Deep Learning for Cyclone-induced Storm Surge Forecasting

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3rd MedCyclones Workshop & Training School

17/07/2024

A brief introduction

Hello, it's Patrick!

- Internal Research Fellow @ ESA since 12/2023

- before: PhD @ TUM in Remote Sensing,

  - satellite image reconstruction
  - uncertainty quantification
  - sensor & data fusion
  - change detection

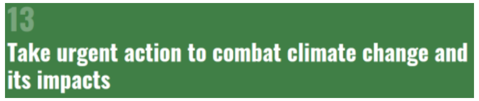
Recent research directions

- short-term forecasting of 1) storm surges & 2) flood maps

  <u>resulting products:</u>
  - time series prediction of storm surges
  - flood inundation map forecast

  <u>potential ROI:</u>
  - Mediterranean sea, EU overseas, developing states

SUSTAINABLE DEVELOPMENT GOALS



Overview: Needs & Interests

More meteorological events that drive compound coastal flooding are projected under climate change

Emanuele Bevacqua, Michalis I. Vousdoukas, Giuseppe Zappa, Kevin Hodges, Theodore G. Shepherd, Douglas Maraun, Lorenzo Mentaschi & Luc Feyen

Communications Earth & Environment **1**, Article number: 47 (2020) | Cite this article

Article | Open access | Published: 16 April 2020

Sea-level rise exponentially increases coastal flood frequency

Mohsen Taherkhani, Sean Vitousek, Patrick L. Barnard, Neil Frazer, Tiffany R. Anderson & Charles H. Fletcher

Scientific Reports **10**, Article number: 6466 (2020) | Cite this article

Satellite imaging reveals increased proportion of population exposed to floods

B. Tellman, J. A. Sullivan, C. Kuhn, A. J. Kettner, C. S. Doyle, G. R. Brakenridge, T. A. Erickson & D. A. Slayback

Nature **596**, 80–86 (2021) | Cite this article

UNDP

Climate change's impact on coastal flooding to increase 5-times over this century, putting over 70 million people in the path of expanding floodplains, according to new UNDP and CIL data

Related Frameworks & Initiatives

esa

Copernicus Europe's eyes on Earth

Emergency Management Service

3rd MedCyclones Workshop & Training School
15–19 July 2024 | ESA-ESRIN | Frascati (Rome), Italy

SUSTAINABLE DEVELOPMENT GOALS

11 Make cities and human settlements inclusive, safe, resilient and sustainable

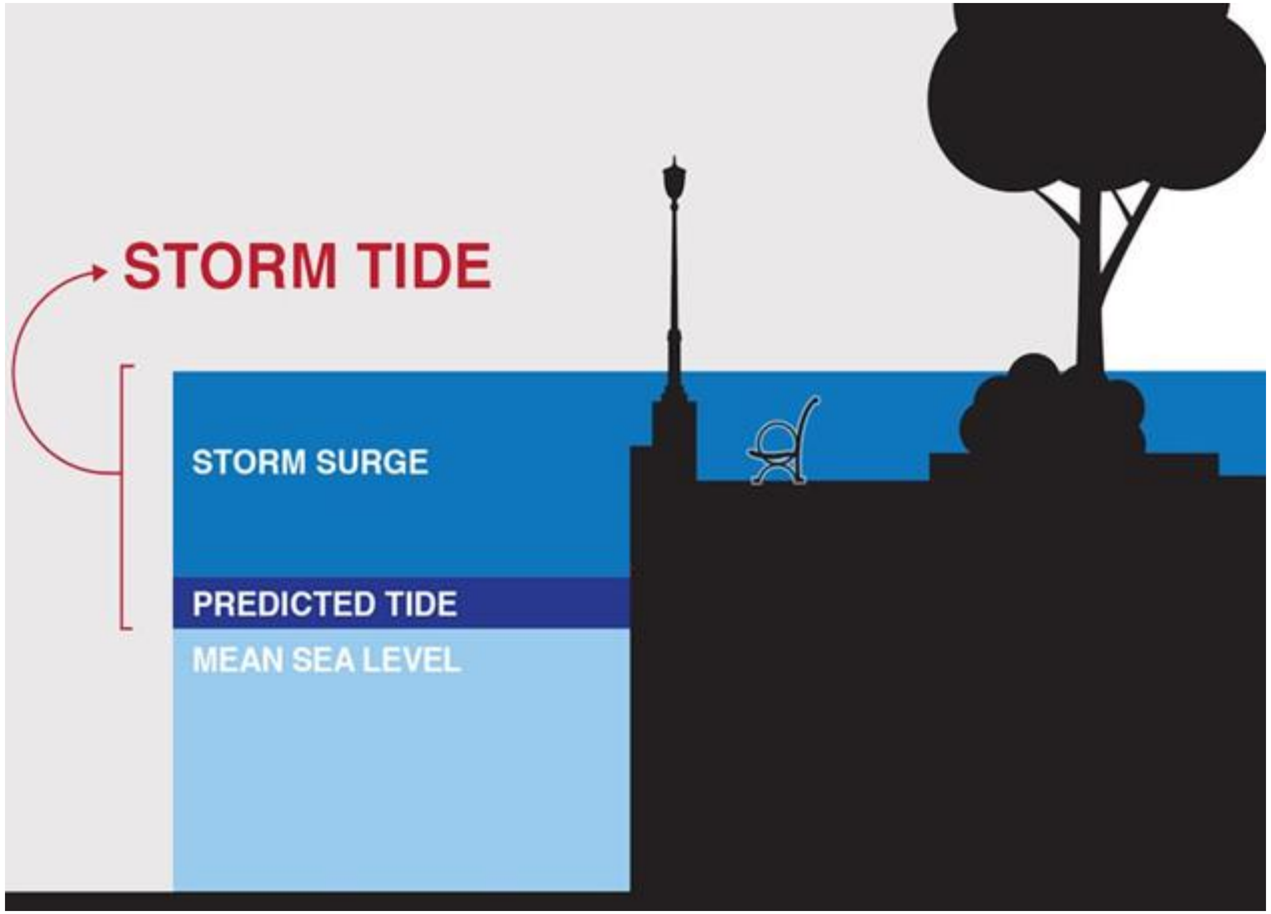
13 Take urgent action to combat climate change and its impacts

