Machine learning for early detection of natural disasters by modality translation

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With the support of the Erasmus+ Programme of the European Union

Copernicus Master in Digital Earth

Vannes, June 25th 2024

Landslides


Reuters 2022

Major risk to public safety

- Damage to infrastructure
- Damage to crop and/or livestock


ARNOLD, R. - AFP Archive

The worldwide death toll per year due to landslides is **in the thousands**. (USGS, 2024)

Overview

Project Context
- LISTIC
- Modality translation work

Change Detection in remote sensing
- Objective

Dataset
- Location
- Pre-processing

Methodology
- Change Detection architectures
- Modality translation architecture

Results & Discussion
- Experimental setup
- Monomodal Change Detection
- Modality Translation
- Change Detection on Translated Images

Conclusion & Perspectives

PROJECT CONTEXT

Project Context

- Two year integrated European Master of Science program
- co-funded by the European Union

COPERNICUS MASTER IN DIGITAL EARTH

With the support of the Erasmus+ Programme of the European Union

- Research unit (UR) of the Université Savoie Mont Blanc (USMB)
  - Machine Learning
  - Information Fusion
  - Networks and Systems
  - Earth Observation

20 YEARS LISTIC

- Funded by National Research Agency as part of project SHINE / France 2030

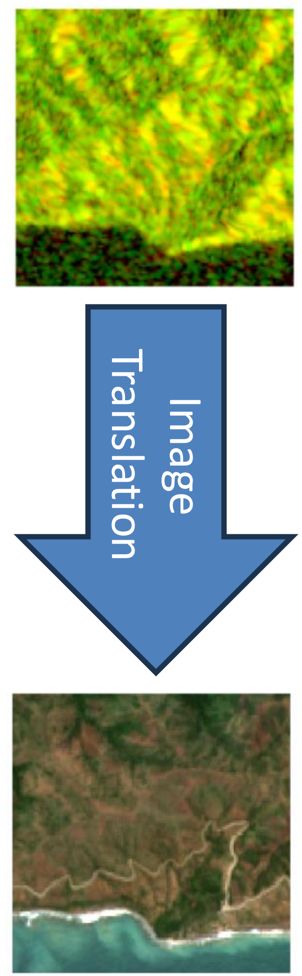
RÉPUBLIQUE FRANÇAISE
Liberté
Égalité
Fraternité

anr® agence nationale de la recherche

Project Context

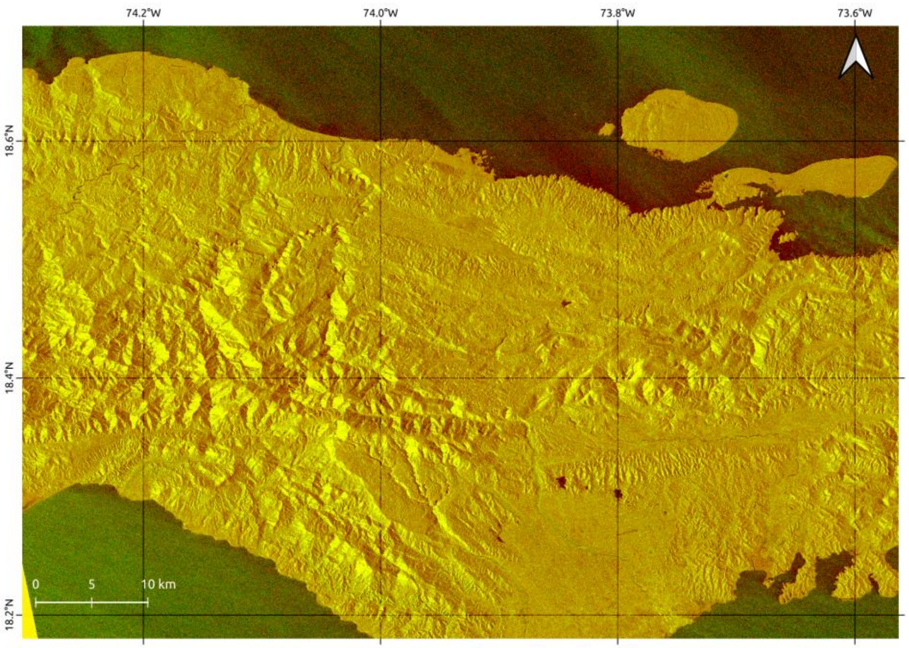
- Aligns with work on modality translation
(Bralet et al., 2022)

- **Develop a use case for translated images**

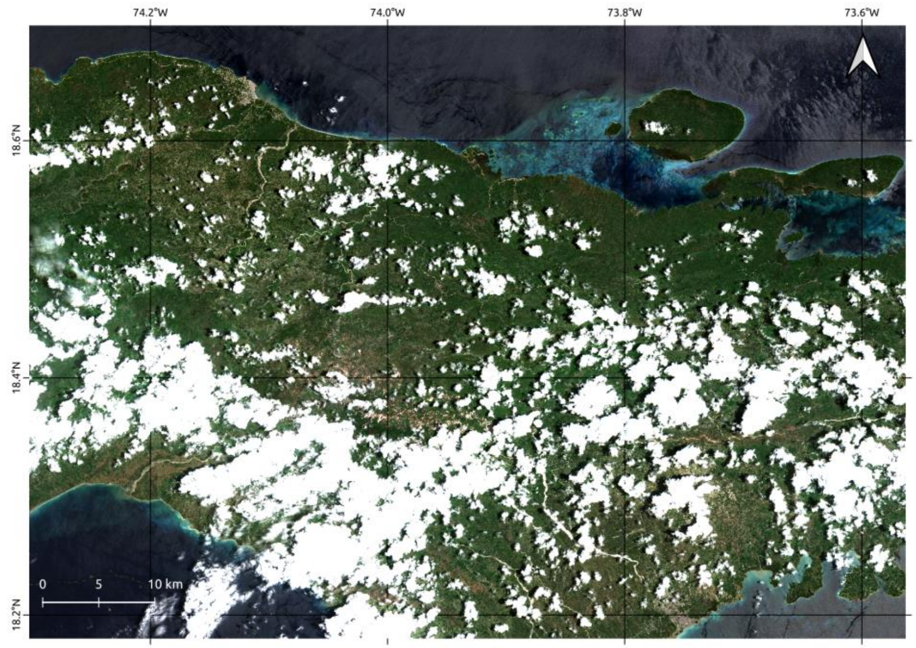


SAR vs Optical Imaging

SAR image



Optical image



- All weather, cloud penetrating capability
- Day-and-night imaging

- Sensitive to the **roughness and texture** of the ground surface

- High-resolution imaging
- Detection of vegetation and water quality

- Sensitive to the **color and reflectance** of the ground surface

CHANGE DETECTION IN REMOTE SENSING

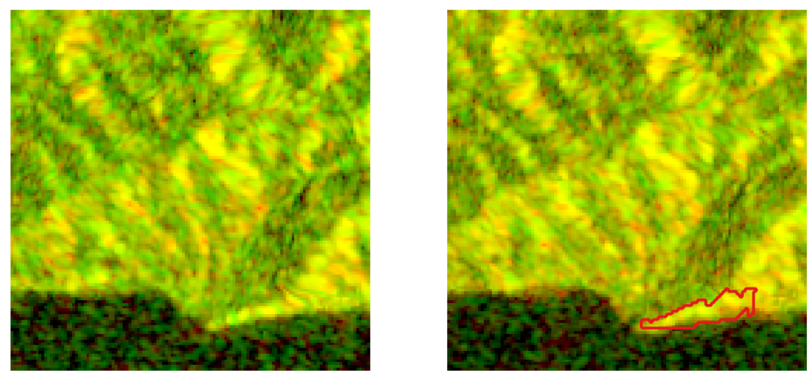
Change Detection in Remote Sensing

What changed between the 2 scenes?

