Change Detection with Deep Learning Models

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Outline

1. Introduction to Change Detection

2. Definition of Change Detection

3. Traditional Change Detection Techniques

4. Deep Learning Models for Change Detection

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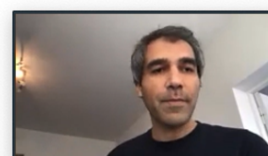
    4.2 Supervised Change Detection with U-Net models
    4.3 Supervised Deep Learning methods for Semantic Change Detection
    4.4 Supervised Bi-temporal Change Detection with GAN
    4.5 Unsupervised Change Detection with Deep Change Vector Analysis (DCVA)
    4.6 Self-Supervised Adversarial Representation Learning for Binary Change Detection

5. Questions?



What is change detection?

What changed?

- ✓ From construction side to building (shopping center)
- ✓ From agriculture to pastures
- ✓ From forest to pastures
- ✓ Tree vegetation
- ✓ Building with a new rooftop
- ✓ Color of the river
- ✓ Height of cereals
- ✓ …

What is change detection?

- ✓ **Change detection** is a process that measures how the attributes of a particular area have changed between two or more time periods. Change detection often involves comparing aerial photographs or satellite imagery of the area taken at different times. Change detection has been widely used to assess shifting cultivation, deforestation, urban growth, impact of natural disasters like tsunamis, earthquakes, and use/land cover changes etc.

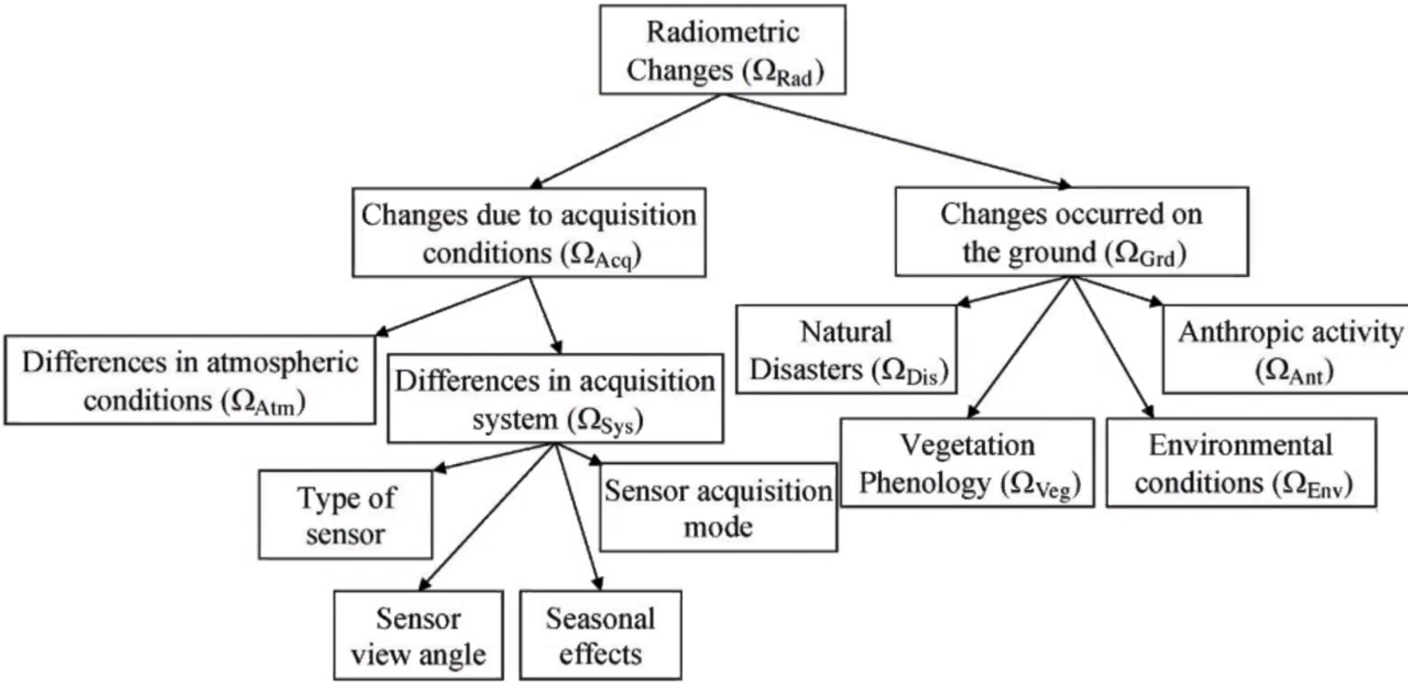
  https://en.wikipedia.org/wiki/Change_detection_(GIS)

- ✓ Applications:
  - ✓ Detection of deforestation
  - ✓ Urban growth
  - ✓ Environmental monitoring
  - ✓ Climate Change
  - ✓ Determination of impact of natural disasters
  - ✓ Agriculture monitoring
  - ✓ …

https://en.wikipedia.org/wiki/Change_detection_(GIS)

Tree of radiometric changes

✓ **Tree of radiometric changes**



Bruzzone, L., & Bovolo, F. (2013). A novel framework for the design of change-detection systems for very-high-resolution remote
Proceedings of the IEEE, 101(3), 609–630. https://doi.org/10.1109/JPROC.2012.2197169

Types of Change detection?

