Deep Learning for Disaster Relief: Generating Synthetic High Resolution Images

Openlab Lightning Talk

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09/24/2020

Satellite Images: Importance

Use of Satellite images:

- Relief Works
- Risk Assessment due to disasters like Flood
- Phenomenal in making strategies for some of the critical problems like refugee management
- Planning and high level overview of the status of different crisis

Applications in Deep Learning

- Building models to make relief works easier
- Ensure efficiency and timeliness of the rescue and rehabilitation operations
- Make systems for sharing information sharing to response teams as early as possible

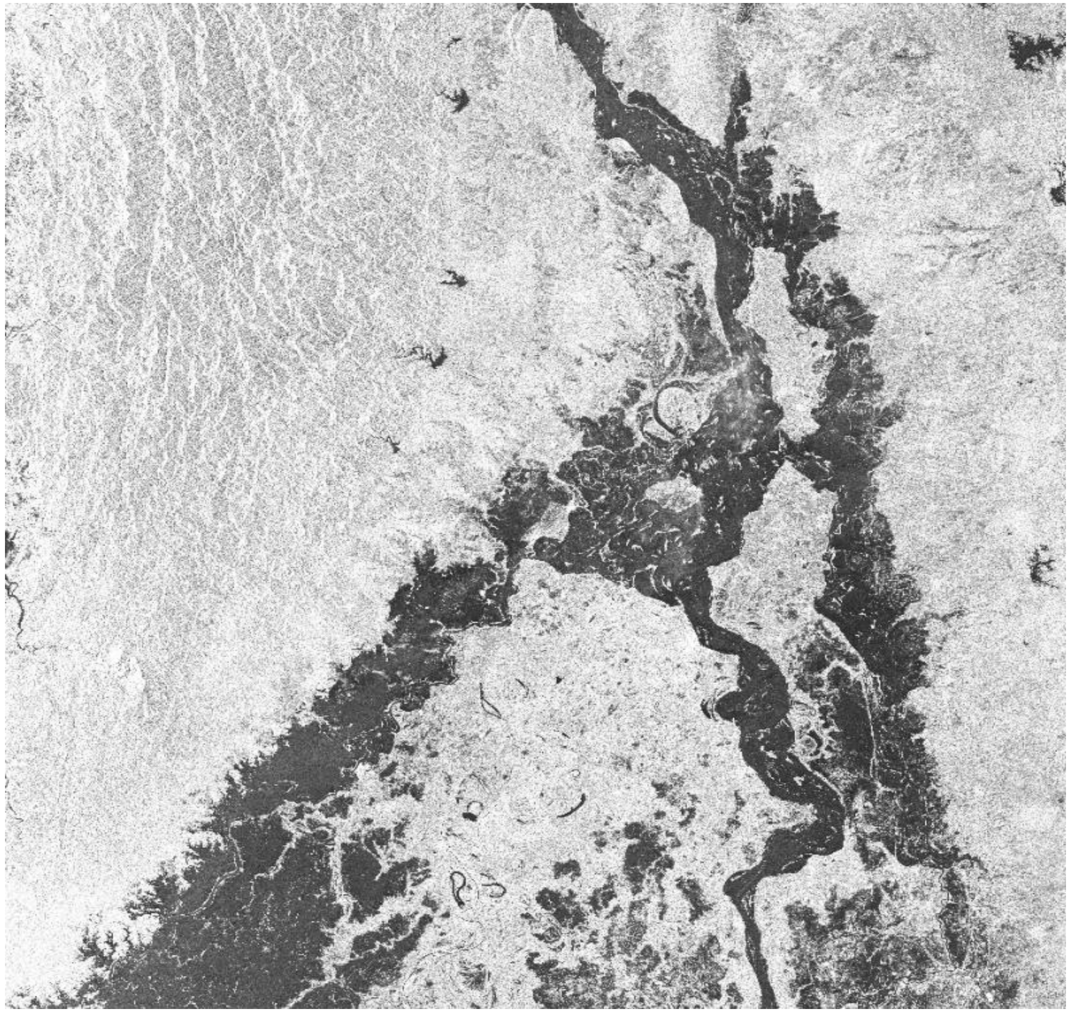
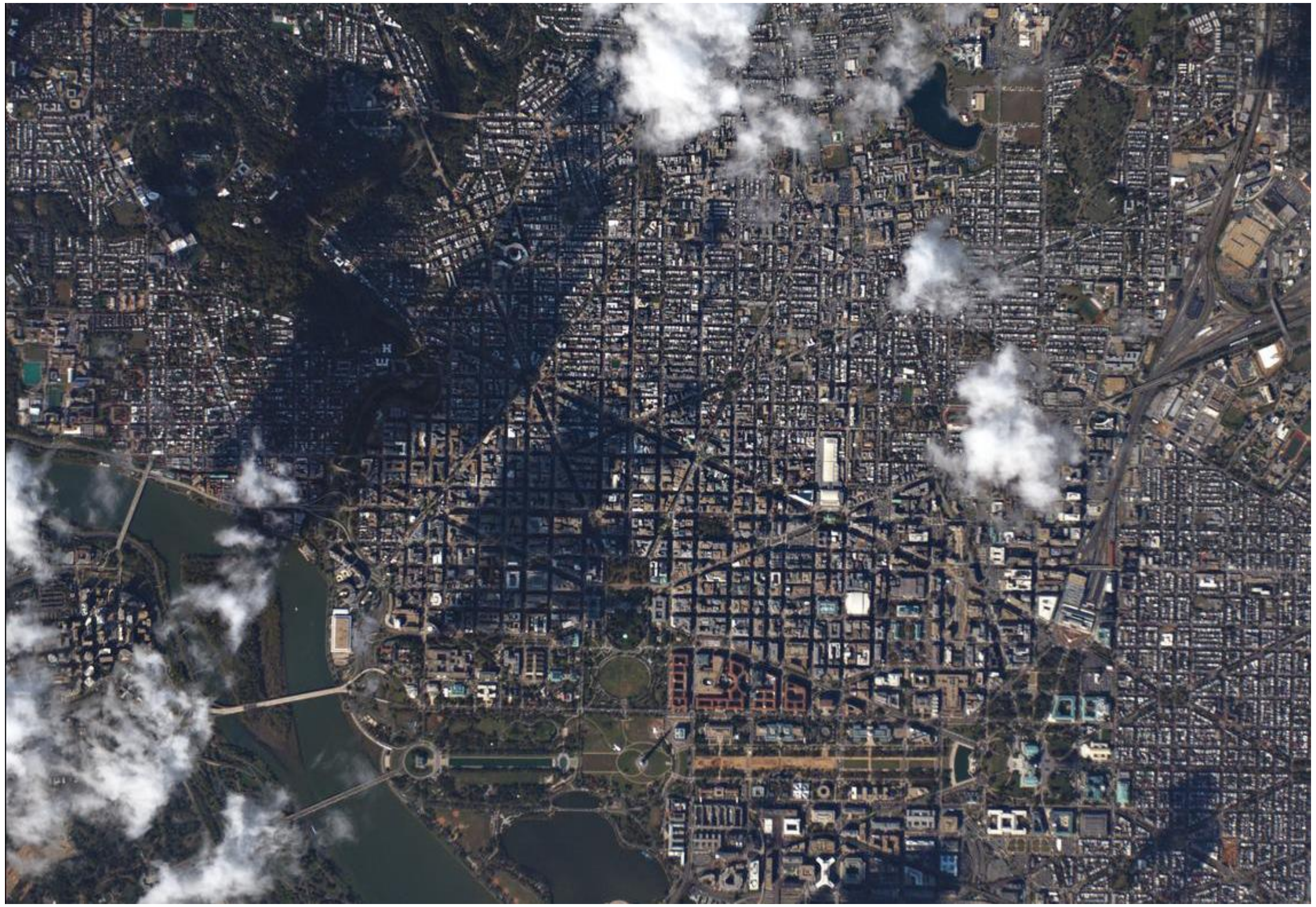


