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Heraklion, Greece

“Unsupervised Cloud Removal and Change Detection on Multi-Temporal Images via Unrolled Tensor Decomposition Network”

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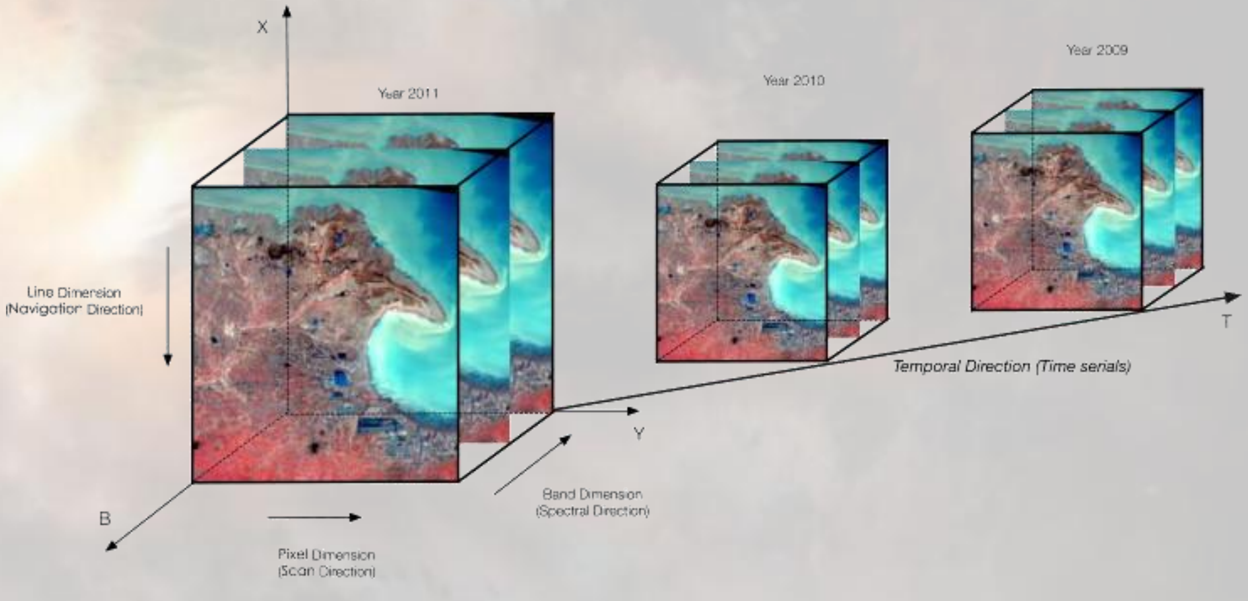
Multi-temporal Observations

- Massive timely and spatio-spectral observations
- Useful information for various applications
- Satellite data from multiple sources can contribute to various earth observation applications:
  - ❖ Disaster assessment
  - ❖ Change detection
  - ❖ Environmental monitoring