Change Detection in Remote Sensing

What changed between the 2 scenes?

Sentinel-1

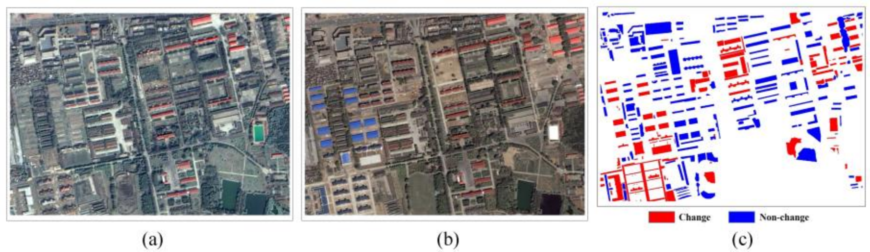


Change Detection in Remote Sensing

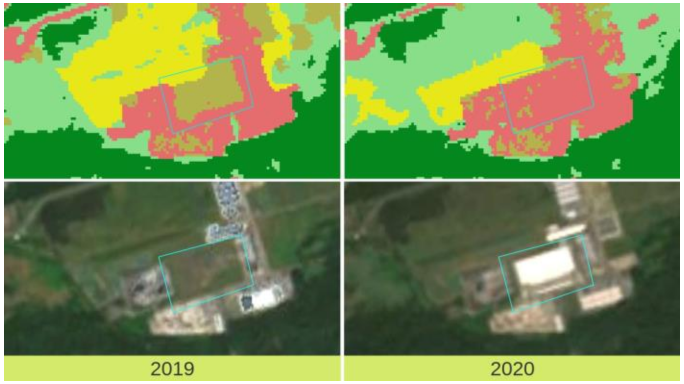
Change Detection
Process of identifying differences in remote sensing images

- Urban building monitoring
- Landcover change
- **Disaster impact assessment (e.g., landslides)**

(Wang et al., 2018)

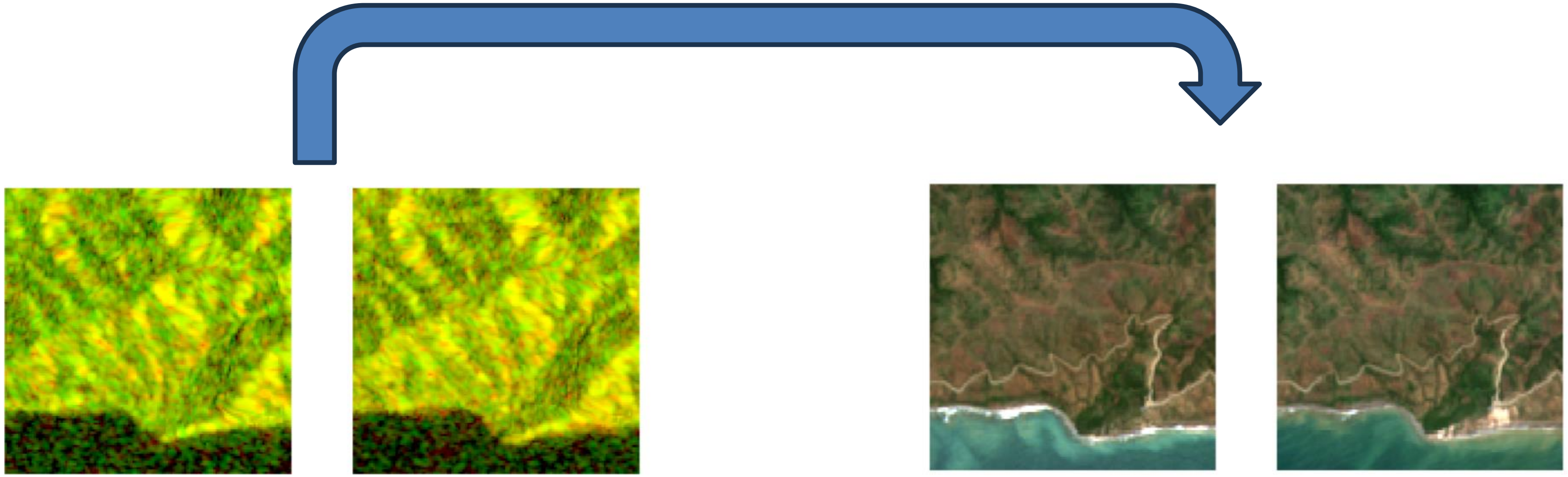


(Mundialis, 2020)



Objectives

- Enhance the usability of SAR images in disaster response
- Translate radar images to optical images
- Investigate the potential of change detection (CD) neural networks applied to translated radar images



DATASET

Area of Interest

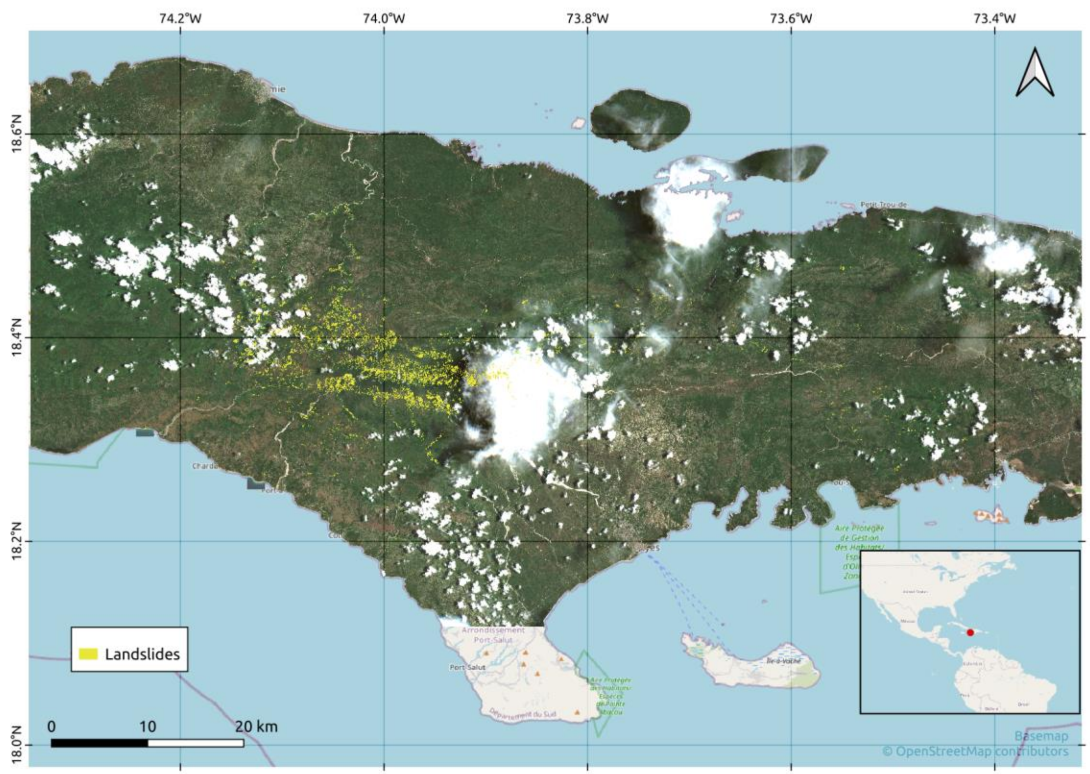
	Sentinel-1	Sentinel-2
Pre-event	05 August in ASC 03 August in DESC	04 August
Post-event	17 August in ASC 15 August in DESC	14 August