Fig. Flood Image of Myanmar provided by UNOSAT

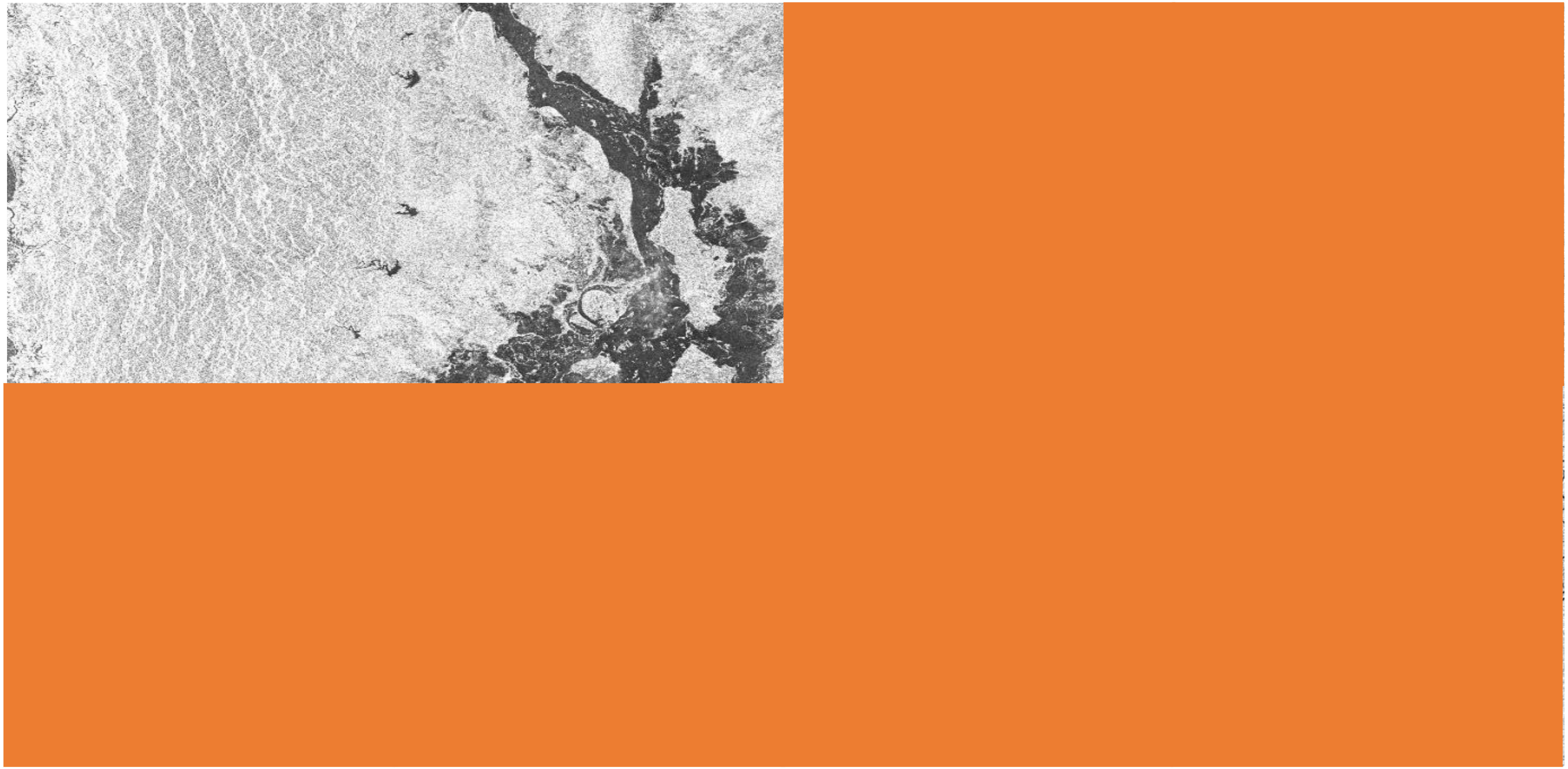
Synthetic Images for Satellite Images
This work was done in collaboration with UNOSAT