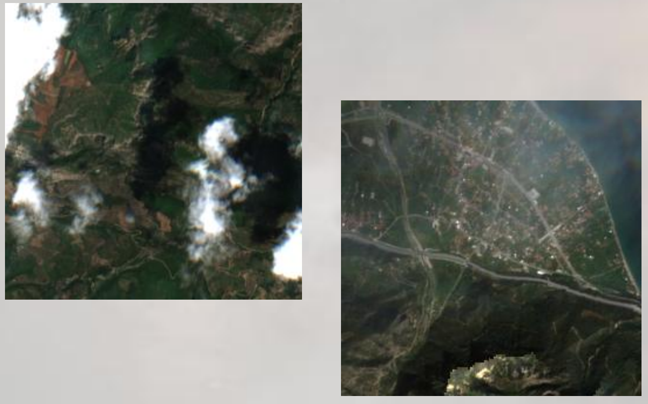


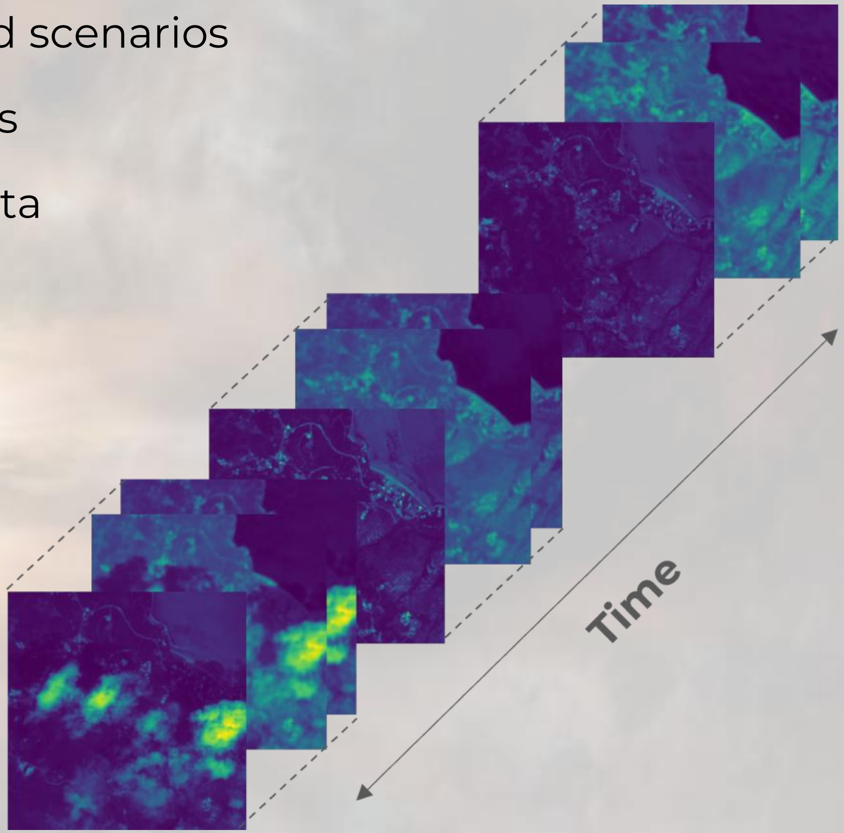
Change detection of extreme events in multi-temporal images

- Monitor and assess the impacts of extreme events
- Multitemporal images enable more accurate detection
- Identify changes in image time series
- Better understanding of their formation, development, and associated impacts

Challenges

- The location of actual changes is not available in real-world scenarios
- Cloud cover and cloud shadows can hinder further analysis
- Consider the structure of the multi-way relations of the data
- Leverage both spatio-spectral and temporal information
- High demands on their analysis process





Related Work

Unsupervised change detection in bi-temporal images:

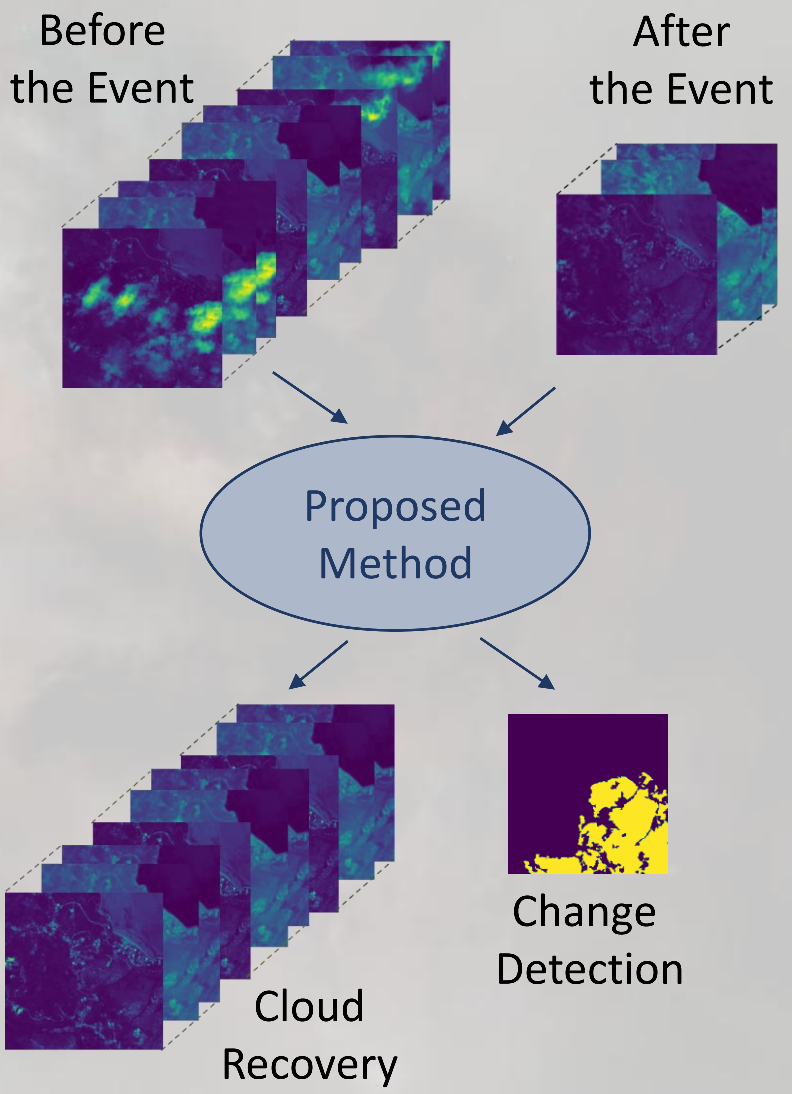
- Pixel-by-pixel analysis to generate a difference image
- Deep learning-based methods
- Tensor-based methods