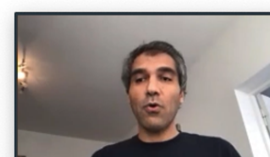
✓ Pixel wise Change Detection vs. Semantic Change Detection

<u>Pixel wise Change Detection</u>

Broad-leaved forest Pastures

<u>Semantic Change Detection</u>

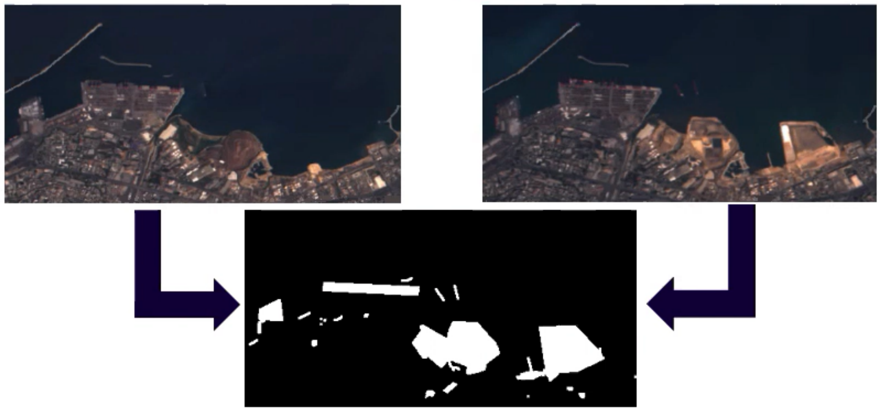
Broad-leaved forest ➡ Pastures



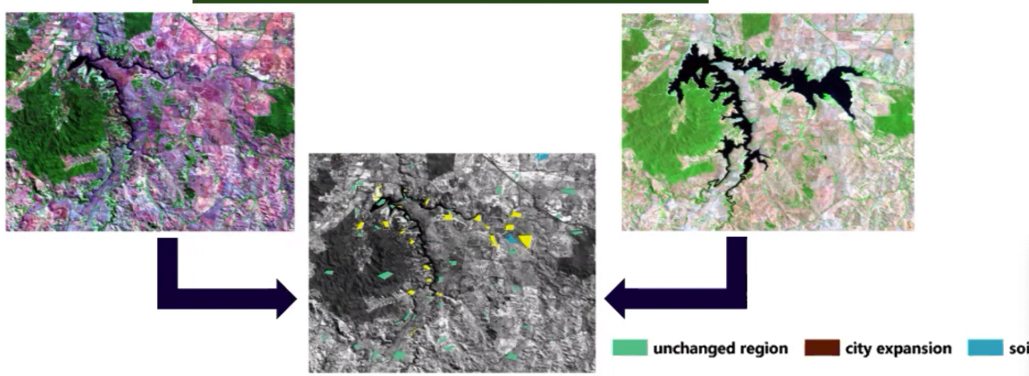
Types of Change detection?

- ✓ Binary Change Detection vs. Multi-class Change Detection

Binary Change Detection



Multi-class Change Detection



Types of Change detection?

Binary Change detection

- ✓ Production of binary maps in which changed and unchanged areas are separated
- ✓ Number of images: 2 (or pairs of images extracted from a series)
- ✓ Application domain: detection of abrupt changes.

Multi-class Change Detection

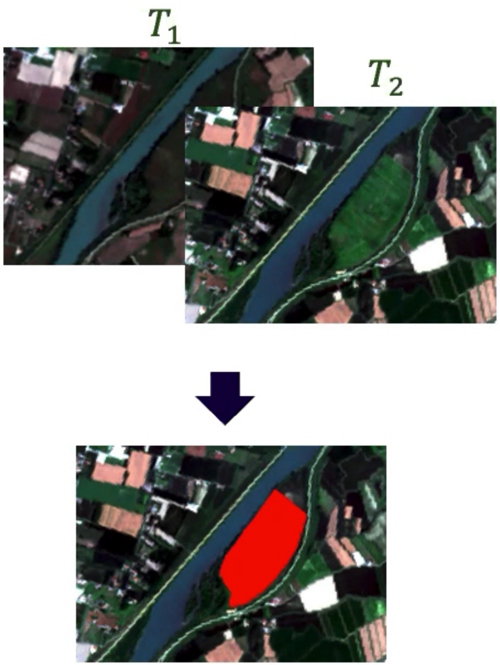
- ✓ Generation of a change-detection map in which land-cover transitions are explicitly identified
- ✓ Number of images: 2 (or pairs of images extracted from a series)
- ✓ Application domain: updating thematic maps, detection of multiple changes

