Hotspot Detection of Coastal Regions

Kathrin Rack*[1], Wadim Koslow[1], Alexander Rüttgers[1]

[1]German Aerospace Center (DLR), Institute for Software Technology, Cologne, Germany
*kathrin.rack@dlr.de

Introduction

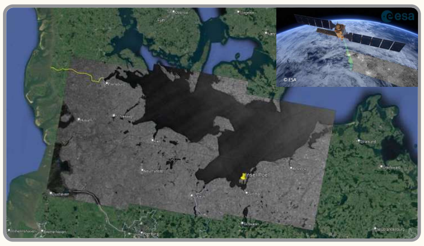
The increasing sea level and number of extreme weather events due to the climate change, affects and imperils the coastal regions and with it the people and logistics located in these regions.

In order to detect threatening trends, we develop an **AI based hotspot detection software applying unsupervised methods.**

Image Data

The data we process are time series of **Synthetic Aperture Radar (SAR)** images. Advantages of SAR data are the

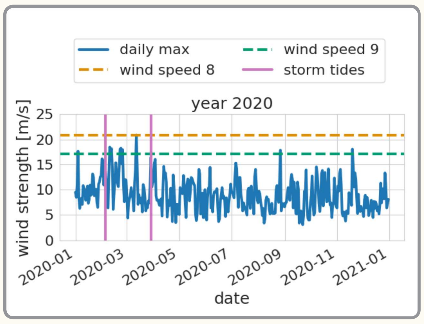
- wavelength $\lambda = 3.75 - 7.5\,\mathrm{cm}$
- day-and-night capability
- all-weather capability
- variety of information (amplitude, phase, and coherence information)



As illustrated, we concentrate on the **Baltic and North Sea**.

Weather data

The provided data is unlabeled. Therefore, we look at the wind speed and storm tides as shown here:



To examine our method we compare results from days with different weather conditions.

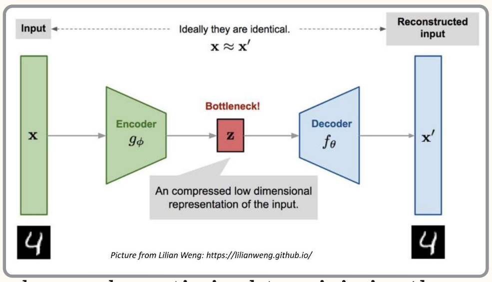
Acknowledgments

We thank our partners from the RESIKOAST project and especially Paola Rizzoli and Luca Dell Amore from the DLR Microwaves and Radar Institute.

Convolutional Autoencoder

The tool we present here is based on a Convolutional Autoencoder (CAE).

The **encoder** reduces the resolution of the image.



The **decoder** reconstructs the image from the low resolution representation.

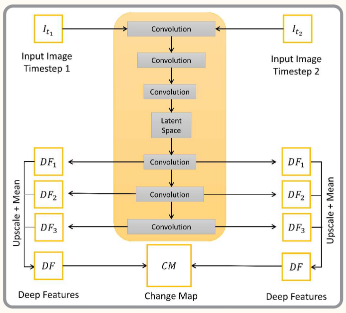
The **encoder and decoder can be optimized to minimize the reconstruction loss.**

Generating Bitemporal Change Maps

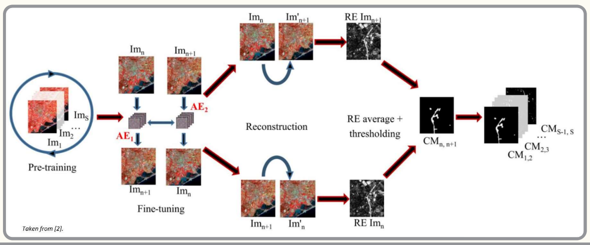
Change maps (CMs) are images were regions of remarkable changes are marked. We apply existing methods for generating CMs for optical satellite image time series and evaluate the ability to be of advantage for our SAR data.

Deep Feature extraction

As suggested in [1], we extract *a priori* chosen hidden layers from the decoder part. The decoder layers can provide interesting spatial information about the change.
The CAE processes the images separately. A bilinear interpolation upscales and merges all extracted features into one feature map. A CM is created by comparing the feature maps of two timesteps.



Temporal Change Reconstruction

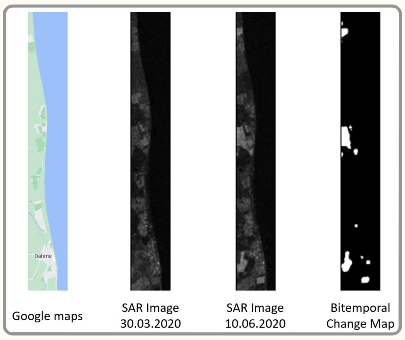


As suggested in [2], we finetune a pretrained CAE to reconctruct the image I_t of time t from I_{t+1} and vice versa. The magnitude of the reconstruction error from both direction refers to the amount of change the region underwent from t to $t+1$.

The final change maps are generated from the model outputs by applying a thresholding method, e.g., Otsu's thresholding [3].

Preliminary results

First results, generated with the Temporal Change Method on a region of the Baltic Sea, show promising change detection capabilities.



Outlook

In the future we plan to

- automatically analyze the **spatiotemporal dynamics**. This includes
  - applying image segmentation within the changed areas,
  - grouping the resulting subareas into evolutional graphs and
  - performing a clustering [2].
- examine other architectures as, for instance, the **vision transformer network** [4] and compare the results of all approaches.

References

[1] L. Bergamasco et al., IEEE Transactions on Geoscience and Remote Sensing 60, (2022)
[2] E. Kalinicheva et al., IEEE J. of Sel. Topics in Appl. Earth Obs. and Rem. Sens. 13, 1450 (2020)
[3] N. Otsu, IEEE transactions on systems, man, and cybernetics 9, 1 (1979)
[4] P. Mishra et al., 2021 IEEE 30th International Symposium on Industrial Electronics (ISIE) (2021)