Unsupervised change detection in multi-temporal images:

- *RaVÆn method*: A variational autoencoder is utilized to generate a latent representation of incoming sensor data.
- *CD-TDL method:* Detect the changes by comparing the features extracted from the representation of the images in the learned feature space using the Tensor Decomposition Learning method

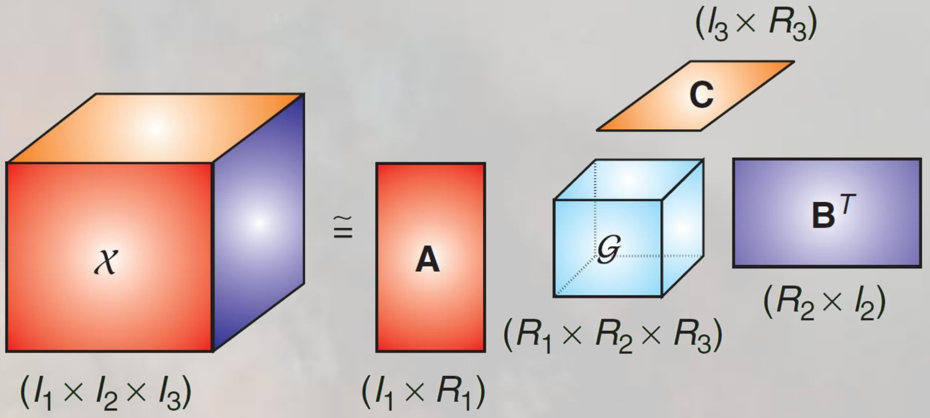
Proposed Method

- *Tensor-based unrolled network* that simultaneously reconstructs cloud-occluded regions and learns the feature space of the images
- *Impute the missing parts* of the images
- Effectively *detect the effects of extreme events* by comparing the learned representation of the images
- *Unsupervised* learning approach (lack of cloud-free observations and ground truth labels)
- Consider the structure of *high-dimensional data*
- Applied to *multi-temporal* multispectral images



Preliminaries

Tensor decomposition techniques:

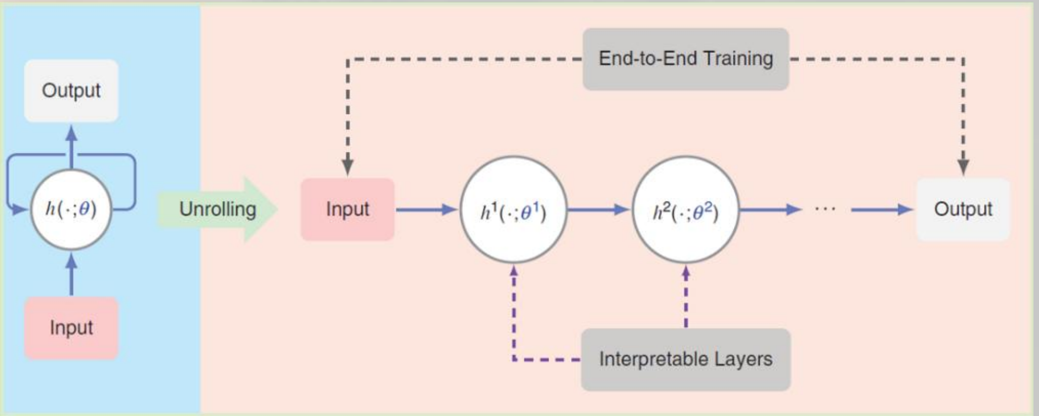


- Reduce the complexity of the representation space
- Capture high-order relationships in the data
- Used in machine/deep learning
- Tucker decomposition: $\mathcal{X} = \mathcal{G} \times_1 \boldsymbol{A} \times_2 \boldsymbol{B} \times_3 \boldsymbol{C}$