- Image imputation for distorted images, for examples the images taken by a satellite in cloudy environment.
- Data Augmentation
- Synthetic Images can be shared with a lot of stake holders outside the imaging organization. This is the objective of **UNOSAT** in particular.
- Similarly, for open-source projects, synthetic images are useful.

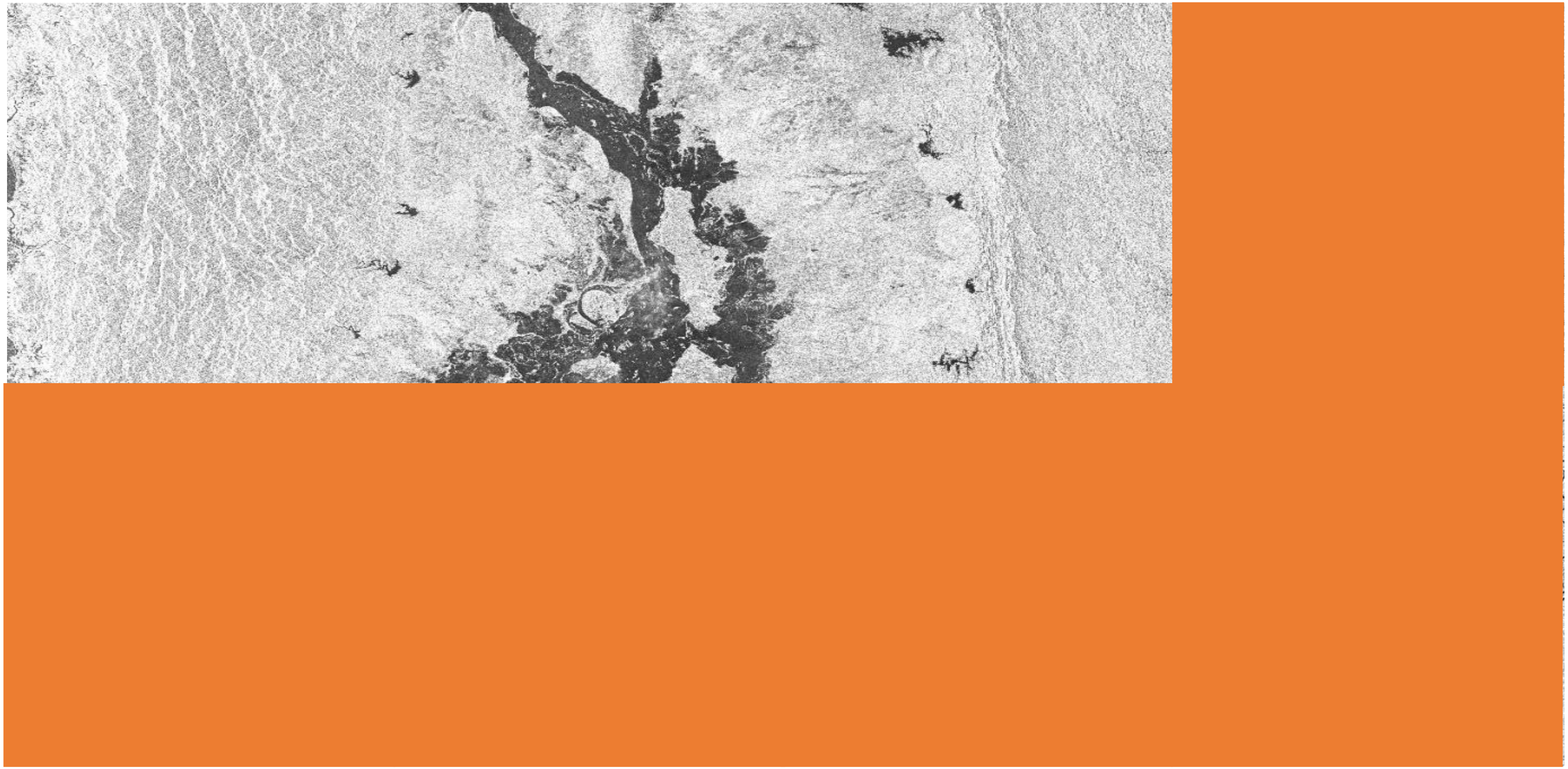


OBJECTIVE OF THE PROJECT: IMAGE COMPLETION WHERE THE GENERATION OF EACH TILES ARE CONDITIONED ON PREVIOUSLY GENERATED TILES