CD dataset

	Sentinel-1	Sentinel-2
Pre-event	06 June in ASC 16 June in DESC	10 June
Post-event	16 September in ASC 14 September in DESC	13 September

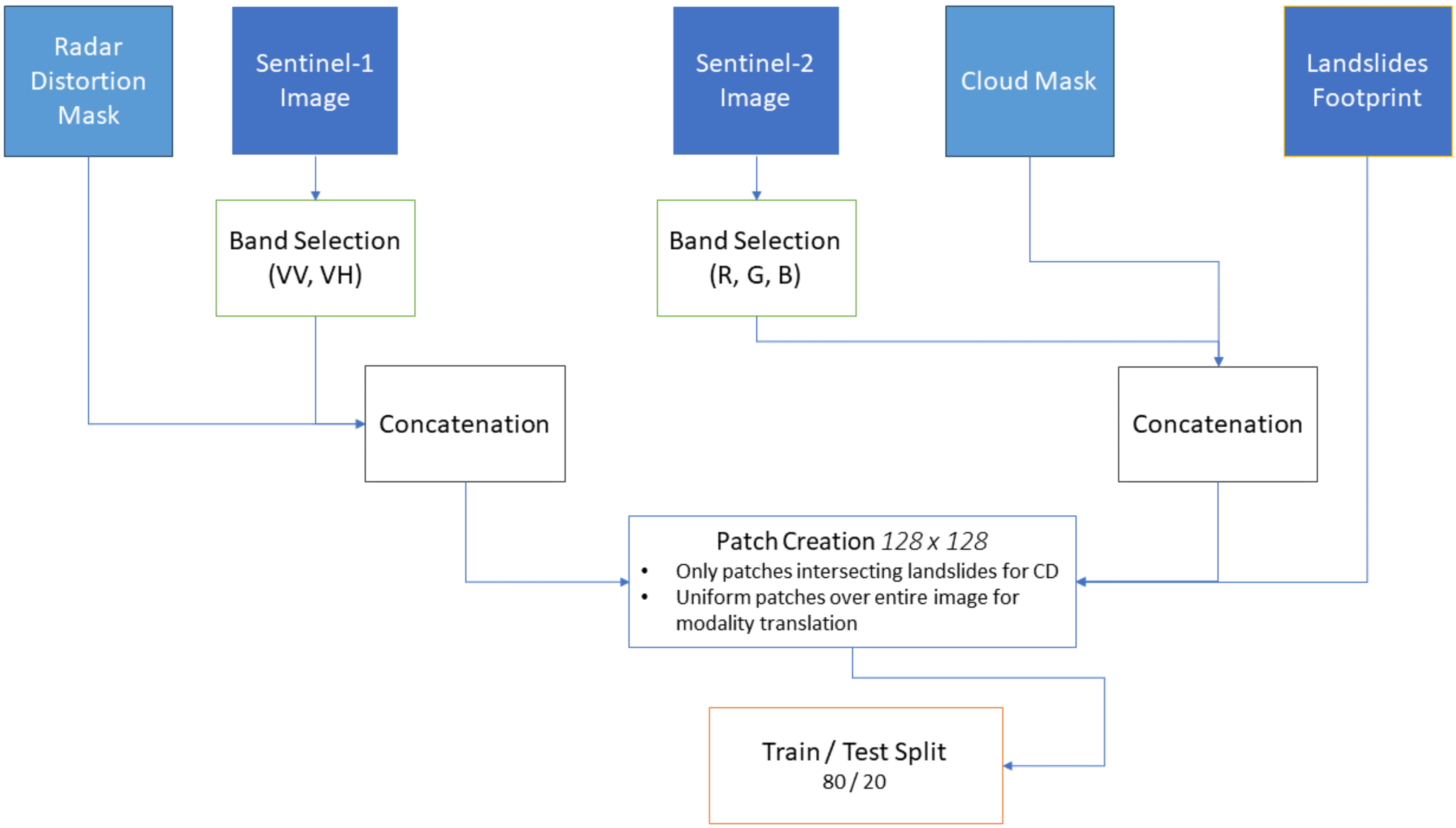
Modality Translation dataset

Landslides caused by an earthquake and a tropical storm
14 August 2021

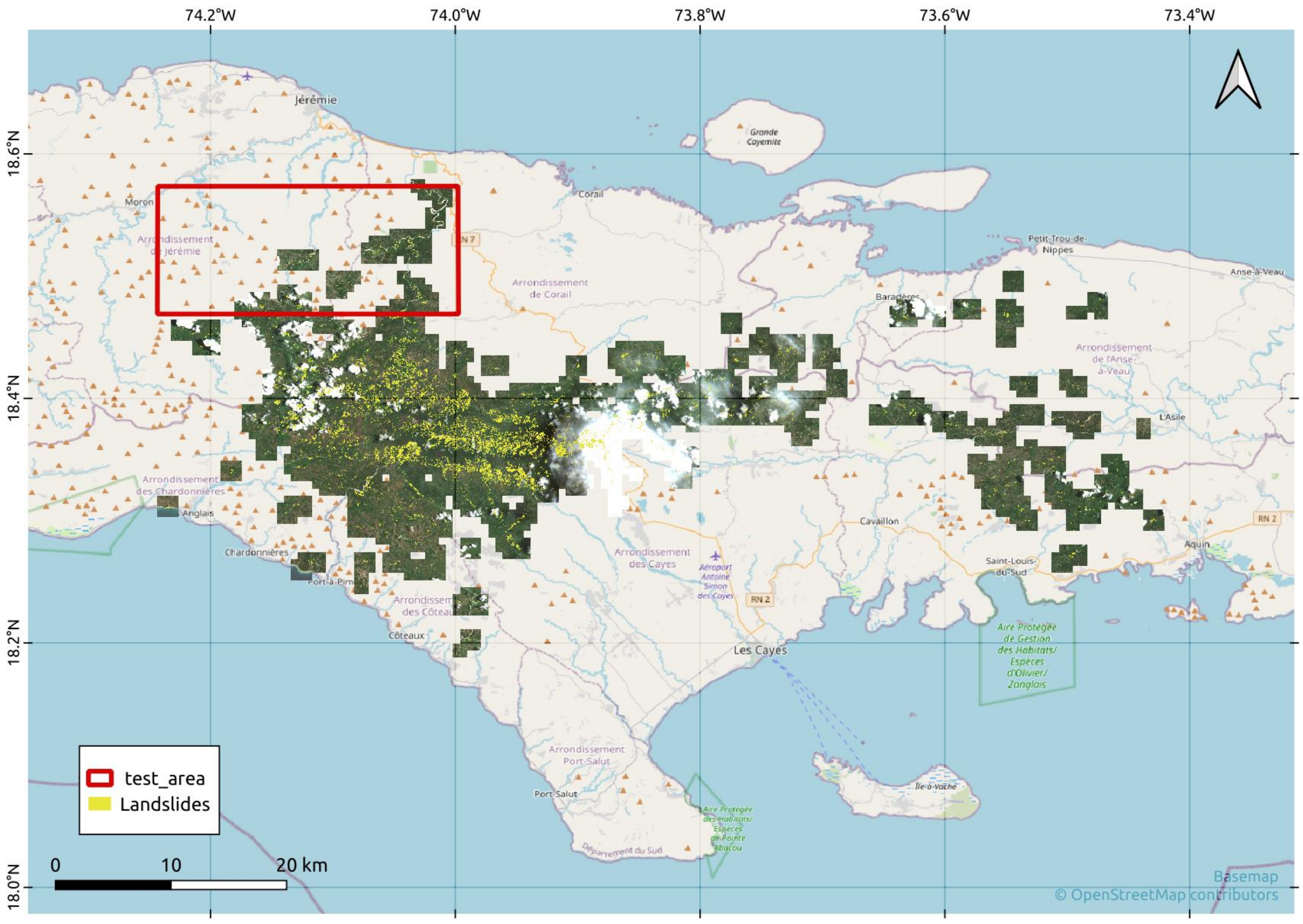


Satellite image : [Copernicus]
Landslide : [NASA COOPR]

