Flood Detection using UAVSAR

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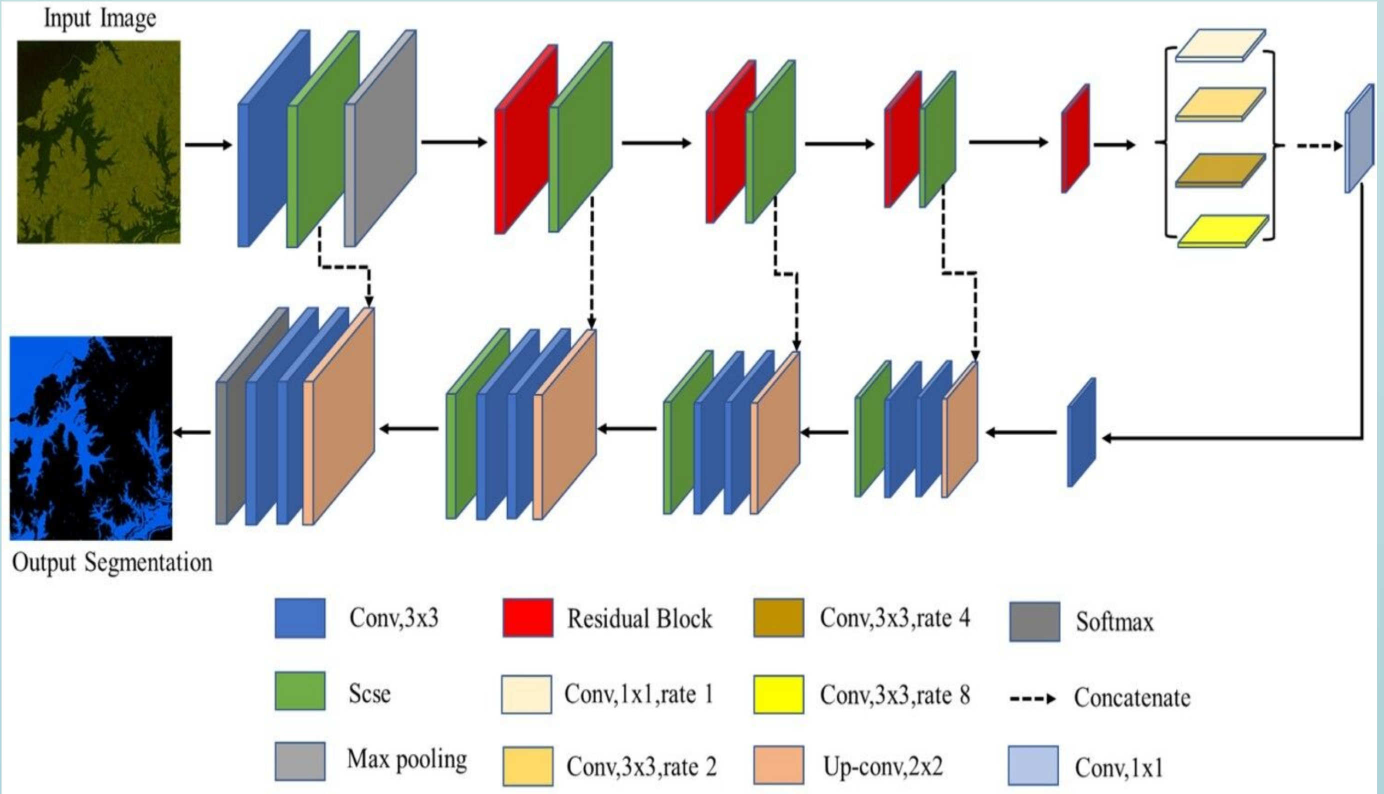
Abstract