https://earth.esa.int/documents/973910/2642313/LB1to3.pdf

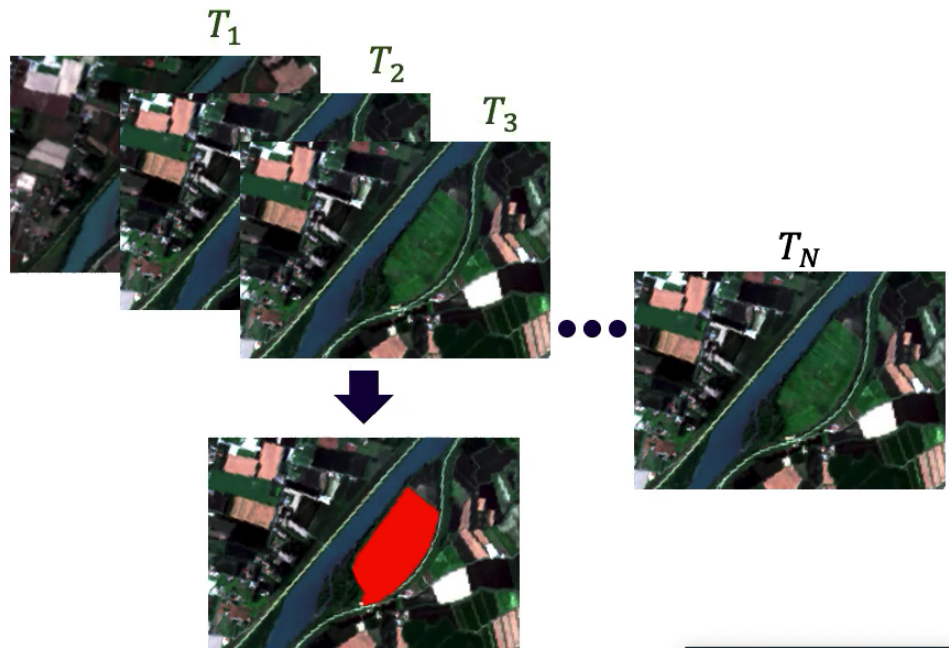
Types of Change detection?

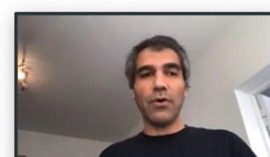
✓ Bi-Temporal Change Detection vs. Multi-temporal Change Detection

Bi-Temporal Change Detection



Multi-Temporal Change Detection





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Types of Change detection?

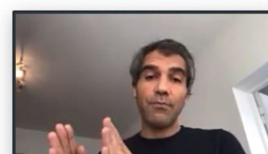
Bi-Temporal Change Detection

- ✓ Detection of changes associated between two timestamps (detection of abrupt changes)
- ✓ Number of images: 2
- ✓ Application domain: monitoring seasonal/annual changes

Multitemporal Change Detection

- ✓ Detection of changes associated with modifications of the behavior of the temporal signature of a land cover between two time series (detection of long term changes and abrupt changes)
- ✓ Number of images: 2 time series made up on n images (n>>2)
- ✓ Application domain: monitoring seasonal/annual changes

https://earth.esa.int/documents/973910/2642313/LB1to3.pdf



Types of Change detection?

Supervised Change Detection

- ✓ Training of classifier based on labeled samples witch change/no change information
- ✓ Usually more accurate than unsupervised methods

Unsupervised/Self-supervised Change Detection

- ✓ Unsupervised methods discriminate the changed class from the unchanged class without any prior information
- ✓ Popular in applications with lacking of the ground truth data

https://earth.esa.int/documents/973910/2642313/LB1to3.pdf

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Change Detection Pre-Processing

- ✓ Atmospheric correction
  - ✓ Process of removing the effects of the atmosphere on the reflectance values of images taken by satellite or airborne sensors

- ✓ Image Registration
  - ✓ Image Registration is a process of aligning two images of the same scene taken at different times, from different viewpoints, and/or different sensors (references and sense images) into a common coordinate system

- ✓ Normalization of satellite data

- ✓ Crop satellite image into image patches

- ✓ …

Shah, U. S., Mistry, D., & Tech, M. (2014). Survey of Image Registration techniques for Satellite Images

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Traditional Change Detection Techniques

Technique	Sub-class	Approach	Advantages	Limitations
Pixel based	Direct comparison	Image differencing	- Simple - Easy to interpret results	- No complete matrices of change information - Optimal threshold selection - The difference value is absolute. Therefore same value may have different meaning depending on the starting class - Binary (change vs. no change
		Image rationing	- It better handles calibration (including sun angle, shadow and topography impact) errors	- No complete matrices of change information - Non-normal distribution of results - Binary (change vs. no change)
	Transformation/ from Image	Vegetation index differencing	- Reduces Impacts of topographic effects and illumination	- Random or coherence noise - Binary (change vs. no change)
		Change vector analysis (CVA)	- Process any number of spectral bands desired - Produce detailed change detection information	- Difficult to identify land cover change trajectories - Strictly Require the remotely sensed data acquired from the same phonological period

Hussain, M., Chen, D., Cheng, A., Wei, H., & Stanley, D. (2013). Change detection from remotely sensed images: From pix
based approaches. *ISPRS Journal of Photogrammetry and Remote Sensing*, *80*, 91–106. https://doi.org/10.1016/j.isprsjprs.

Traditional Change Detection Techniques

Technique	Sub-class	Approach	Advantages	Limitations
Pixel based	Classification based change detection	Post-classification comparison	-Atmospheric, sensor and environmental impact reduction - Complete matrices of change - Also minimizes the impact of using multi-sensor images	- Require accurate and complete training data set - Final accuracy is dependent on classification accuracy of individual image
	Machine Learning	Support Vector Machine	- Non-Parametric and no assumption on data distribution - Able to handle small training data sets and often produces higher classification accuracy than the traditional method	- Difficulty in choosing the best kernel function - The computational time for classification and achieving optimization during the learning phase increases polynomially with the increase of data dimensionality
		Decision Tree	- Non-Parametric and no assumption on data distribution - Can provide rule set for change and no-change classes	- Sensitive to training data quality and the number of training samples per class, and they can be “over-trained” such that the model is not applicable to datasets from other areas or time periods - Do not search for optimal fit - Can grow much larger in sizes and make it difficult to interpret

Hussain, M., Chen, D., Cheng, A., Wei, H., & Stanley, D. (2013). Change detection from remotely sensed images: From pixel-based to object-based approaches. *ISPRS Journal of Photogrammetry and Remote Sensing*, *80*, 91–106. https://doi.org/10.1016/j.isprsjprs.2013.03.006