Pre-processing



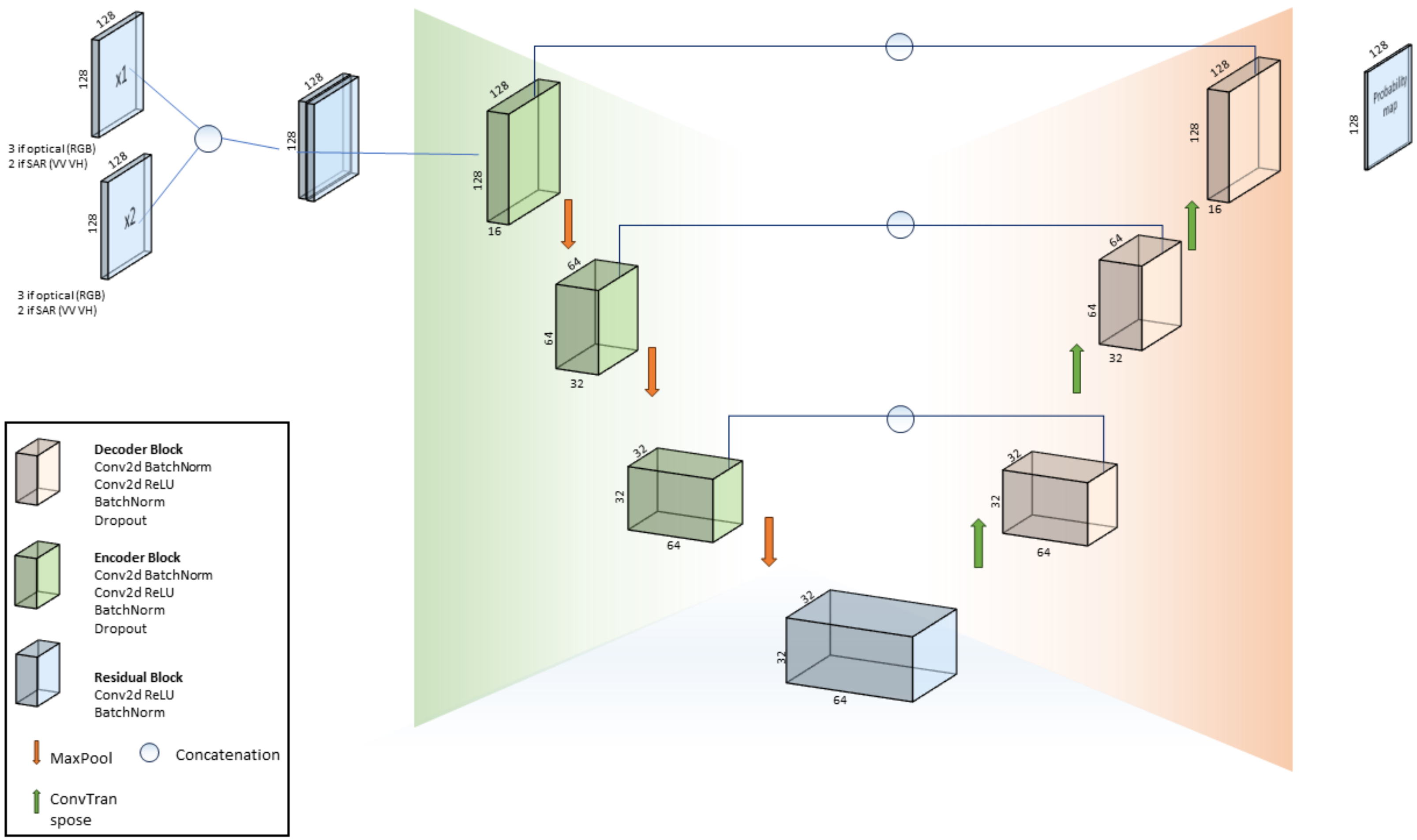
Dataset



74.2°W
74.0°W
73.8°W
73.6°W
73.4°W
18.6°N
18.4°N
18.2°N
18.0°N
Jérémie
Corail
Grande Cayemite
Petit-Trou-de-Nippes
Anse-à-Veau
Baradères
Arrondissement de Corail
Arrondissement de l'Anse-à-Veau
L'Asile
Cavaillon
Aquin
Saint-Louis-du-Sud
Arrondissement des Chardonnières
Anglais
Chardonnières
Port-à-Piment
Coteaux
Arrondissement des Cayes
Les Cayes
Arrondissement Port-Salut
Port-Salut
Île-à-Vache
test_area
Landslides
0
10
20 km
Basemap
© OpenStreetMap contributors

