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GraphCast for SITS

Forecasting water resources from satellite image time series using a graph-based learning strategy

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CONTEXT

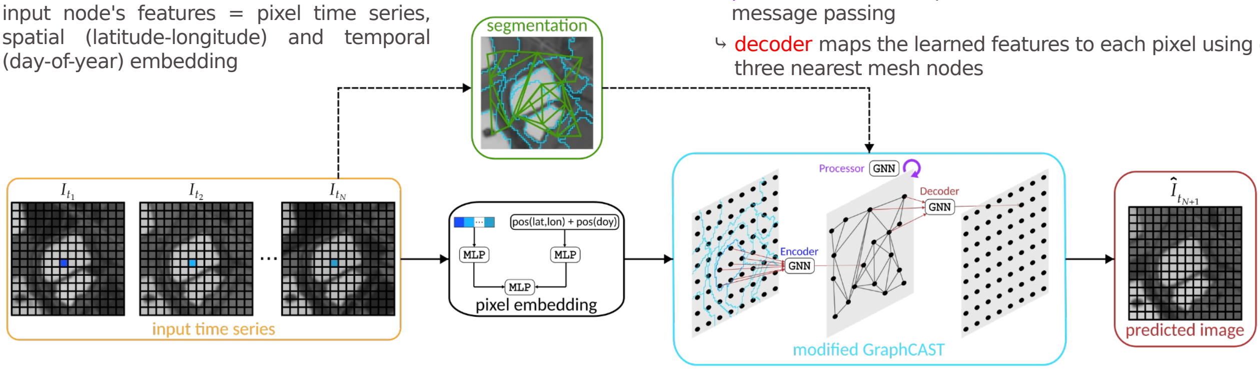
- ⊳ Constellations of satellites with high spatial and temporal resolution enable precise and dynamic resource monitoring
- ⊳ **Graph-based learning** can be used to exploit spatio-temporal dependencies in **Satellite Image Time Series** (SITS) [1]
- ⊳ **GraphCast** is a state-of-the-art model for global meteorological forecasting based on graph neural networks [2]

How to adapt a model for global meteorological forecasting like GraphCast to a monitoring task of local water resources from satellite image time series?

METHODOLOGY

⊳ **Objective:** forecast the next image of a sequence of N satellite images

- ⊳ Use of a **single region-specific mesh**
  - ↳ SLIC segmentation applied to the stack of input images
  - ↳ input node's features = pixel time series, spatial (latitude-longitude) and temporal (day-of-year) embedding
- ⊳ **Encoder-processor-decoder** architecture
  - ↳ encoder projects the pixel's features into the mesh nodes
  - ↳ processor learns representations of the mesh nodes via message passing
  - ↳ decoder maps the learned features to each pixel using only the three nearest mesh nodes



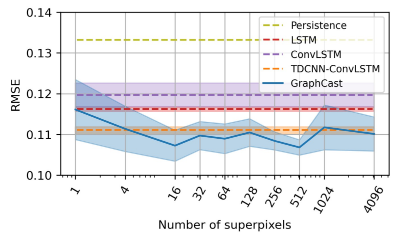
DATA & RESULTS

SEN2DWATER dataset [3]

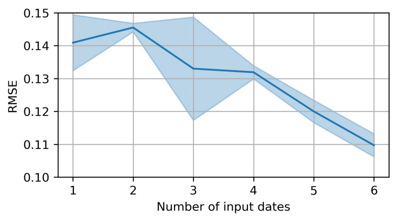
- ⊳ consisted of Sentinel-2 time series
- ⊳ gathered from July 2020 to Dec. 2022
- ⊳ over 17 basins in Spain and Italy
- ⊳ at a 10 m spatial resolution
- ⊳ about one cloud-free image every 2 months
- ⊳ 3 682 NDWI patches of size 64 × 64 pix

	# Params	RMSE ↓	PSNR ↑	SSIM ↑	Runtime/epoch (s)
Input average	-	0.1550	23.32	0.7465	-
Persistence	-	0.1332	25.03	0.7897	-
LSTM	17,345	0.1162$\pm$0.0005	25.53$\pm$0.05	**0.8282**$\pm$0.0005	26
ConvLSTM	150,721	0.1197$\pm$0.0029	25.28$\pm$0.19	0.8113$\pm$0.0030	31
TDCNN-ConvLSTM	407,681	0.1111$\pm$0.0008	25.68$\pm$0.08	0.8083$\pm$0.0008	55
Ours	228,673	**0.1097**$\pm$0.0035	**26.42**$\pm$0.27	0.8170$\pm$0.0070	49

Influence of the number of superpixels



Influence of the input time-series length



PROSPECTS

- ⊳ Explore the capability of GraphCast roll-out
- ⊳ Analyze more complex (multi-)mesh, especially for large patch predictions

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3. Mauro, F., Rich, B., Muriga, V. W., Janku, F., Sebastianelli, A., & Ullo, S. L. (2023). SEN2DWATER: A Novel Multispectral and Multitemporal Dataset and Deep Learning Benchmark for Water Resources Analysis. In IEEE International Geoscience and Remote Sensing Symposium (IGARSS) (pp. 297-300).