Traditional Change Detection Techniques

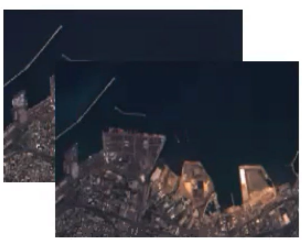
Technique	Sub-class	Approach	Advantages	Limitations
Object based	Direct Object comparison based	Objects extracted from one image and the assigned to or searched from image data from second acquisition	Straightforward comparison of objects Ease of implementation Image objects have same geometric properties at two times Change geometrical propertied (shape parameters i.e. border length, size) Change by spectral or extracted features (texture)	Dependent on the accuracy of the segmentation Do not provide 'from–to' change Difficulty in searching spatially corresponding objects in multitemporal images
	Object classification comparison based	Two segmentation created separately and compared	All the available objects could be used for object-based change detection	Difference in sizes and correspondence of image objects from multi-temporal images because of segmentation

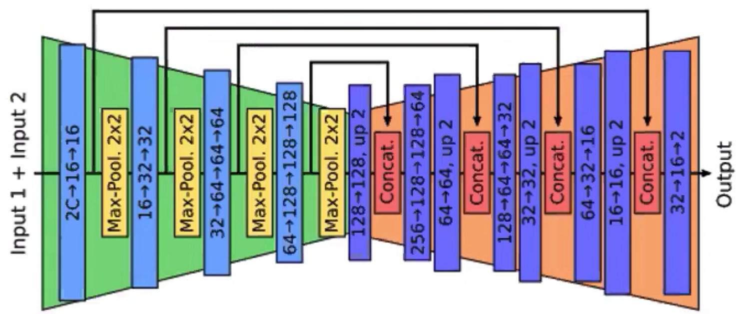
Hussain, M., Chen, D., Cheng, A., Wei, H., & Stanley, D. (2013). Change detection from remotely sensed images: From pixel-based to object-based approaches. *ISPRS Journal of Photogrammetry and Remote Sensing*, *80*, 91–106. https://doi.org/10.1016/j.isprsjprs.2013.03.006

Change Detection with U-Net models

- ✓ U-Net architectures that perform change detection on multi-temporal pairs of images
- ✓ Concatenating the two patches before passing them through the net-work, treating them as different color channels.
- ✓ Usage of skip connections - links between layers at the same subsampling scale before and after the encoding part of an encoder-decoder architecture
- ✓ Patch size: 32px x 32px, Channels: 2 x 12 = 24

32 x 32 x 24



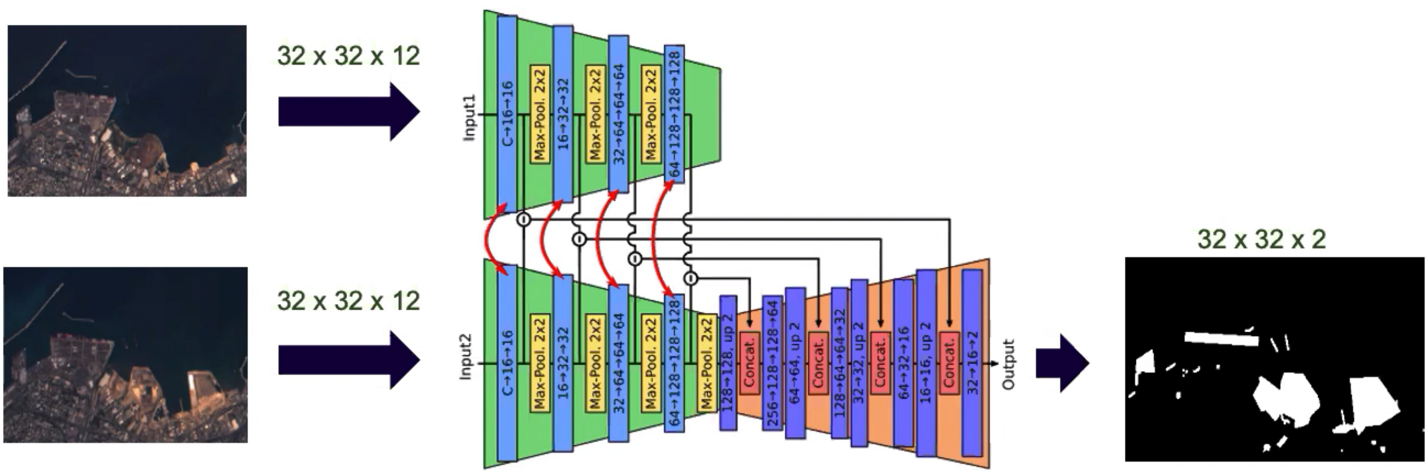


32 x 32 x 2

R. Caye Daudt, B. Le Saux and A. Boulch, (2018) "Fully Convolutional Siamese Networks for Change Detection," 2018 25th IEEE International Conference on Image Processing (ICIP), pp. 4063-4067, doi: 10.1109/ICIP.2018.8451652.