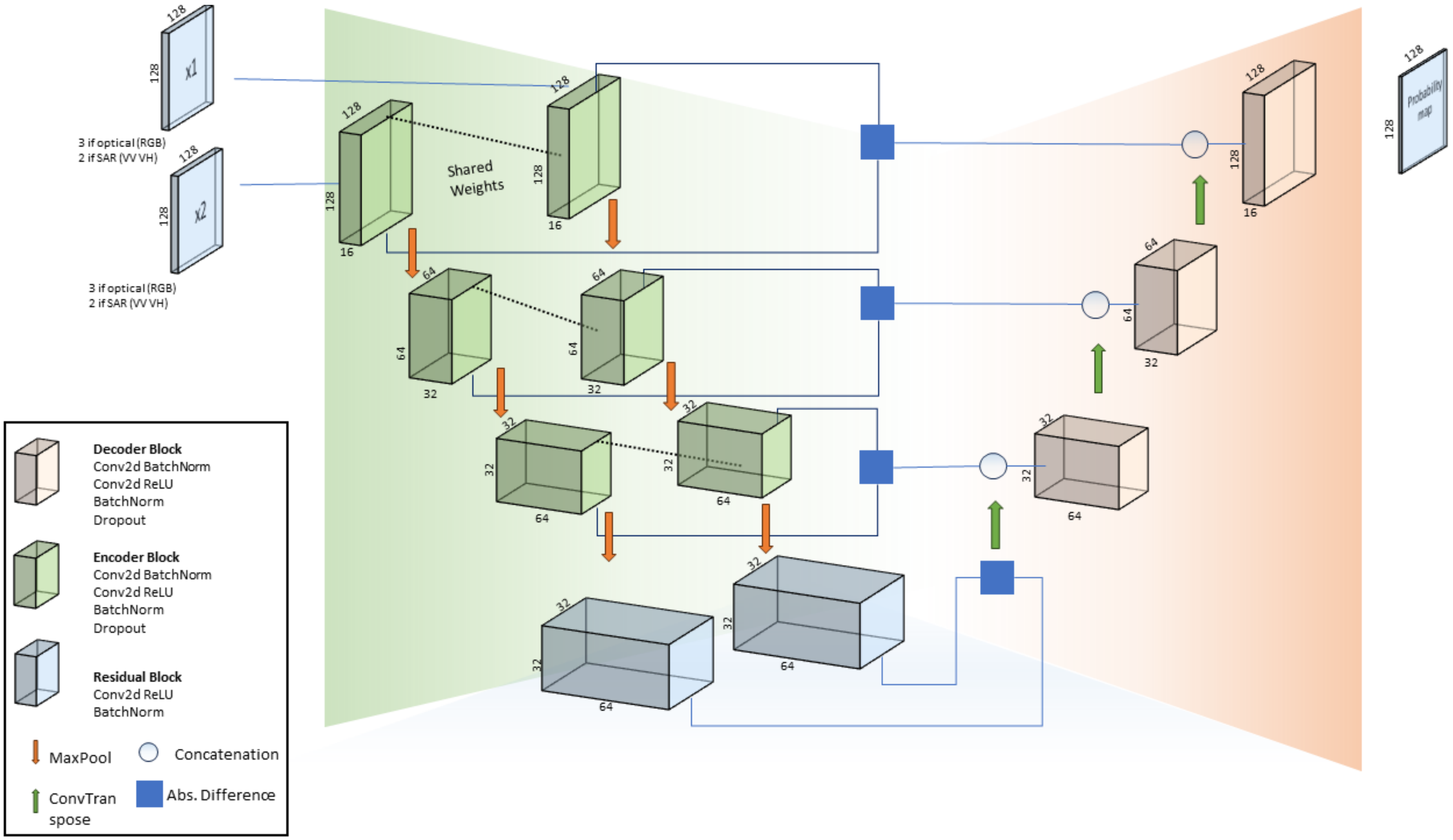
METHODOLOGY

Early Fusion Architecture



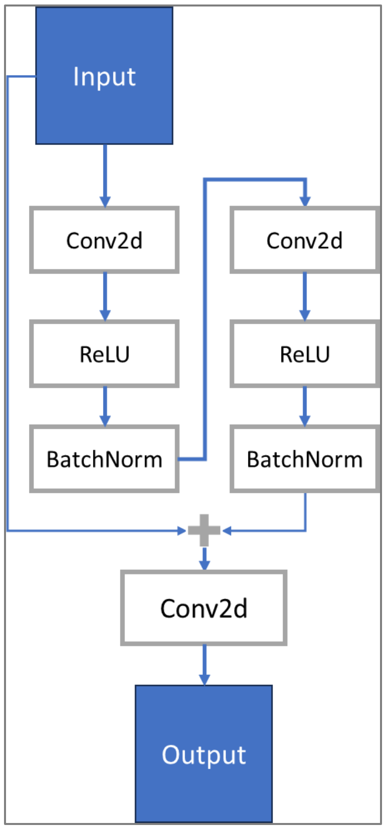
Early Fusion Architcture with 3 Encoder-Decoder Blocks

Siamese Architectures



Siamese Architcture with 3 Encoder-Decoder Blocks

Change Detection Architectures



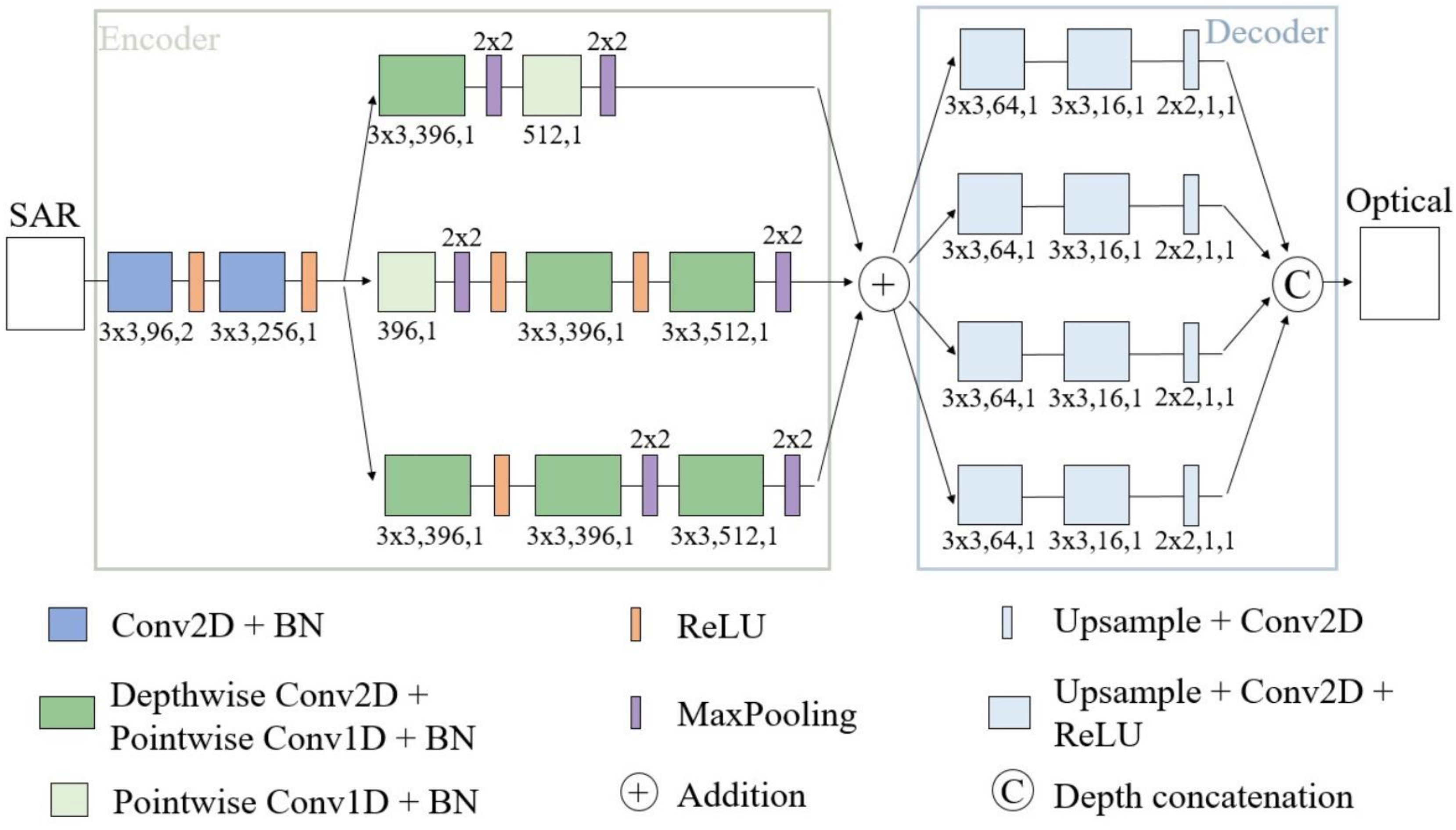
Residual Block

- Designed and tested
  - SiamNet
  - EF-Net
  - ResSiamNet
  - ResEF-Net

With 2, 3, 4 blocks

SARDINet – Modality Translation

(Bralet et al,, 2022)



RESULTS & DISCUSSION

Change Detection Loss

$$BCE(y,p) = \frac{-1}{N} \sum_{i=1}^{N} (y \log(p) + (1-y)\log(1-p))$$

y is the ground truth label for each pixel indicating whether a change has occurred (1) or not (0) ;

p is the predicted probability (by the model) that a change has occurred at each pixel ;

N is the number of pixels in the image or batch of images;

yi is the ground truth label for the i-th pixel;

pi is the predicted probability for the i-th pixel:

Change Detection Evaluation Metrics

$$Recall = \frac{TP}{TP + FN}$$

The model's capability to recognize all real changes in satellite images

$$Precision = \frac{TP}{TP + FP}$$

The Changes detected by the model are correct

$$F1- = \frac{2 * Precision * Recall}{Precision + Recall} = \frac{2 * TP}{2 * TP + FP + FN}$$