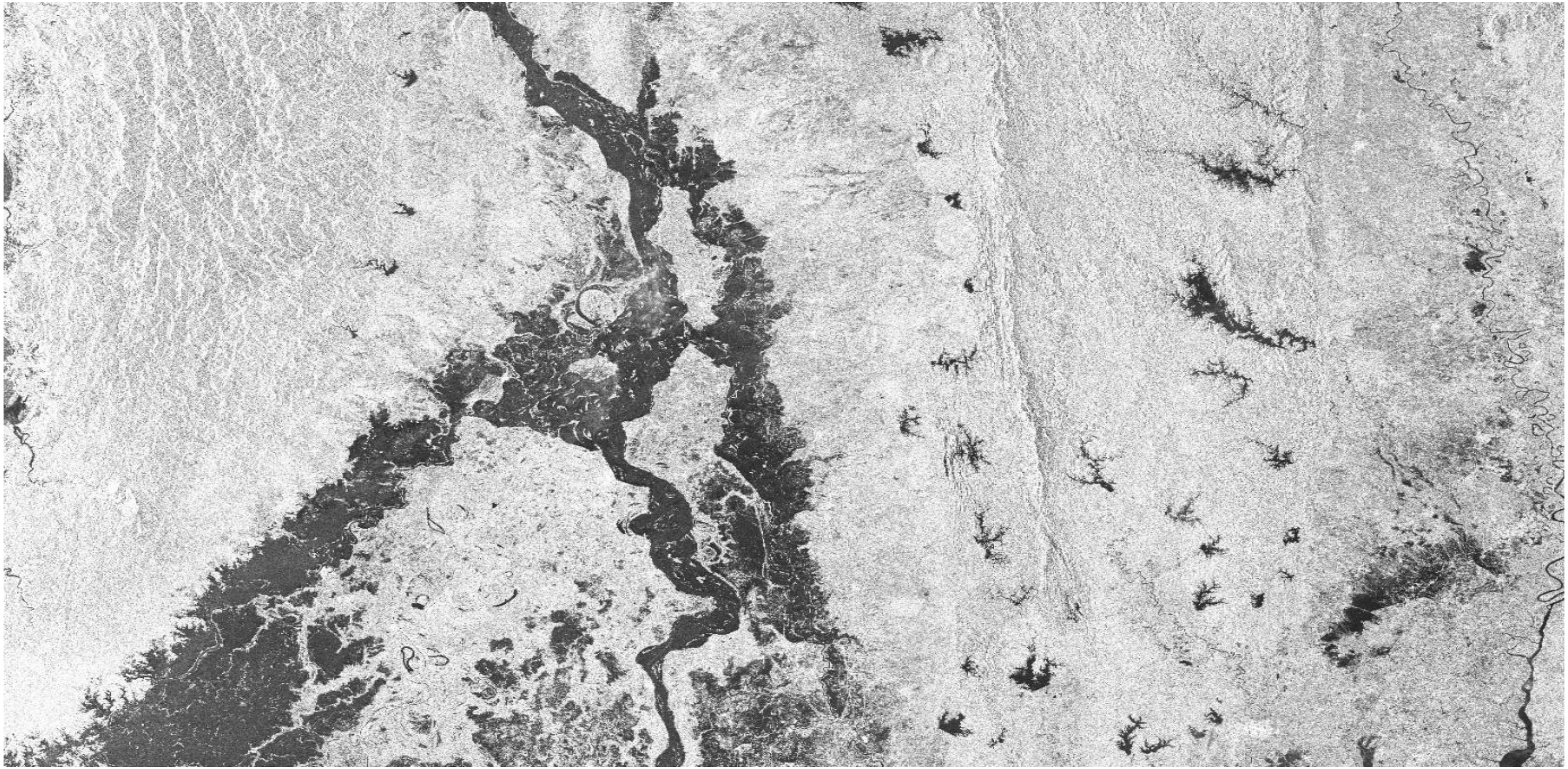
FIRST STEP: CONDITIONING THE GENERATION OF SECOND TILE WITH INFORMATION FROM FIRST