Change Detection with U-Net models

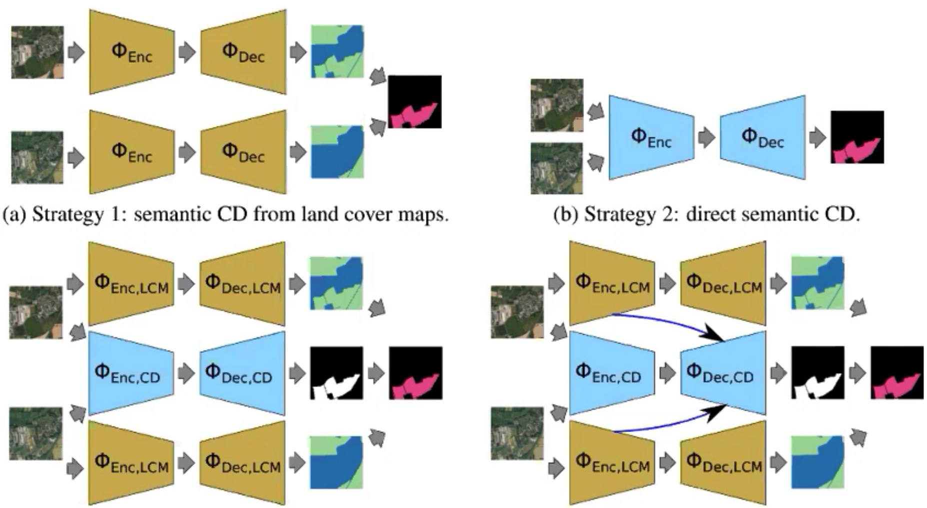
- ✓ Siamese U-Net separated with two streams of equal structure with shared weights as in a traditional Siamese network
- ✓ Concatenation of the absolute value of their difference of features in every level
- ✓ Patch size: 32px x 32px
- ✓ Channels: 12



R. Caye Daudt, B. Le Saux and A. Boulch, (2018) "Fully Convolutional Siamese Networks for Change Detection," 2018 25th IEEE International Conference on Image Processing (ICIP), pp. 4063-4067, doi: 10.1109/ICIP.2018.8451652.

Deep learning methods for semantic change detection

- ✓ Simultaneous change detection and land cover mapping
- ✓ Semantic change detection strategies:
  - ✓ Direct comparison of land cover maps
  - ✓ Direct semantic change detection
  - ✓ Separate land cover mapping and change detection
  - ✓ Integrated land cover mapping and change detection

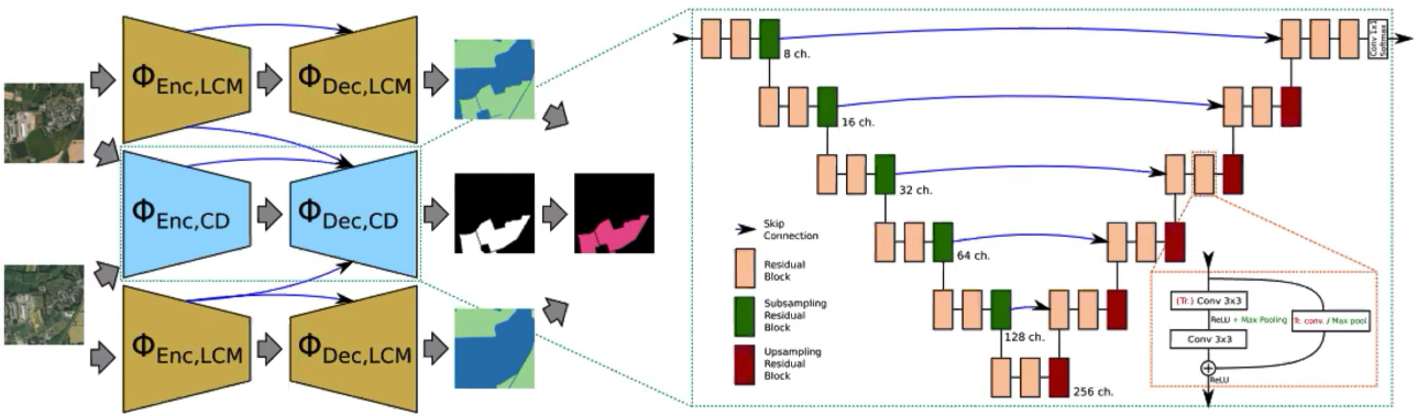


(a) Strategy 1: semantic CD from land cover maps.
(b) Strategy 2: direct semantic CD.
(c) Strategy 3: separate CD and LCM.
(d) Strategy 4: integrated CD and LCM.

Stine, R. R., & Matunis, E. L. (2018). High Resolution Semantic Change Detection. *Advances in Experimental Medicine and Biology*, *786*, 247–267. https://doi.org/10.1007/978-94-7-6621-1_14