Small Island Developing States

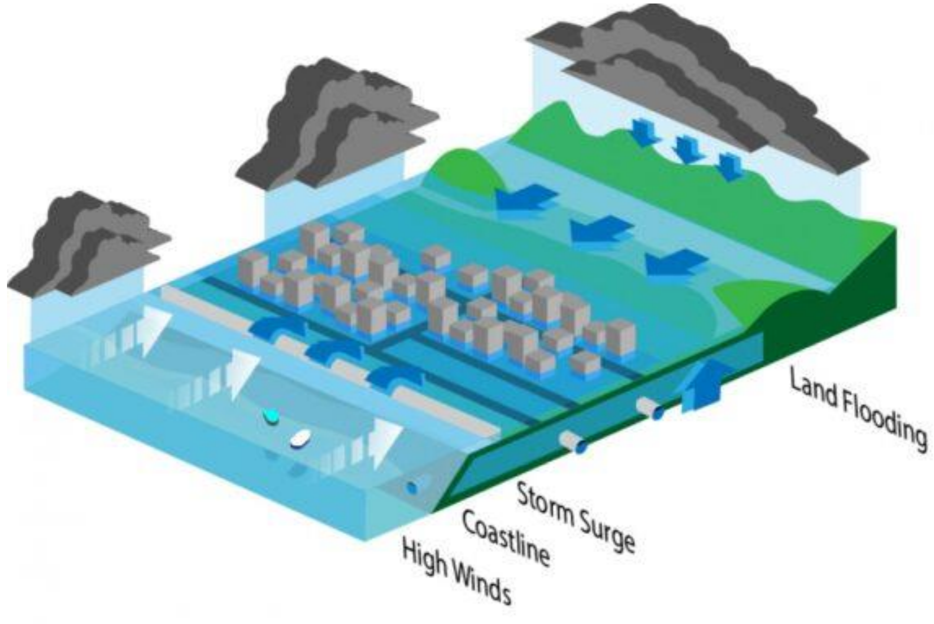
Related Goals

2 5 6 7 12 13 14 15 17

Overview: Background



https://oceanservice.noaa.gov/facts/stormsurge-stormtide.html



Mean Sea Level

- static, but subject to climate change