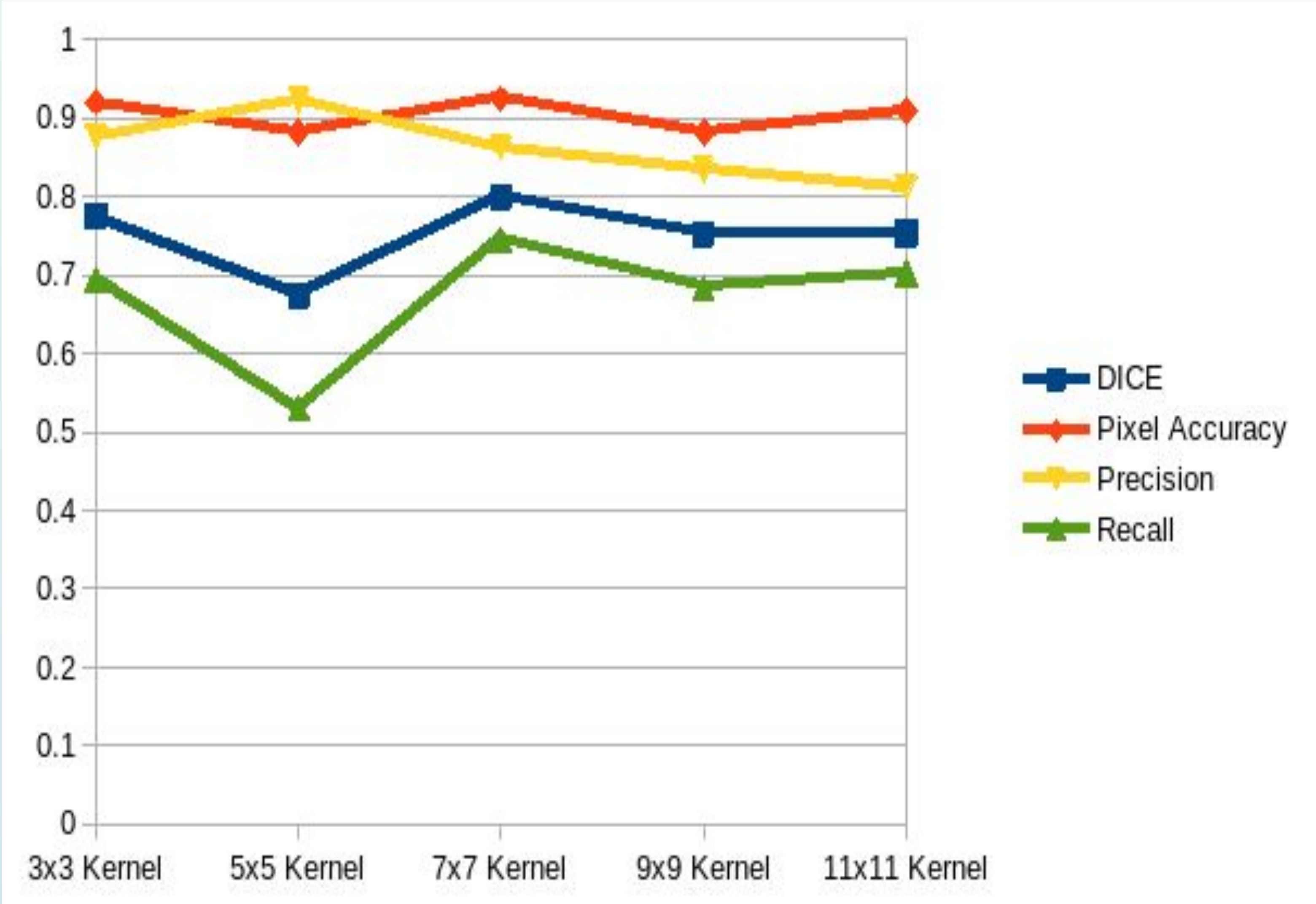
Floods are frequent and devastating natural disasters, causing an estimated average of $5 billion in damages annually in the United States alone [8]. This study will utilize deep learning and NASA's UAVSAR data to improve flood detection capabilities. There are two architectures that will be covered: U-Net architecture and a Flood Water Extraction Network (FWENet) [6]. The FWENet uses Residual Layers to avoid gradient loss and is inspired by the U-net. A dataset of 1,008 images was constructed by a previous research group, which contains the UAVSAR images and the mask images indicating where flooding has occurred. After careful analysis, The FWENet architecture shows to be the most accurate compared with the U-net architecture previously used.