The model is effectively identifying changes while also reducing false alarms

$$Jaccard(U, V) = \frac{|U \cap V|}{|U \cup V|}$$

The alignment between detected changes and real changes

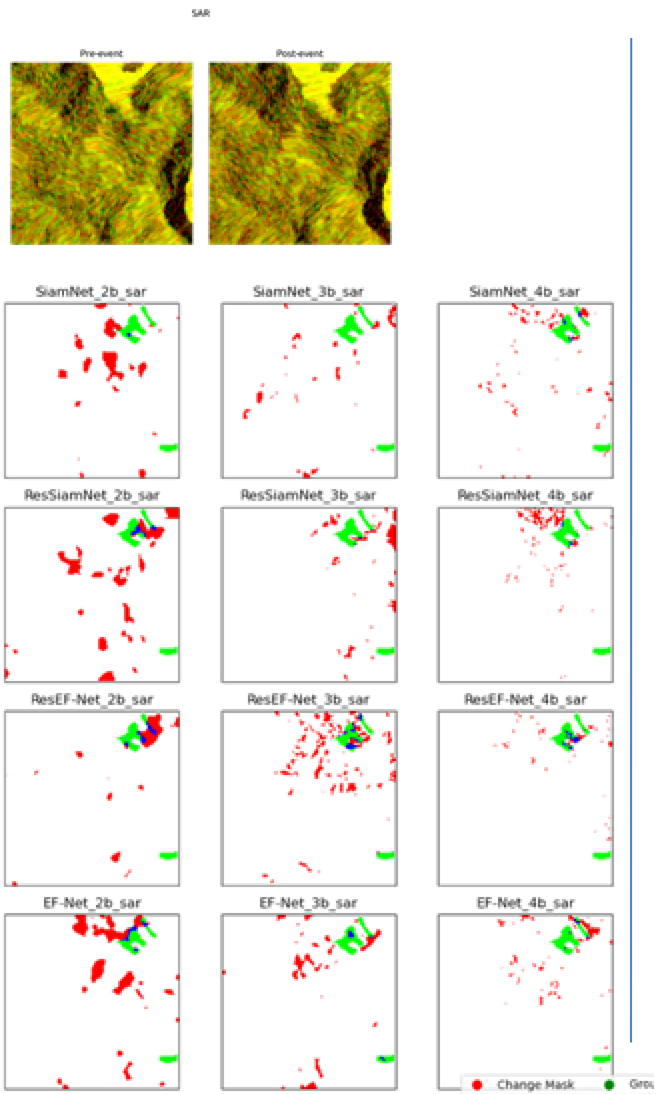
Image Translation Loss & Evaluation Metrics

$$Loss(x, l) = L1Loss(x, l) + SSIM(x, l)$$

L1Loss
measures the absolute differences between the predicted and ground truth images

SSIM
evaluates the structural similarity between the predicted and ground truth images

Change Detection Results



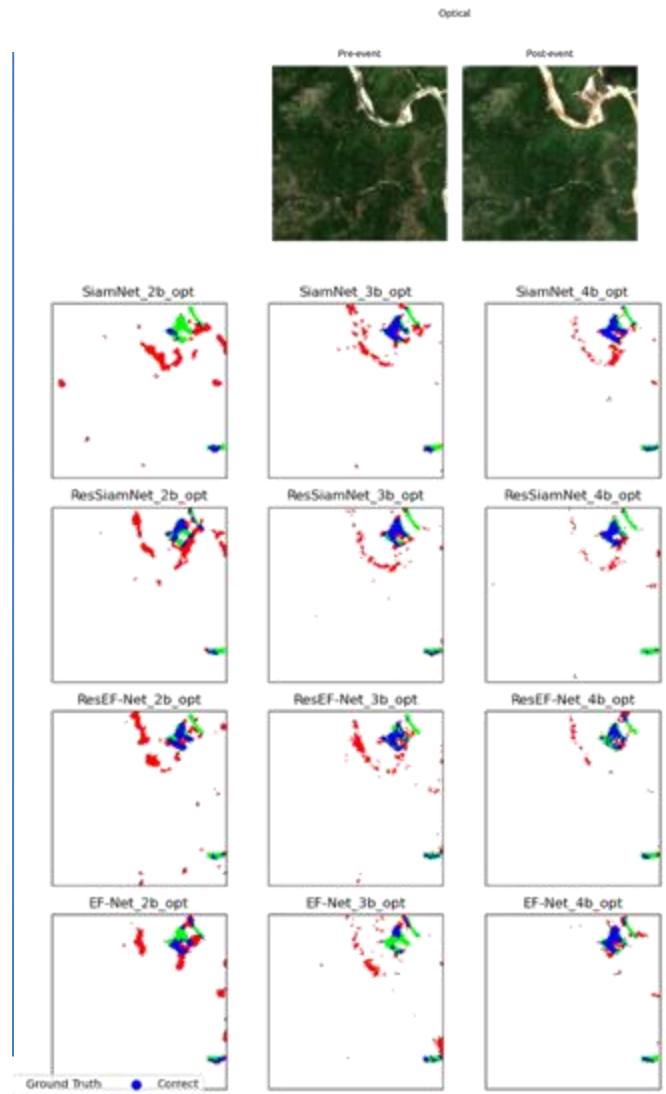
Models with 4 blocks	Jaccard	F1-score	Recall	Precision
ResSiamNet	**0,58**	**0,73**	**0,63**	**0,86**
ResEF-Net	0,53	0,69	0,61	0,80
EF-Net	0,52	0,68	0,57	0,84
SiamNet	0,48	0,65	0,56	0,77

Passable results :

- Inherent SAR characteristics (backscatter of radar signals)
- speckle noise and lack the detailed texture
- high variability in SAR images (acquisition geometries, distortion)

Change Detection Results

Models with 4 blocks	Jaccard	F1-score	Recall	Precision
ResSiamNet	**0,80**	**0,89**	**0,85**	0,93
ResEF-Net	0,79	0,88	0,83	**0,94**
EF-Net	0,78	0,87	0,84	0,91
SiamNet	0,74	0,85	0,81	0,90



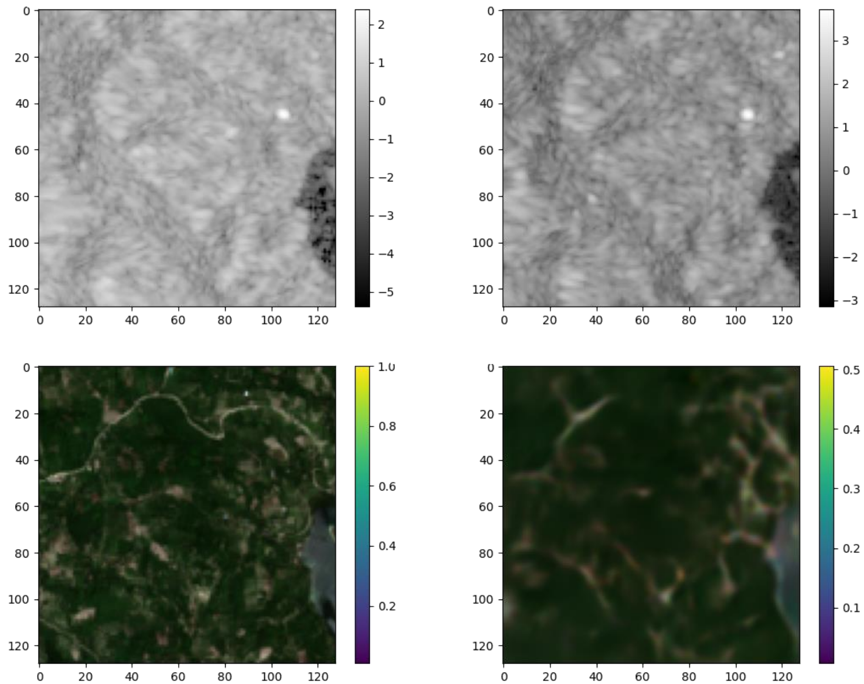
Acceptable results

- detailed information about colors, textures, and shapes
- Less noise than SAR
- Consistent quality with intuitive features