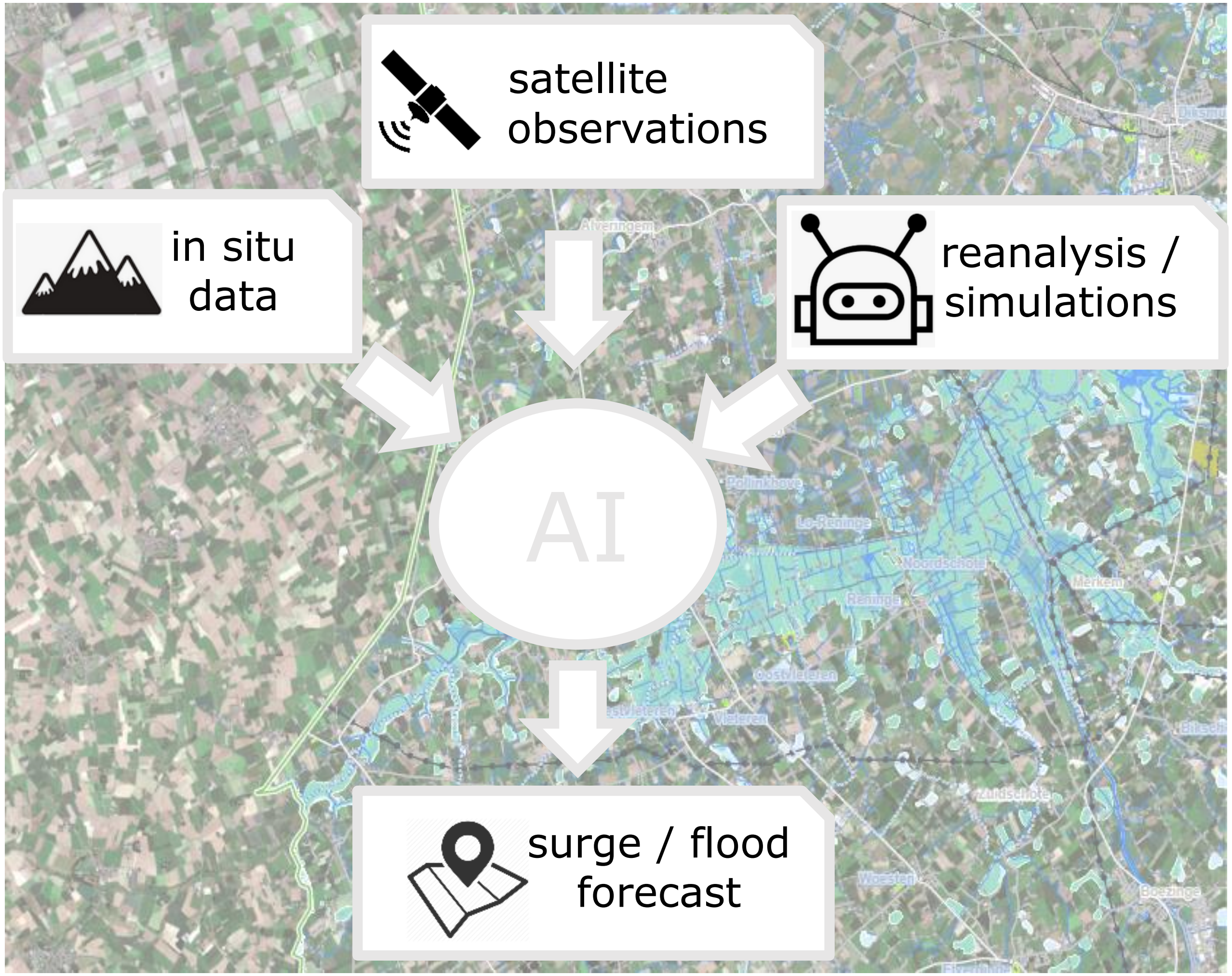
Tides

- rhythmic, driven by astronomical matters

Storm surge

- dynamic, caused by extreme weather

Overview: Needs & approach



Needs

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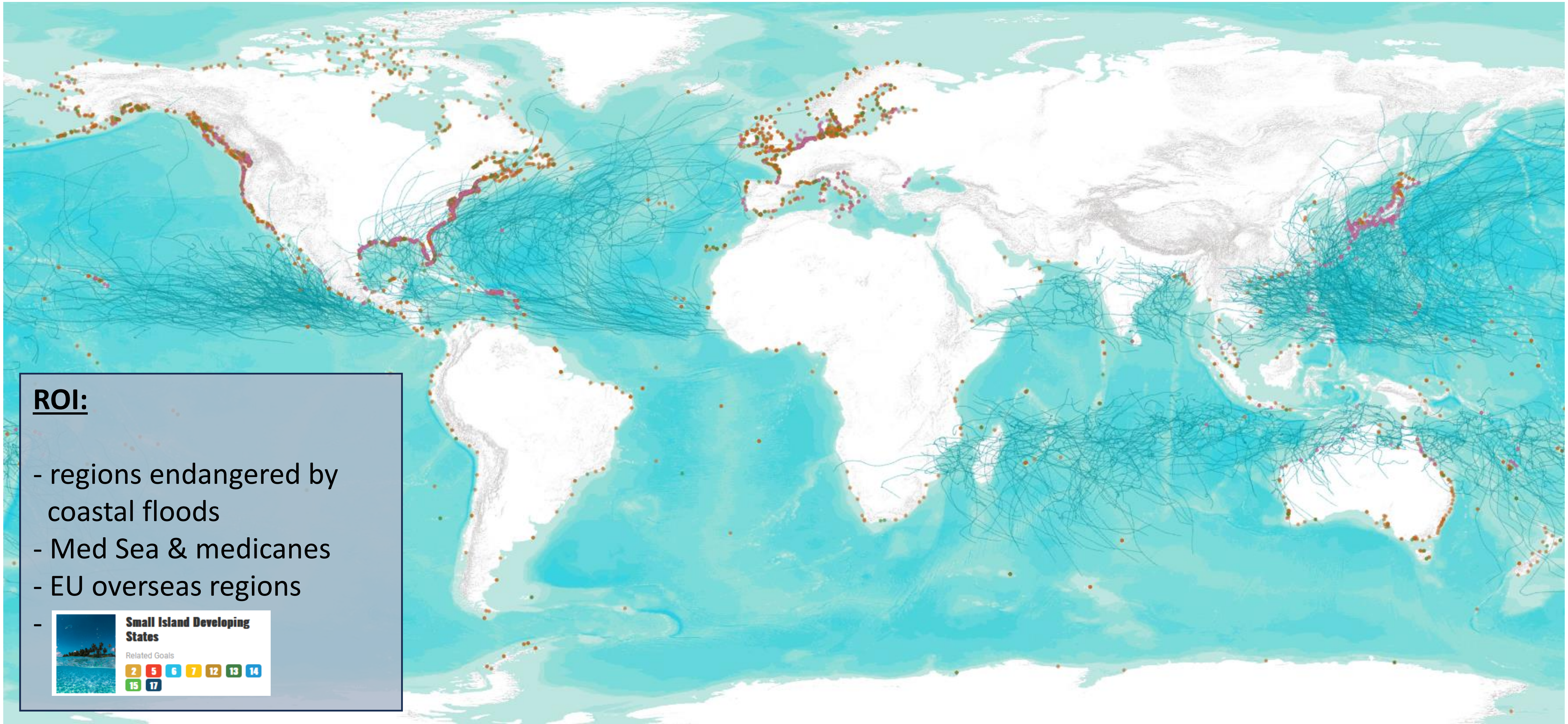