Deep learning methods for semantic change detection

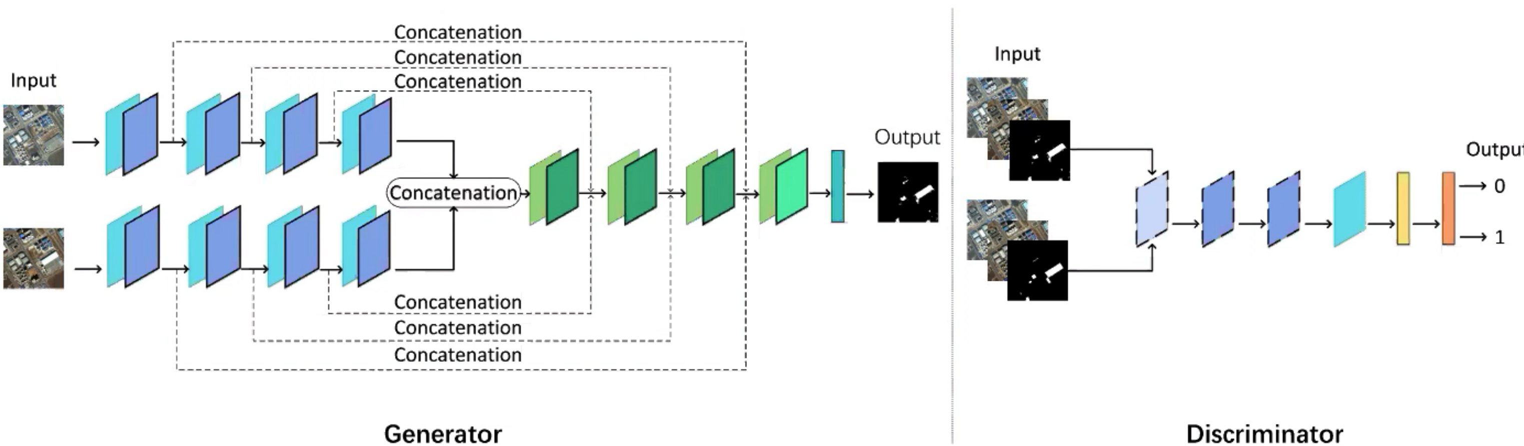
- ✓ Integrated change detection and land cover mapping network
- ✓ Traditional convolutional layers are replaced by residual blocks



Stine, R. R., & Matunis, E. L. (2018). High Resolution Semantic Change Detection. *Advances in Experimental Medicine and Biology*, *786*, 247–267. https://doi.org/10.1007/978-94-7-6621-1_14

Bi-temporal Change Detection with GAN

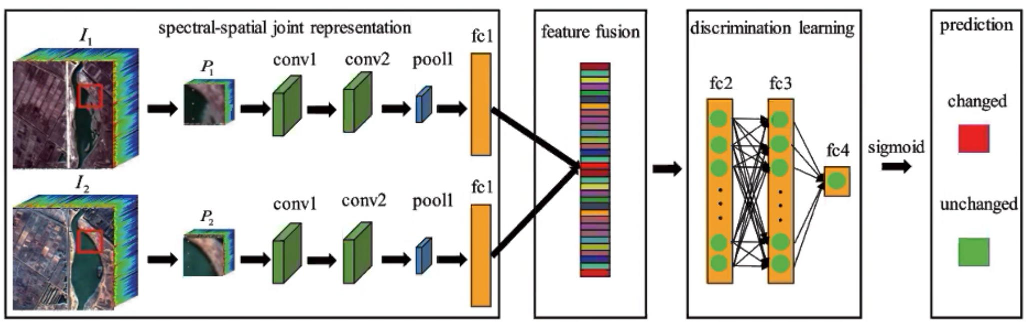
- ✓ Proposing an end-to-end dual-branch architecture (W-Net), with each branch taking as input one of the two bi-temporal images
- ✓ Calculating the difference in the feature domain rather than in the image domain
- ✓ Reformulating change detection as an image translation problem by applying the Generative Adversarial Network (GAN
- ✓ W-Net as the Generator of the GAN for change detection.



B. Hou, Q. Liu, H. Wang and Y. Wang, (2020) "From W-Net to CDGAN: Bitemporal Change Detection via Deep Learning Techniques," in IEEE Transactions on Geoscience and Remote Sensing, vol. 58, no. 3, pp. 1790-1802, doi: 10.1109/TGRS.2019.2948659.

Spectral-Spatial Joint Learning Network

- ✓ Spectral-Spatial Joint Learning Network (SSJLN)
- ✓ Contains of three parts: spectral-spatial joint representation, feature fusion, and discrimination learning
- ✓ Spectral-spatial joint representation is extracted from the Siamese CNN network
- ✓ Extracted features are fused to represent the difference information that proves to be effective for the change detection
- ✓ Discrimination learning to explore the underlying information of obtained fused features to better represent the discrimination
- ✓ Losses of the spectral-spatial joint representation procedure and discrimination learning



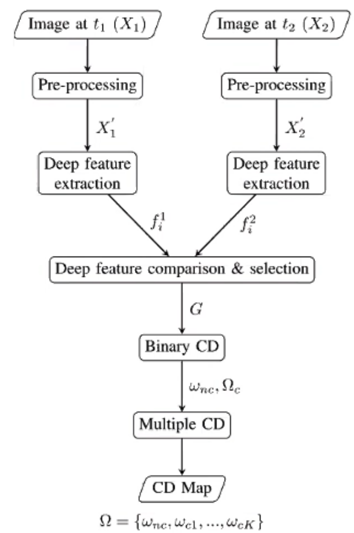
Zhang, W. (2019). The Spectral-Spatial Joint Learning for Change Detection in Multispectral Imagery, Remote Sensing, 11(3), 240.