Modality Translation Results

SAR

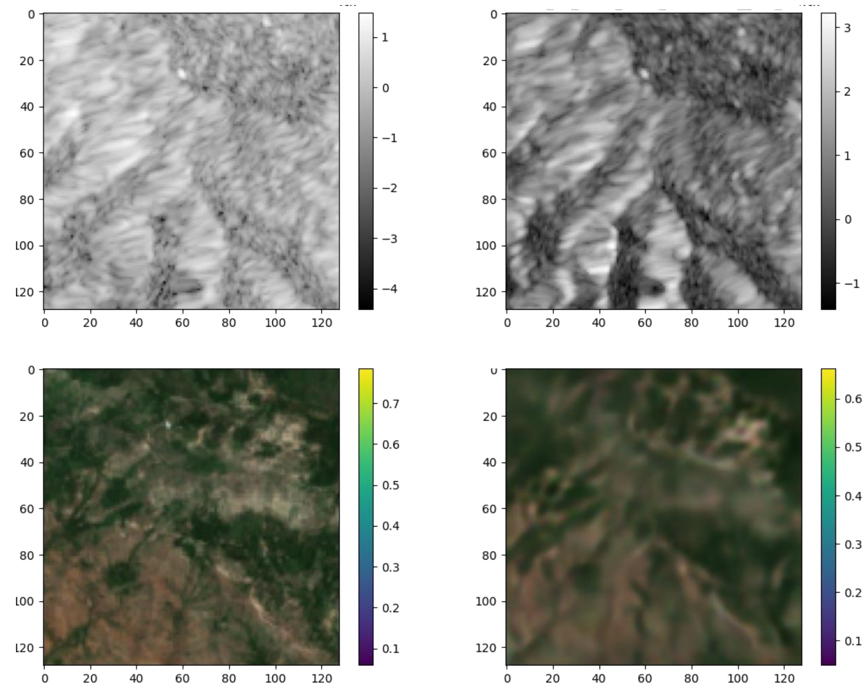
VV VH



Optical Ground Truth Translated

SAR

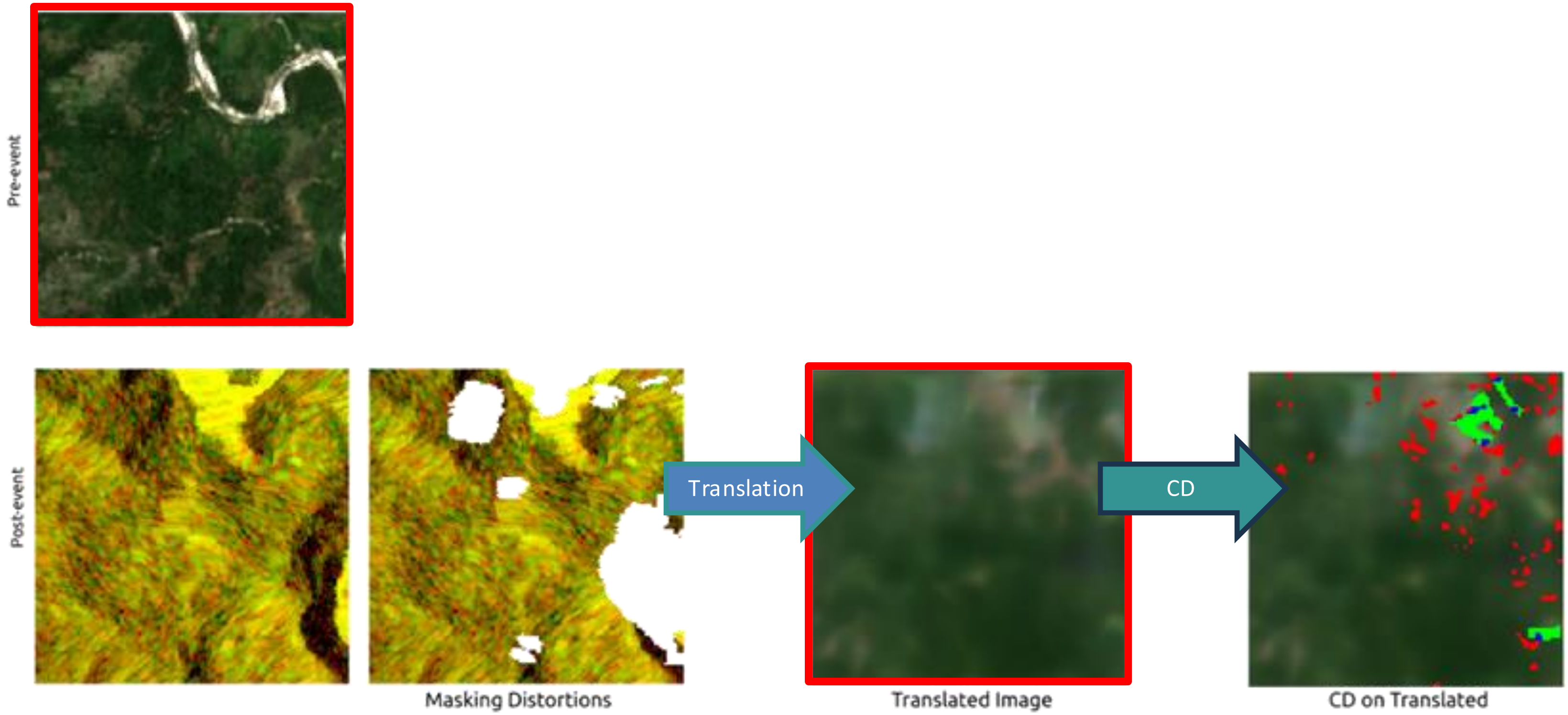
VV VH



Optical Ground Truth Translated

Examples of translated images

Change Detection on Translated Images



Middling results

- Lacks texture details (blurriness)
- Difference in the features (optical / translated)


Optical Ground Truth

CONCLUSION & PERSPECTIVES

Conclusion

Investigated modality translation for early disaster detection using change detection neural networks

Designed and compared four neural network architectures for change detection

Key findings:

Change detection networks performed well on optical images	Performance dropped significantly when applied to radar images	SARDINet effectively translated SAR images to optical images	Change detection networks struggled with translated images due to texture differences

Future Directions

Integrated Network Pipeline:	Develop combined SARDINet and change detection networks pipeline.
	Aim: Improve translation and detection simultaneously.
Generative Adversarial Networks (GANs):	Explore GANs for modality translation.
	Goal: Enhance translated image quality and network performance.
Attention Mechanisms:	Investigate use in change detection networks.
	Objective: Capture long-range relationships and focus on relevant features in translated images.
Transfer Learning:	Apply transfer learning for better adaptation to translated images.
	Benefit: Efficient learning of translated image properties.
Performance Assessment:	Evaluate change detection networks on various translated image types.
	Purpose: Determine efficacy in early disaster identification.