Our approach

- combine AI forecasting with data from
  - dense satellite observations
  - sparse in-situ recordings
  - static geospatial characteristics

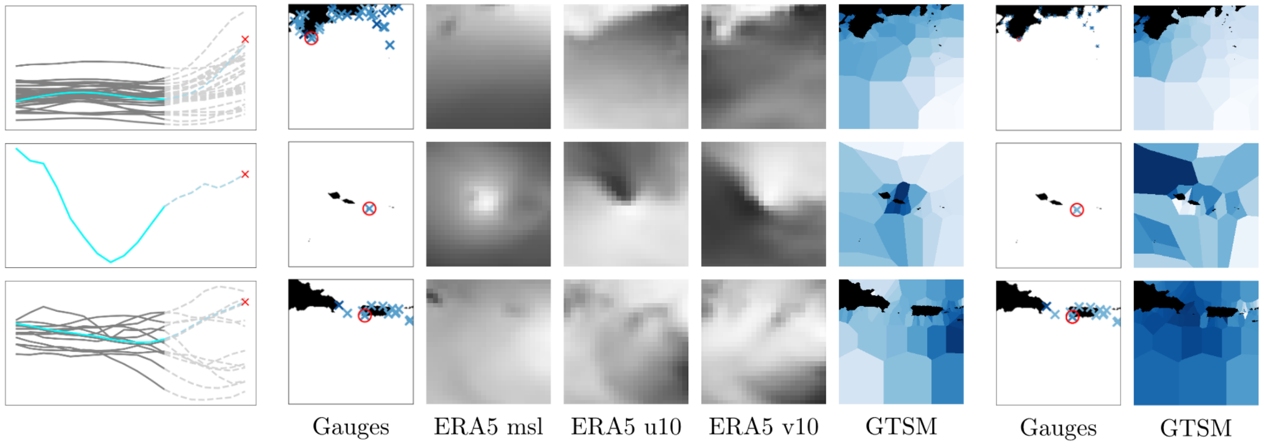
Map of in-situ gauges & cyclone tracks 2014-19