  Factor matrices = Set of basis functions onto which the data is projected

Algorithmic unrolling technique:

- Connection of iterative algorithms with neural networks
- Higher representation power than the iterative algorithms
- Better generalization than generic networks
- Fewer parameters and less training data



Optimization Problem

Our model is formulated by:

$$\min \frac{1}{2}\|\mathcal{Z} - \mathcal{G} \times_H \boldsymbol{D}_H \times_W \boldsymbol{D}_W \times_C \boldsymbol{D}_C \times_T \boldsymbol{D}_T\|_F^2 + \frac{1}{2}\|\mathcal{G} \times_T \boldsymbol{A}\|_F^2$$

$$\text{s.t. } \mathcal{P}_\Omega(\mathcal{Z}) = \mathcal{P}_\Omega(\mathcal{X})$$

By introducing the auxiliary variable $\mathcal{W}$, we solve the problem by minimizing the Lagrangian function:

$$\mathcal{L}(\mathcal{Z}, \mathcal{G}, \boldsymbol{D}_H, .., \boldsymbol{D}_T, \mathcal{W}, \mathcal{U}, \mathcal{Y}) = \frac{1}{2}\|\mathcal{Z} - \mathcal{G} \times_H \boldsymbol{D}_H \times_W \cdots \times_T \boldsymbol{D}_T\|_F^2$$

$$+\frac{1}{2}\|\mathcal{W}\|_F^2 + \mathcal{U} \cdot (\mathcal{W} - \mathcal{G} \times_T \boldsymbol{A}) + \frac{\rho}{2}\|\mathcal{W} - \mathcal{G} \times_T \boldsymbol{A}\|_F^2$$

$$+\mathcal{Y} \cdot (\mathcal{P}_\Omega(\mathcal{Z}) - \mathcal{P}_\Omega(\mathcal{X})) + \frac{\beta}{2}\|\mathcal{P}_\Omega(\mathcal{Z}) - \mathcal{P}_\Omega(\mathcal{X})\|_F^2$$

using ADMM. We optimize each variable alternatively while fixing the others.

Tensor Decomposition Network

Trainable Parameters: Factor matrices $\boldsymbol{D}_H, \boldsymbol{D}_W, \boldsymbol{D}_C, \boldsymbol{D}_T$, and the step sizes $\rho,\ \beta$

(the same for all layers)

At each **layer** l we update the variables:

- Core tensor $\mathcal{G} = (\mathcal{Z} \times_H \boldsymbol{D}_H^T \times_W \cdots \times_T \boldsymbol{D}_T^T + \mathcal{U} \times_T \boldsymbol{A} + \rho \mathcal{W} \times_T \boldsymbol{A}^T) \times_T (\boldsymbol{I} + \rho \boldsymbol{A}^T \cdot \boldsymbol{A})^{-1}$
- Auxiliary variable $\mathcal{W} = \frac{1}{1+\rho}(\rho \mathcal{G} \times_T \boldsymbol{A} - \mathcal{U})$
- Recovered tensor $\mathcal{Z} = \mathcal{R}_\Omega(\mathcal{G} \times_H \boldsymbol{D}_H \times_W \cdots \times_T \boldsymbol{D}_T - \mathcal{P}_\Omega(\mathcal{Y}) + \beta \mathcal{P}_\Omega(\mathcal{X}))$

  where $\mathcal{R}_\Omega(x) = \begin{cases} \frac{1}{1+\beta}, & x \in \Omega \\ 1, & \text{otherwise} \end{cases}$
- Lagrange multipliers: $\mathcal{U}^{l+1} = \mathcal{U}^l + \rho(\mathcal{W} - \mathcal{G} \times_T \boldsymbol{A}),$