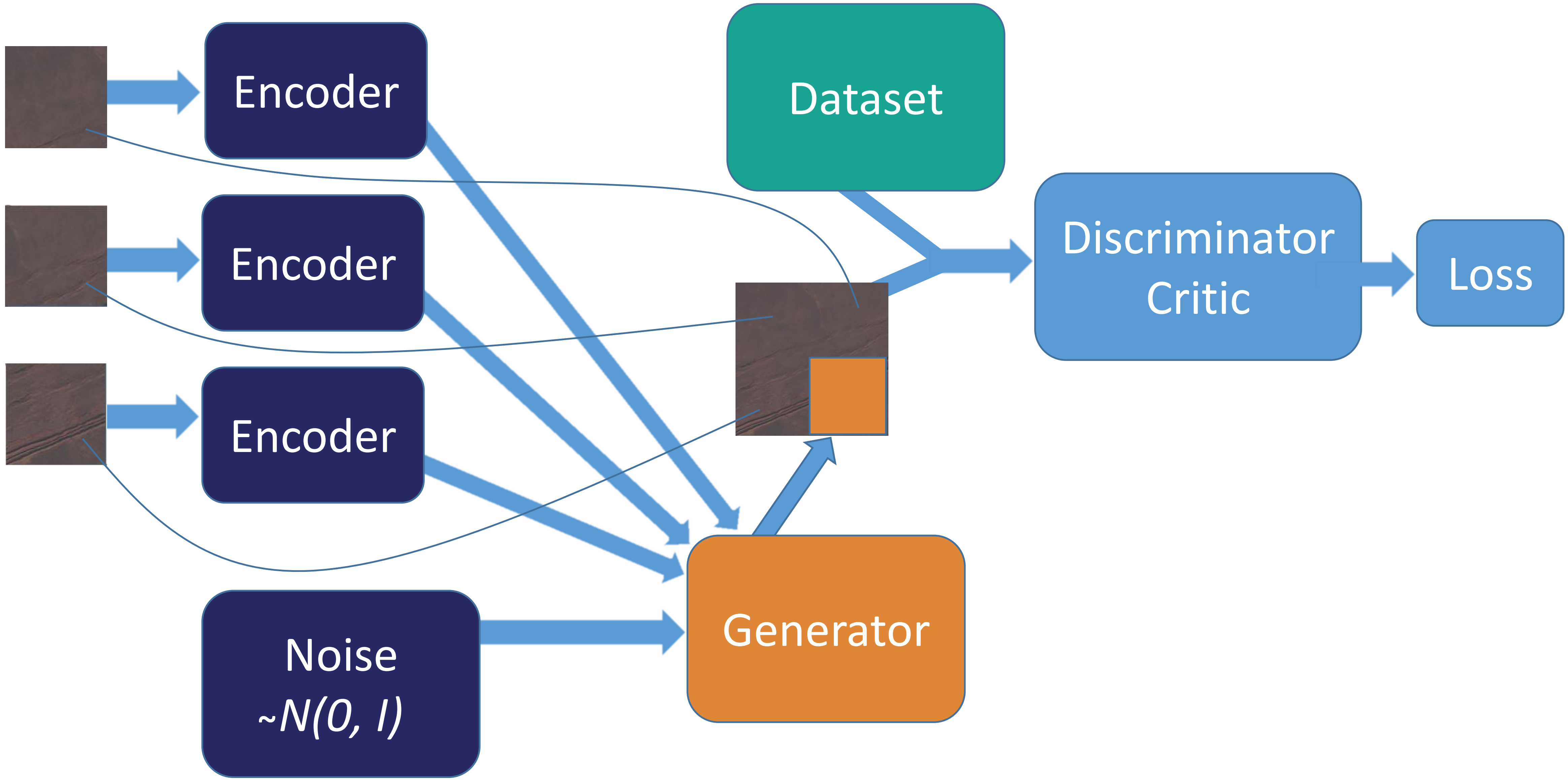
SECOND STEP: COMPLETING THIRD TILE WITH INFORMATION FROM FIRST AND SECOND (GENERATED) TILE



