the input images into lower resolutions through downsampling,extracting high level features from the images. Then, their decoders increase the resolution of the images and merge this with the feature information extracted previously. We trained for a maximum of 100 epochs and monitored the validation loss each epoch. If validation loss did not improve for 10 consecutive epochs, training was stopped and the model from the epoch with best validation loss was saved for evaluation. The data is augmented with vertical and horizontal flips as well as rotations. We evaluated a variety of segmentation-specific loss functions on these widely used image segmentation architectures: U-Net, U-Net++, MANet, LinkNet, FPN, PSPNet, PAN, DeepLabV3+, UPerNet, and Segformer [7].

LAND COVER CLASSIFICATION RESULTS

We trained the 10 segmentation models mentioned above with six loss functions. We selected the Segformer architecture with a Jaccard loss function as the best model because it achieves the highest mean intersection over union (IoU) score. This model achieved 86.1% pixel accuracy, 0.576 mean IoU, and 0.696 mean Dice coefficient. The model predicts the Water, Trees, Crops, and Built Area classes the most, while it struggles to identify Flooded Vegetation, Bare Ground, and Rangeland. Some example predictions are included in the figure.

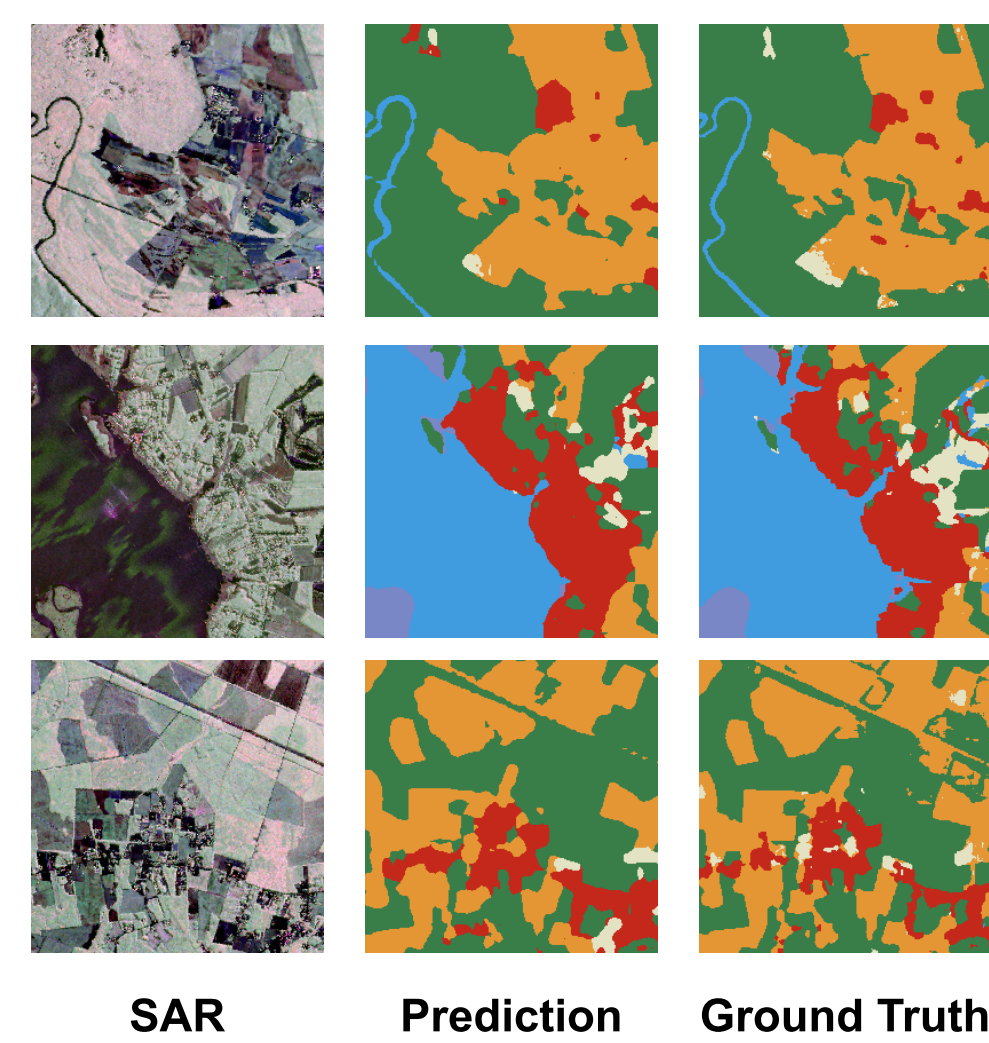


Figure: Example SAR inputs, Segformer predictions, and ground truth for land cover classification.

CONCLUSION

Overall, our application achieves 90.0% pixel accuracy for identifying newly flooded areas and 86.1% pixel accuracy for predicting land cover type. The dataset that we trained our models on contained very little of the Snow/Ice and Clouds land cover classes. To correctly predict these classes in the future, we would need a more extensive and diverse dataset to retrain the model. Future work also includes adding more functionality to our flooded land cover prediction application, like analyzing particular parts of the image.

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