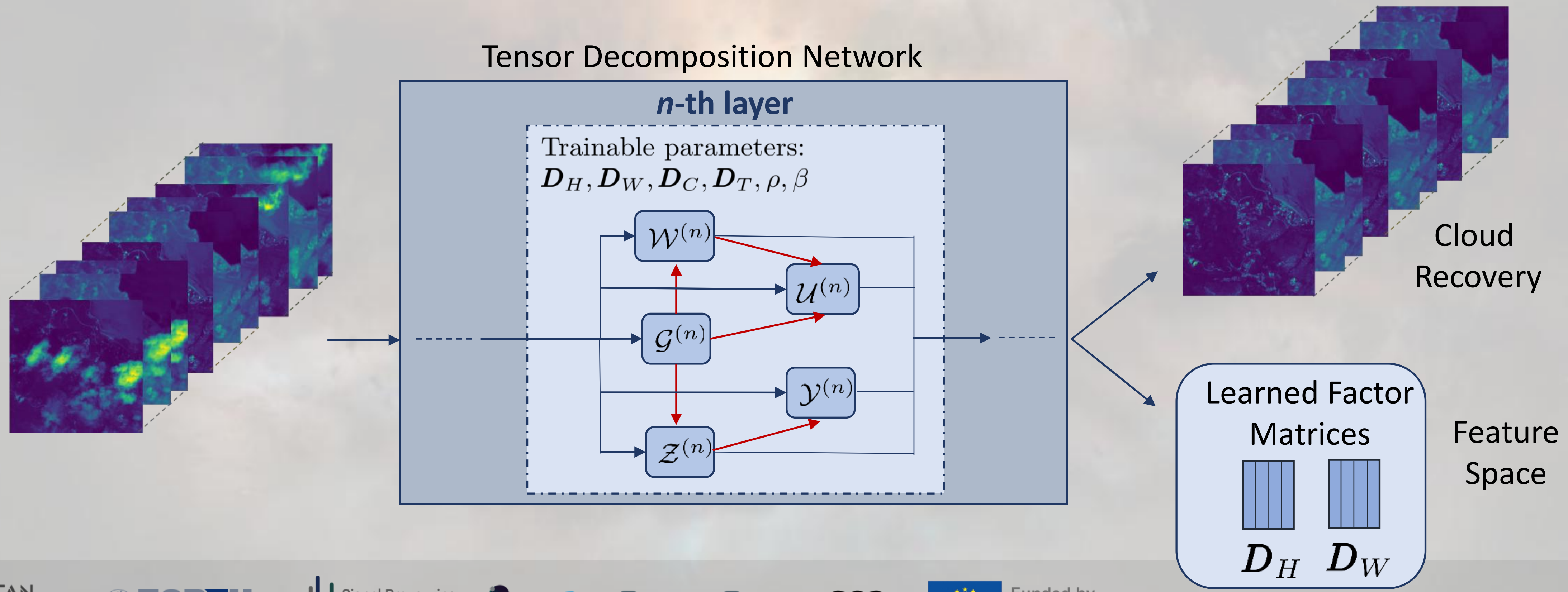
  $\mathcal{Y}^{l+1} = \mathcal{Y}^l + \beta(\mathcal{P}_\Omega(\mathcal{Z}) - \mathcal{P}_\Omega(\mathcal{X}))$

Loss function $= \mathrm{MAE}(\mathcal{P}_\Omega(\mathcal{X}), \mathcal{P}_\Omega(\mathcal{Z}^L)) + TotalVariation_T(\mathcal{Z}^L)$

where L is the number of layers.