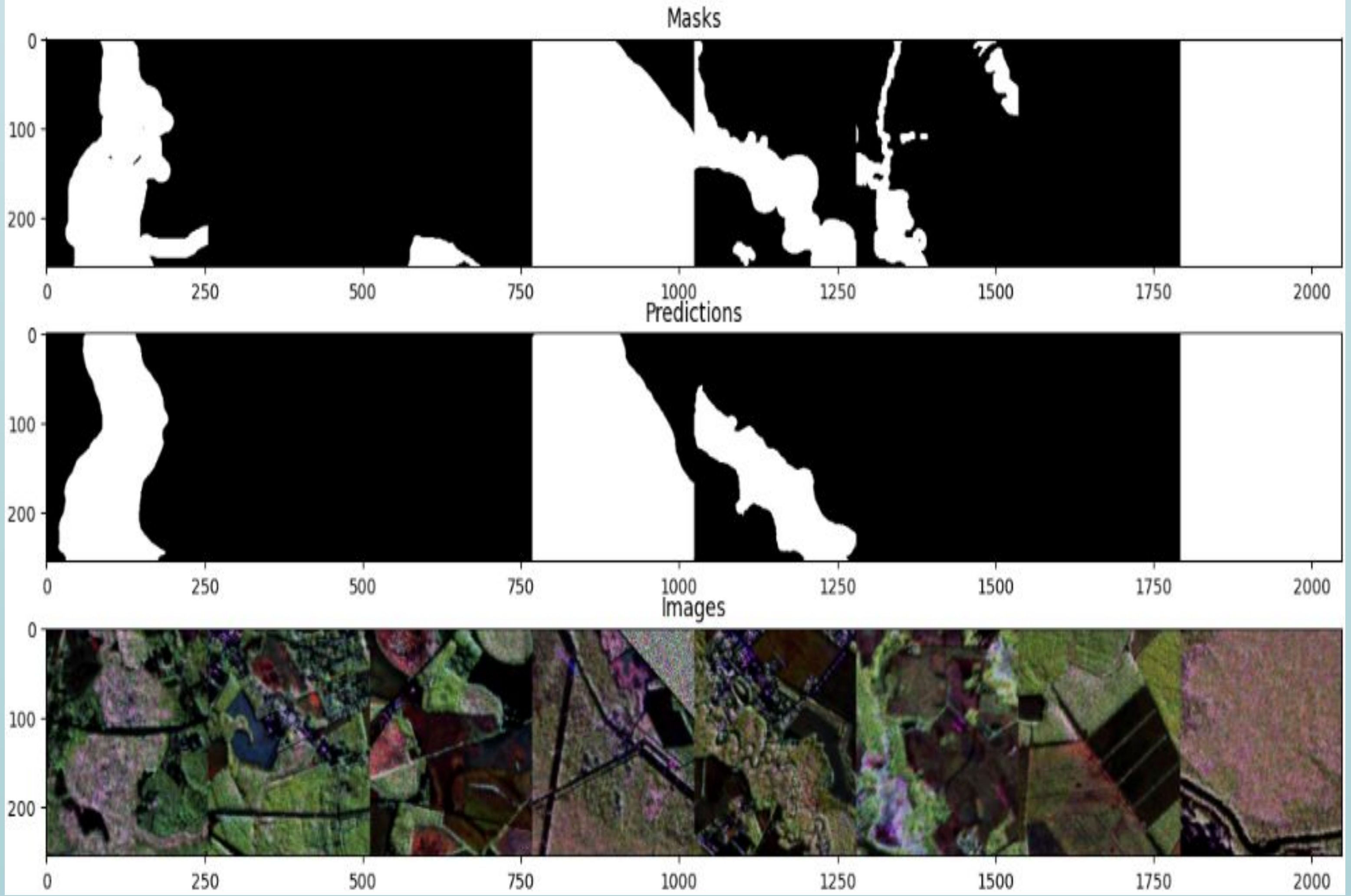
Method

- UAVSAR Data Pre-processing and Labeling
  - We Pre-Process the Images using a Lee Filter and Randomizing blank region pixels
  - To create labels we extract the exact region of the image from the flood extent map
- Deep Learning Models
  - We Implemented a Flood Water Extraction Network
  - Using the above model we compare the performance to a previous REU groups U-Net model



	DICE	Pixel Accuracy	Precision	Recall
FWENet Filter	0.799548023769902	0.925115386051918	0.862867468191162	0.74488633943404
FWENet No Filter	0.798289456863619	0.912811111001407	0.869790682704937	0.737650802452894
UNet Filter	0.735254952320538	0.897704451831419	0.764128495581184	0.708484005168326
UNet No Filter	0.743953714925578	0.881601558012121	0.752695130121115	0.735413005462096





Results

As shown above, The FWENet utilizing filtered images performs the best in every metric aside from precision where the non-filtered FWENet barely surpasses the filtered FWENet. With this in mind, we can say that the FWENet with the Lee Filter applied seems to perform the best. with the least amount of drawbacks.

Conclusion

With the new data, our model and other models have the potential to be more generalized than they are currently allowing for a wider range of applications. This way when flooding occurs, we can more easily map out the extent of diverse flooding events to allow response teams more opportunity to perform their jobs

References and Acknowledgements

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This work is funded by NSF CNS-2149591 under Research Experiences for Undergraduates (REU) Program and by the NASA MUREP Data Science Equity, Access and Priority for Research and Education (DEAP) Program.