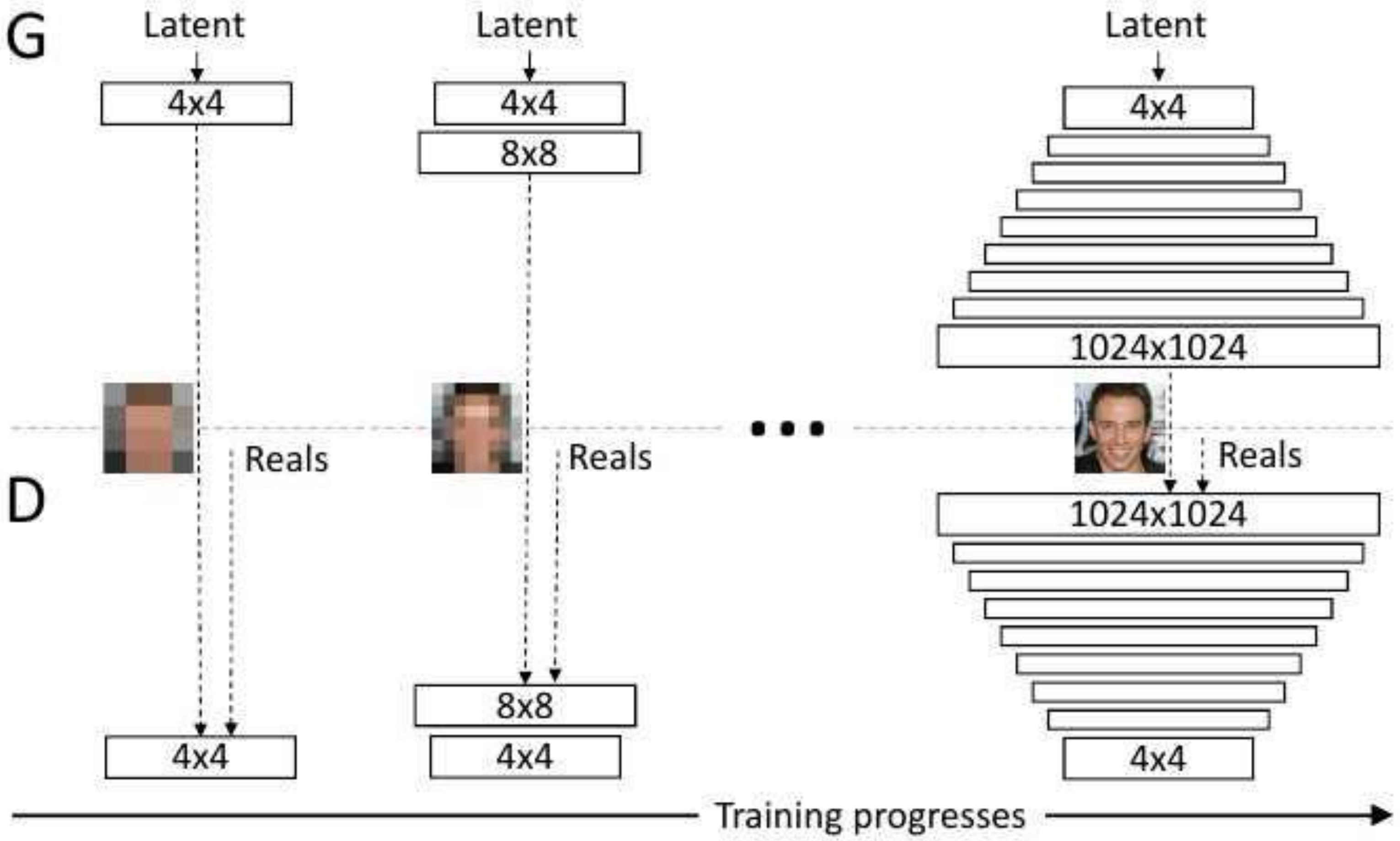
FINAL STEP: THE COMPLETE IMAGE WHICH IS COMPLETED BY CONDITIONING THE GENERATION OF EACH TILES



Progressive Conditional GAN



Progressive GANs



Karras, Tero, et al. "Progressive growing of gans for improved quality, stability, and variation."

A slightly different approach…

Conditional Progressive GANs with Multiple Encoders

Nature of Conditional GAN

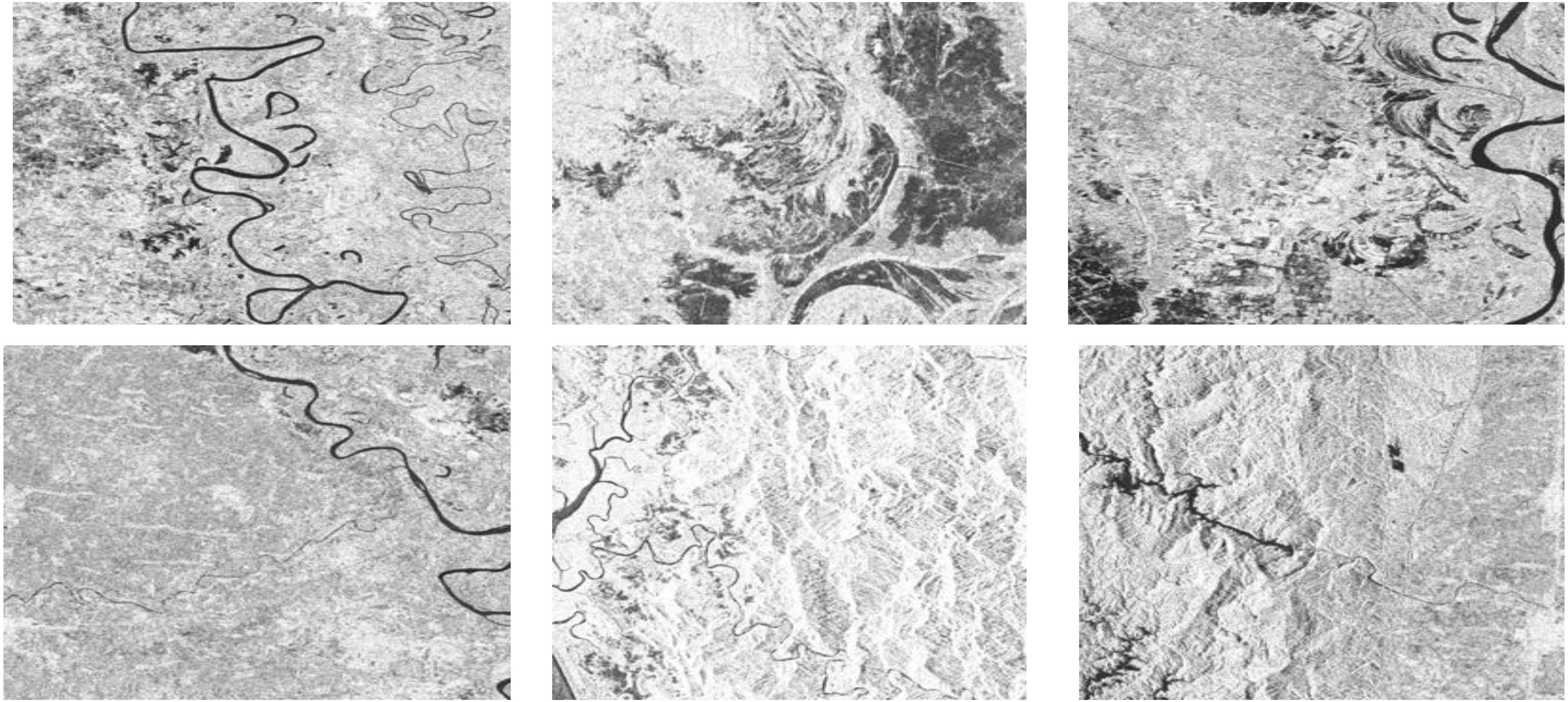
- Unlike most of the previous works using a combination of reconstruction, contextual or/and adversarial losses, our method is strictly conditional and only (Conditional) GAN-based so that it preserves the key-feature of CGAN.