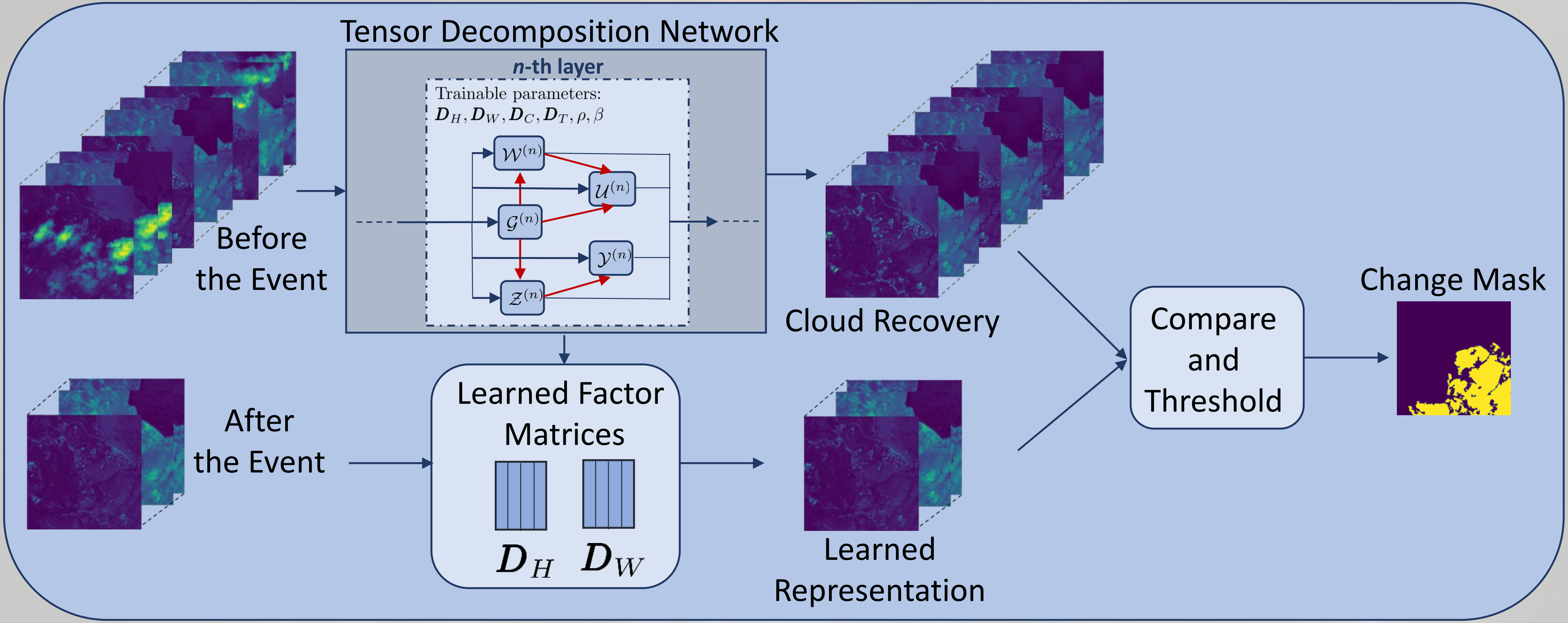
Training Process: Tensor Decomposition Network

- Impute the cloud-occluded regions of the image time series
- Learn the feature space, e.g., the factor matrices
- Use available satellite image time series for training



Run-time Phase: Change Detection Method

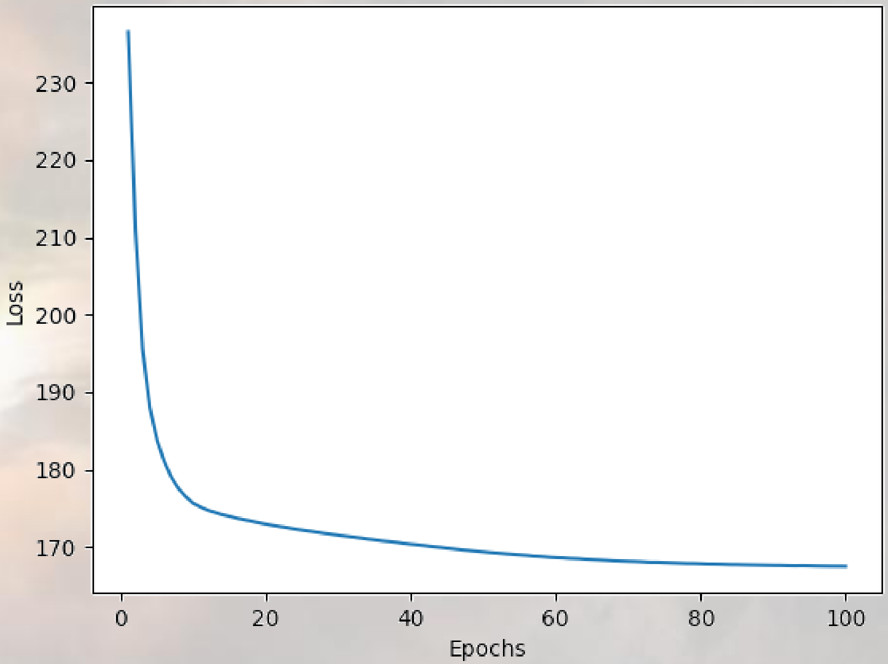
It is applied to small patches of the images, and we classify each pixel by examining the patch around it.