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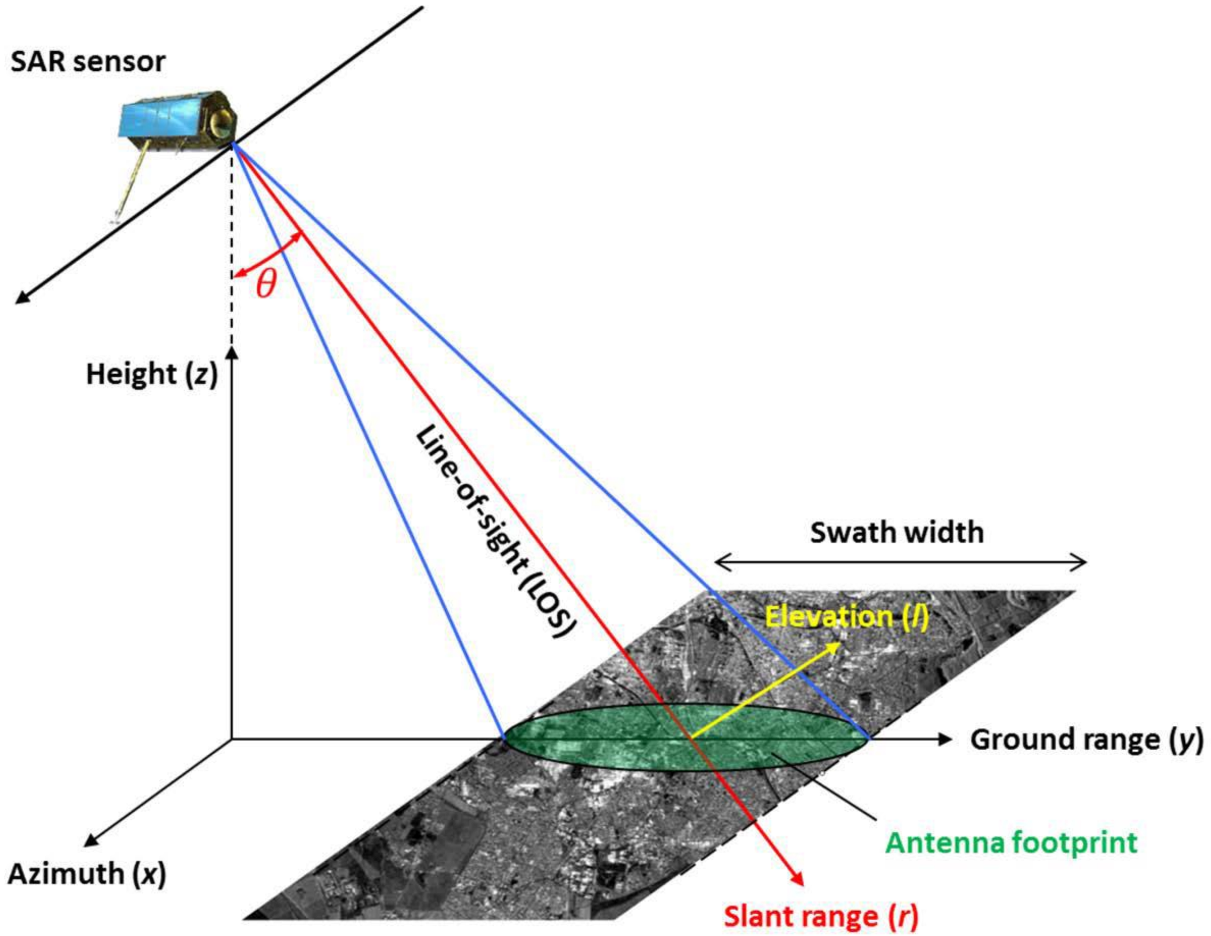
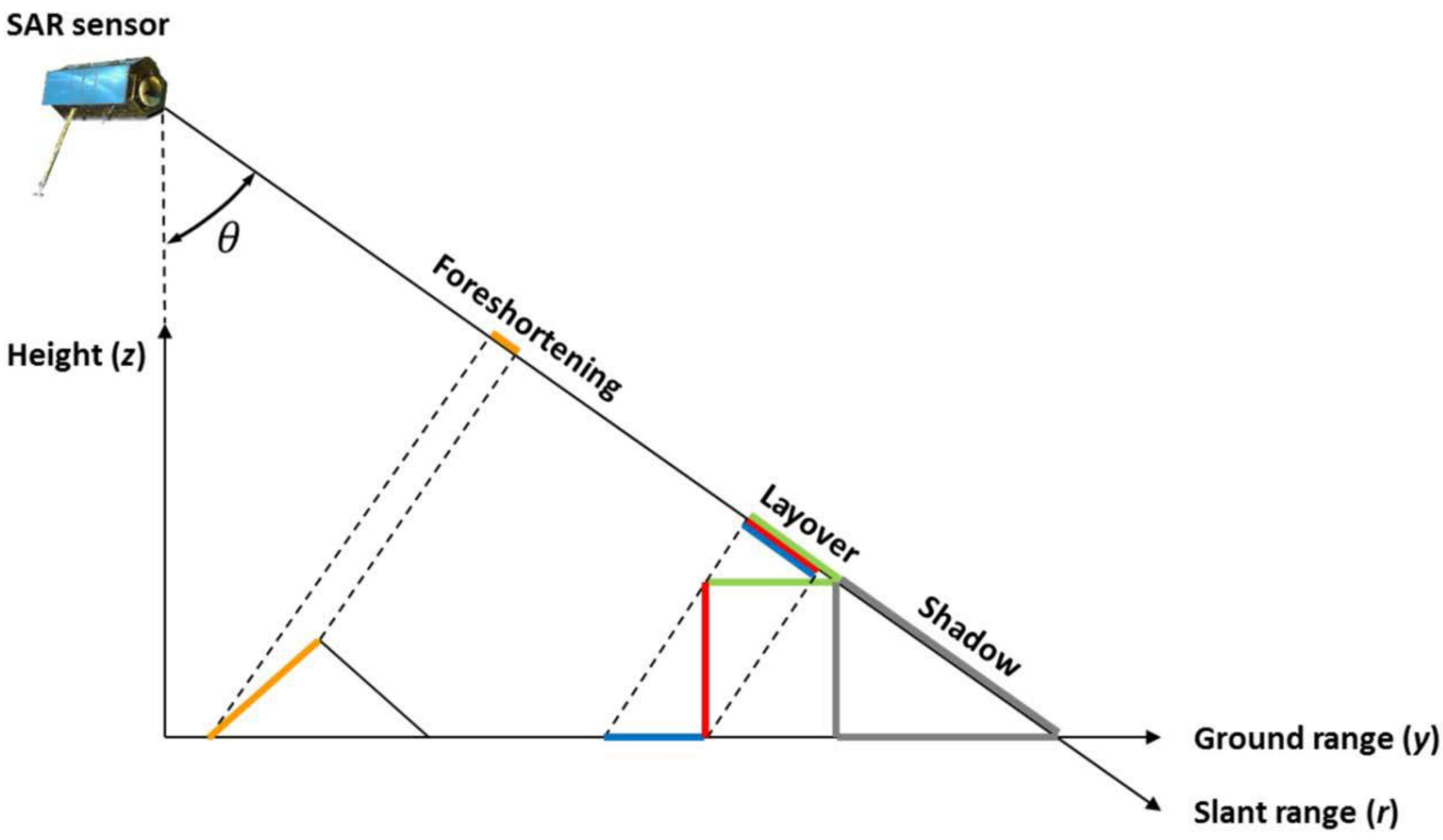
ADDITIONAL MATERIAL

SAR acquisition geometry



(Goel. K., 2013)

SAR Distortions



(Goel. K., 2013)