Why Encoders?

- The major issue having a strict GAN architecture lies in the fact that the conditional part is too large to be directly injected as input into the Generator. It should be encoded creating a bottle neck limiting the quantity of information transmitted to the Generator.
- To tackle this issue, we introduced secondary encoders re-injecting information at each stage of the Progressive Generator.

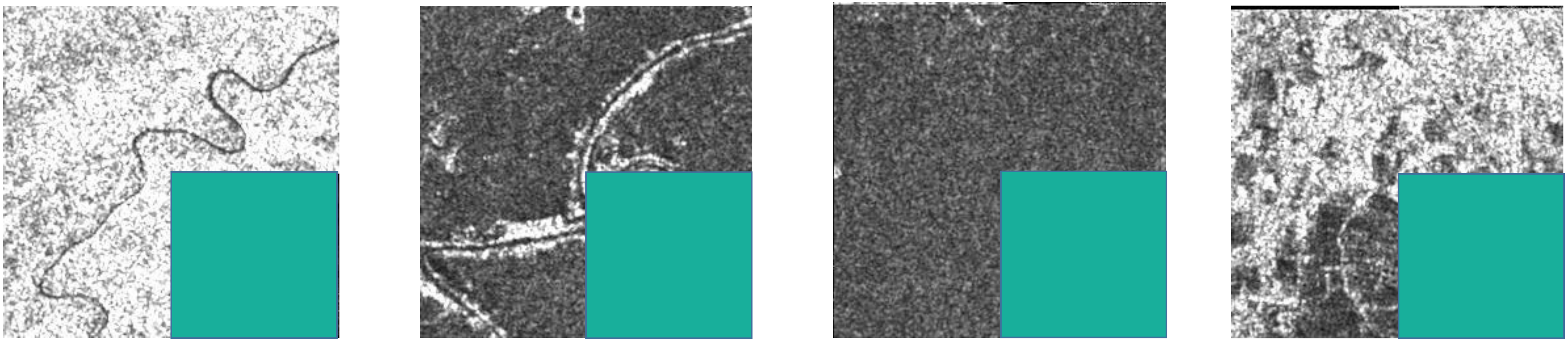
THE DATASET

UNOSAT Flood Dataset



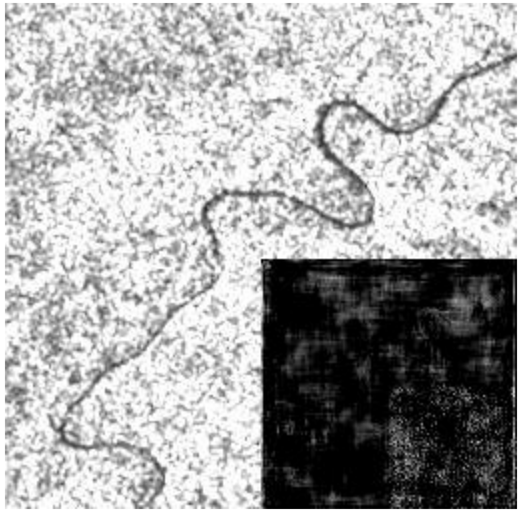
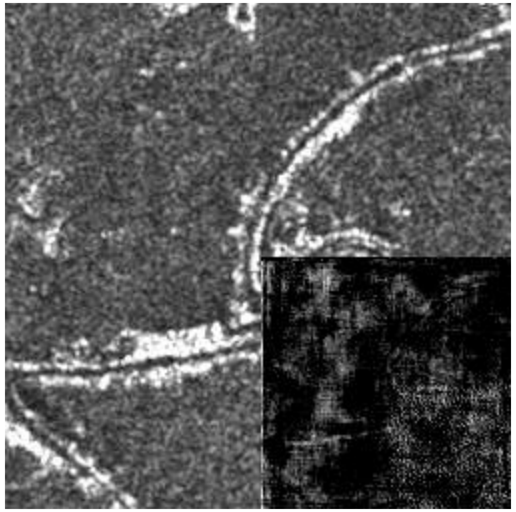
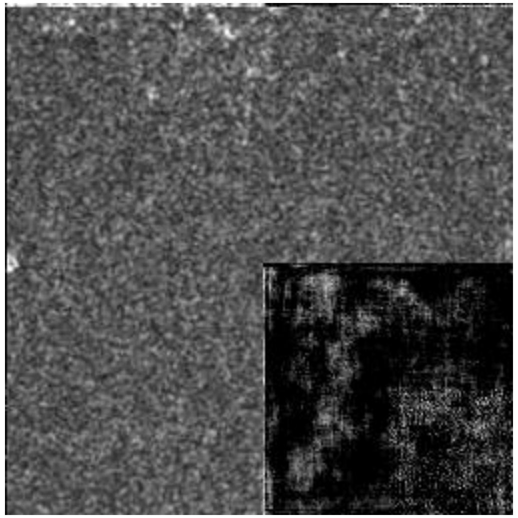
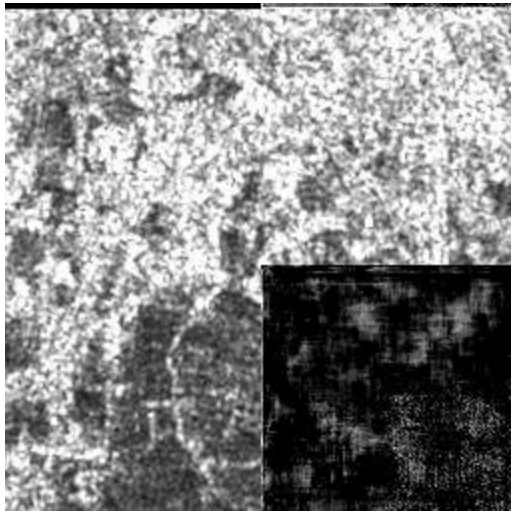
THE FIRST STEP