Experiments

Training:

- *Samples:* 46080 patches of size 8 x 8 x 13 x History acquired from a location in Attica for an entire year (2022)
- 10 layers
- Reduction of spectral and temporal dimensions



Testing Dataset

- Wildfires in different locations in Greece
- Multi-temporal multi-spectral optical images acquired by Sentinel-2
  (12 images before the event, 1 image after the event)
- 13 spectral bands, 10m pixel resolution
- Patches of images of each location of size 256 x 256
- Event masks representing the affected areas

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Recovery Results

Change Detection Results

Table: *Change detection performance of the proposed method for different numbers of history frames at 5 different locations.*

AUPRC	Eastern Peloponnese	Corfu	Euboea Prefecture	Attica (Koropi)	Korinthia
3 History Frames	0.8980	0.8397	0.9174	0.9045	0.7904
12 History Frames	**0.9813**	**0.9650**	**0.9813**	**0.9065**	**0.8923**

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Comparison

Table: *Comparison of the proposed method with the existing unsupervised change detection approaches for multitemporal data at 5 different locations, using 3 history frames.*

AUPRC	Eastern Peloponnese	Corfu	Euboea Prefecture	Attica (Koropi)	Korinthia
Proposed Method	**0.8980**	**0.8397**	**0.9174**	**0.9045**	**0.7904**
CD-TDL	0.8793	0.8021	0.8895	0.8444	0.7209
RaVÆn	0.8279	0.7834	0.8259	0.6909	0.6576

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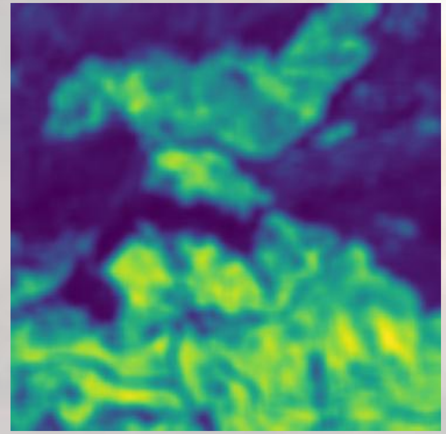
Predicted Maps

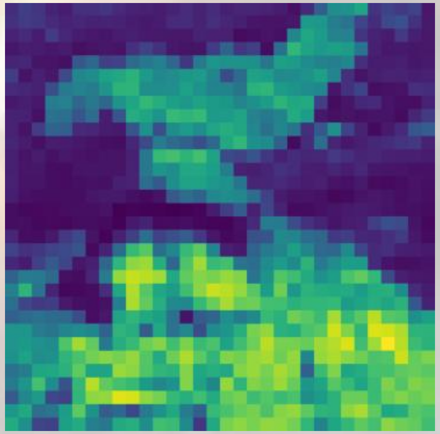
Before Fire

After Fire

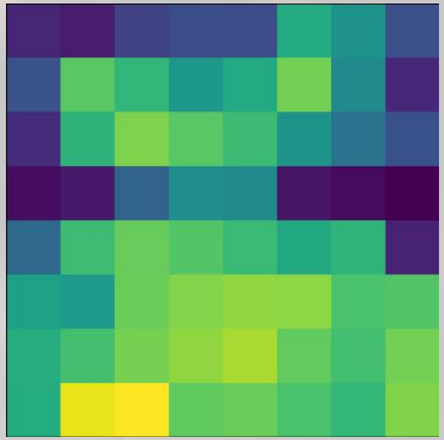
Change Mask



Prediction-
Proposed Method
AUPRC: 0.9936



Prediction-
CD-TDL
AUPRC: 0.9857



Prediction-
RaVÆn
AUPRC: 0.9051

Conclusion

- Proposed unsupervised tensor-based unrolled network
- Simultaneous cloud removal and change detection of extreme events effects
- Applied to multitemporal observations
- Tensor decomposition in the deep learning context
- Experiments on real satellite images of wildfire event detection

Thank you