Unsupervised Change Detection with Deep Change Vector Analysis (DCVA)

- ✓ Unsupervised Deep Change Vector Analysis for Multiple-Change Detection in VHR Images

- ✓ DCVA starts from a suboptimal pretrained multilayered CNN for obtaining deep features that can model spatial relationship among neighboring pixels and thus complex objects

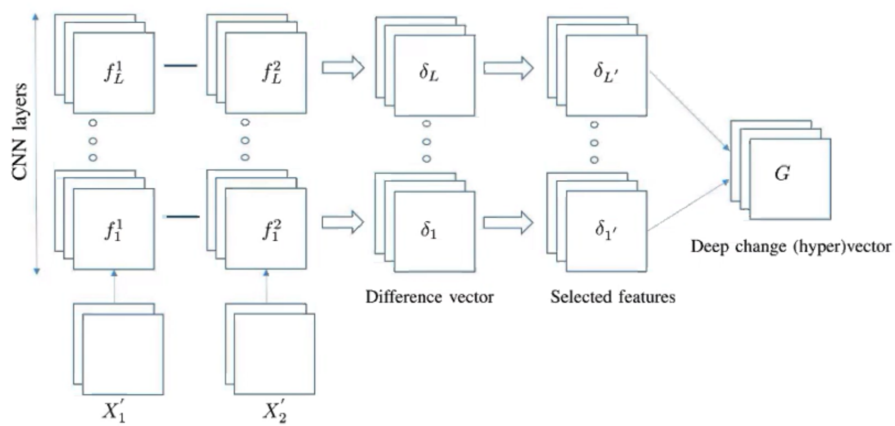
- ✓ Selected features from multiple layers are combined into a deep feature hypervector providing a multiscale scene representation



Saha, S., Bovolo, F., & Bruzzone, L. (2019). Unsupervised Deep Change Vector Analysis for Multiple-Change Detection in VHR Images. *IEEE Transactions on Geoscience and Remote Sensing*, *PP*, 1–17. https://doi.org/10.1109/TGRS.2018.2886643

Unsupervised Change Detection with Deep Change Vector Analysis (DCVA)

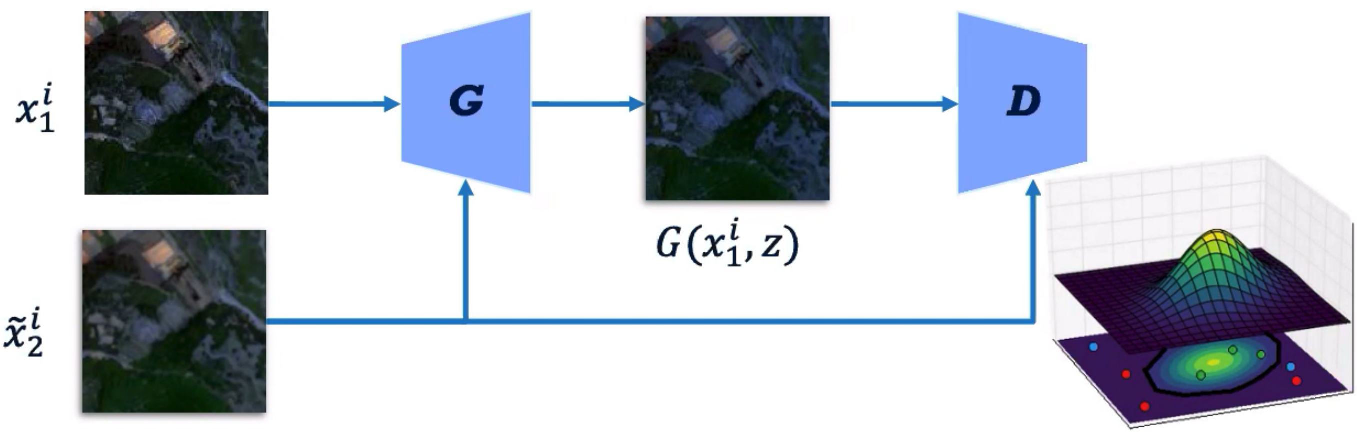
- ✓ Deep change vectors contain semantically rich information relevant to both binary and multiple CD
- ✓ Identification of relevant features, with feature selection strategy based on a variance measurement
- ✓ Multiple CD is performed by identifying the direction of changes after a compression of deep change vectors based on a binarization process and a subsequent clustering



Saha, S., Bovolo, F., & Bruzzone, L. (2019). Unsupervised Deep Change Vector Analysis for Multiple-Change Detection in VHR Images. *IEEE Transactions on Geoscience and Remote Sensing*, *PP*, 1–17. https://doi.org/10.1109/TGRS.2018.2886643

S2-cGAN: Self-Supervised Adversarial Representation Learning for Binary Change Detection in Multispectral Images

- ✓ Achieve a binary change detection with high performance **without** using any **labeled** multitemporal training set.
- ✓ Provide a **self-supervision** to train an end-to-end CD model.
- ✓ Proposing a Self-Supervised Conditional Generative Adversarial Networks (S2-cGAN) in the context of binary CD for RS images.