Correctly guessing the fourth tile!



THE APPROACH

Initializing the training

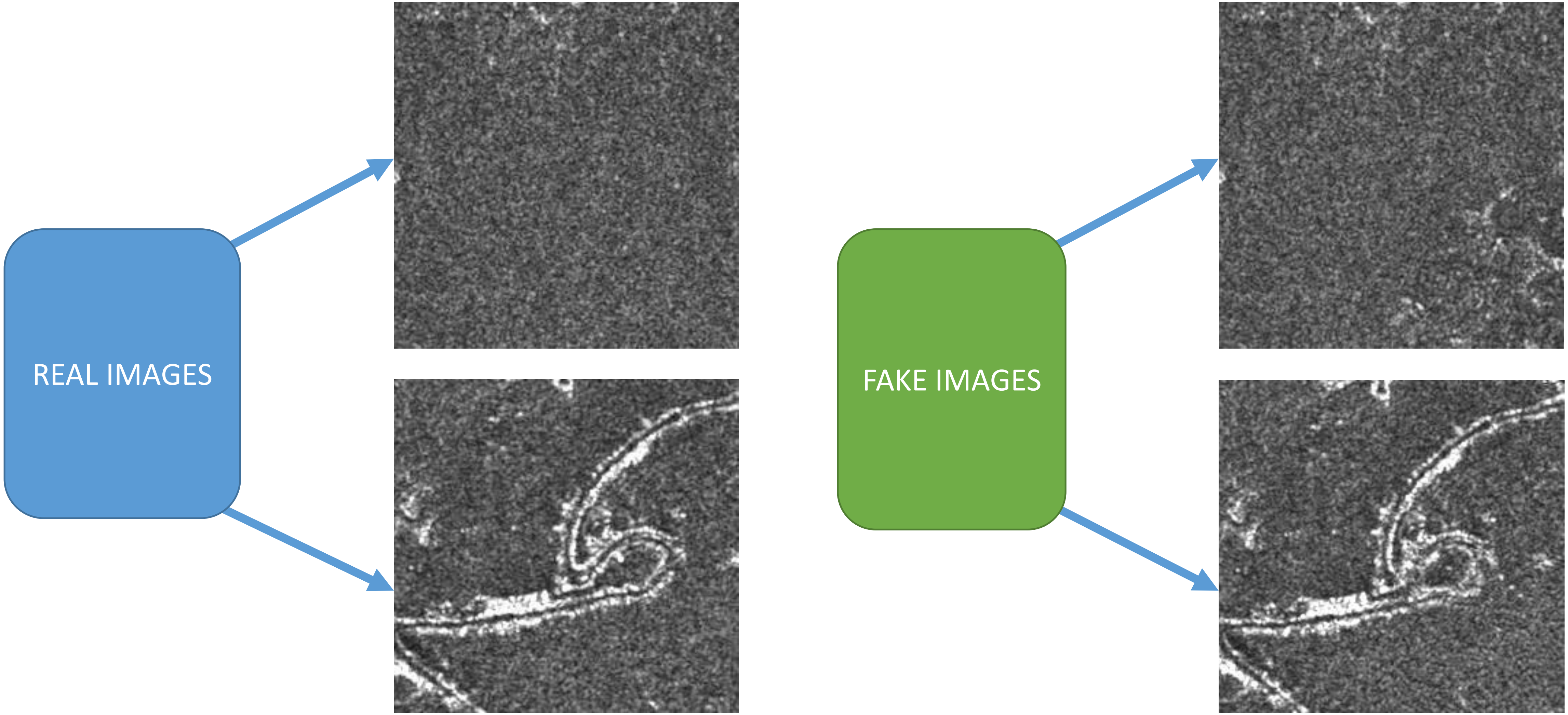





Nature of the dataset

256 X 256

Single Channel

RESULTS



FURTHER WORKS

- Completing a bigger image tile by tile rather than filling the fourth tile only.
- Assessing the quality of the GAN by testing on various datasets.
- Evaluating the performance with standard evaluation metrics.

QUESTIONS?

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