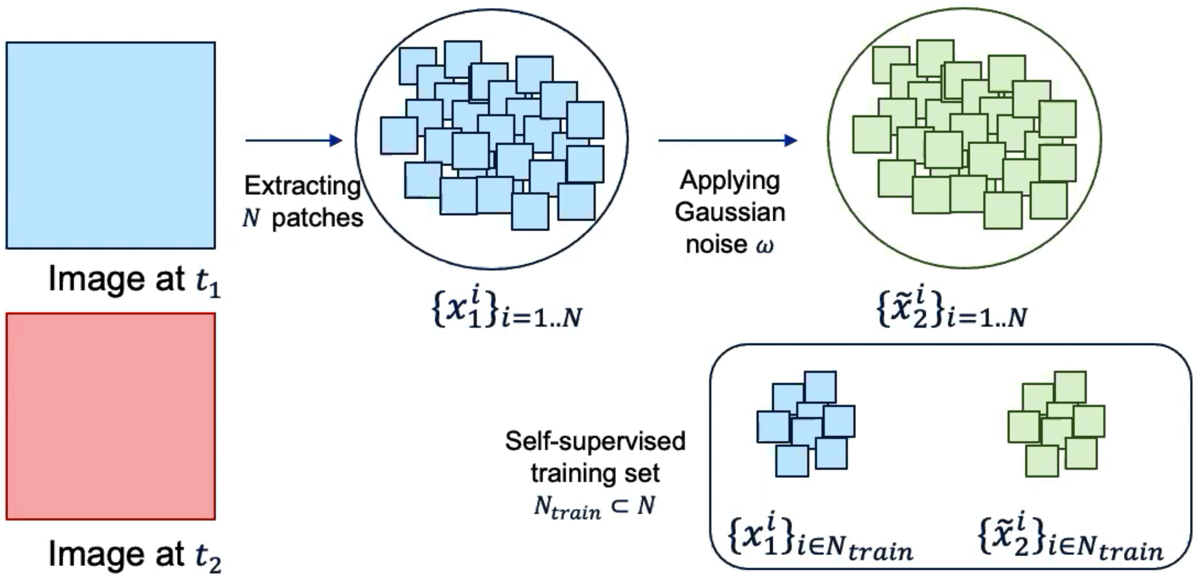


J. L. Holgado Alvarez, M. Ravanbakhsh, and B. Demir. (2020) "S2-cGAN: Self-Supervised Adversarial Representation Learning for Binary Change Detection in Multispectral Images." in press, IEEE International Geoscience and Remote Sensing Symposium.

S2-cGAN: Self-Supervised Adversarial Representation Learning for Binary Change Detection in Multispectral Images

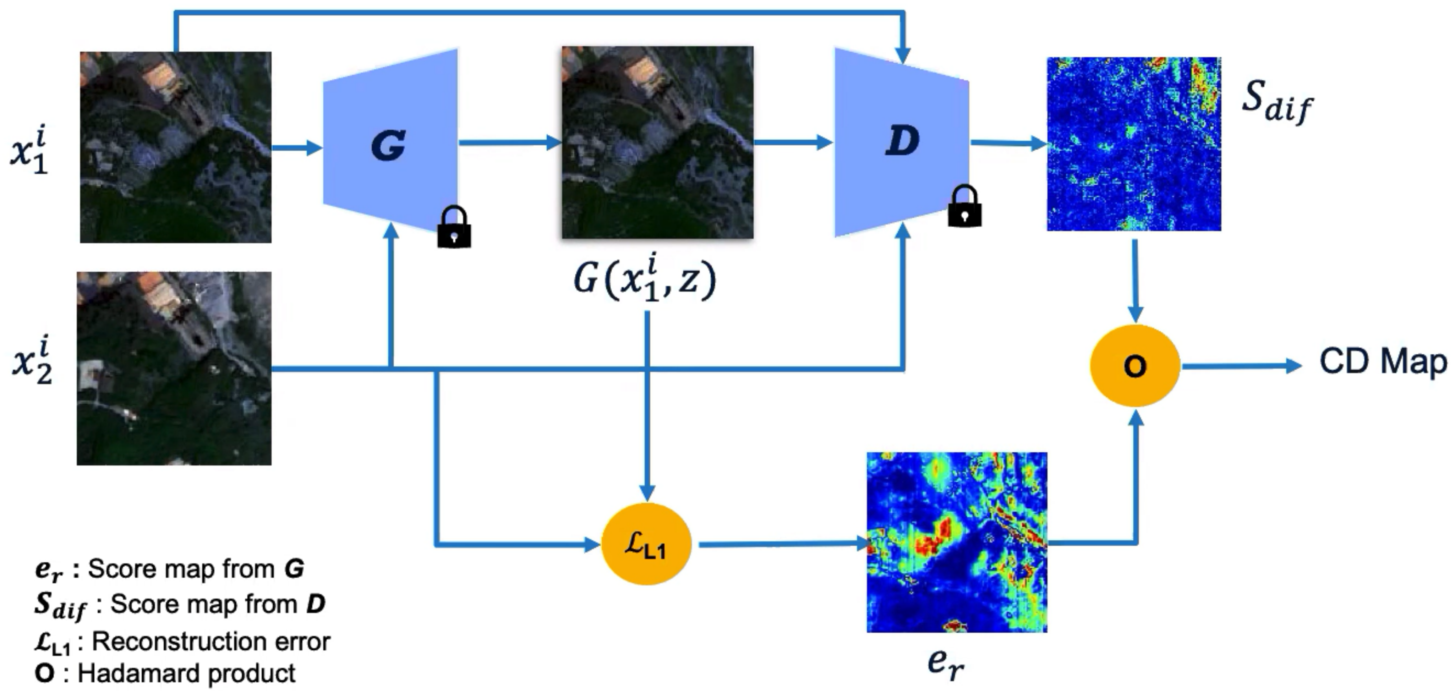
✓ Proposed method includes two steps:
1) Generating a self-supervised training set;
2) Learning the adversarial representation for CD.

✓ Self-supervised training set consists of pairs of unchanged samples that are reconstructed from a single image (at time $t1$) without using any human annotation effort.



S2-cGAN: Self-Supervised Adversarial Representation Learning for Binary Change Detection in Multispectral Images

✓ To detect the changes two score maps (differences maps) obtained from ***G*** and ***D*** are fused together.



$\boldsymbol{e_r}$: Score map from ***G***

$\boldsymbol{S_{dif}}$: Score map from ***D***

$\mathcal{L}_{L1}$: Reconstruction error

O : Hadamard product