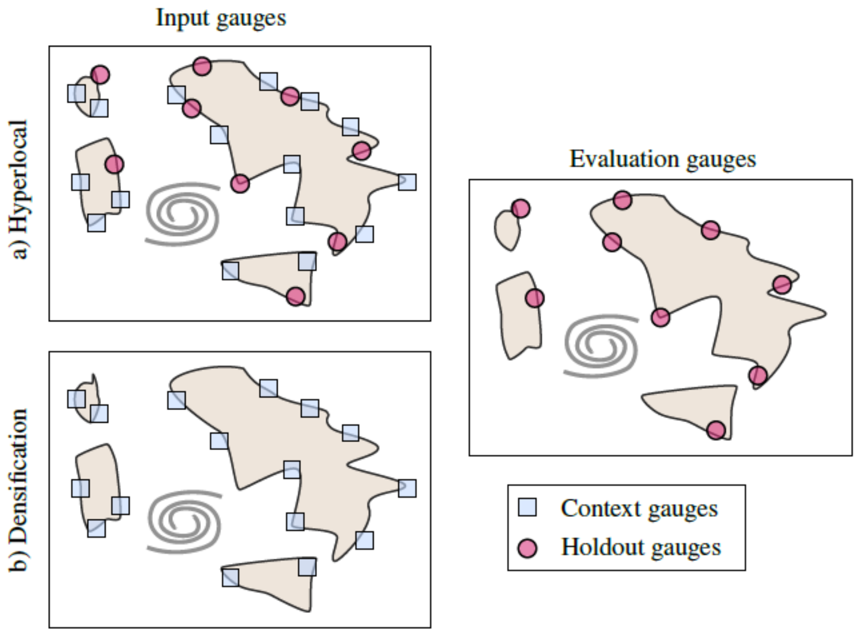
ROI:

- regions endangered by coastal floods
- Med Sea & medicanes
- EU overseas regions
-

Task & experimental setup



(a) In situ time series. (b) Input (c) Target



Task

- IN: time series data of

  1. sparse in-situ tidal gages
  2. ERA5 atmospheric state
  3. ocean state simulations

- OUT: image of future storm surge @ lead time L

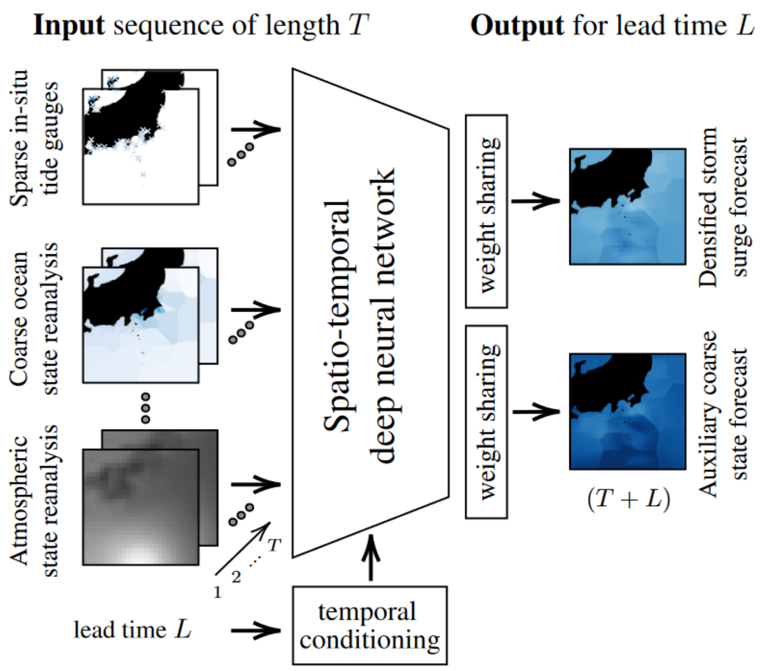
  1. forecast trained with tidal gauges
  2. and with ocean state

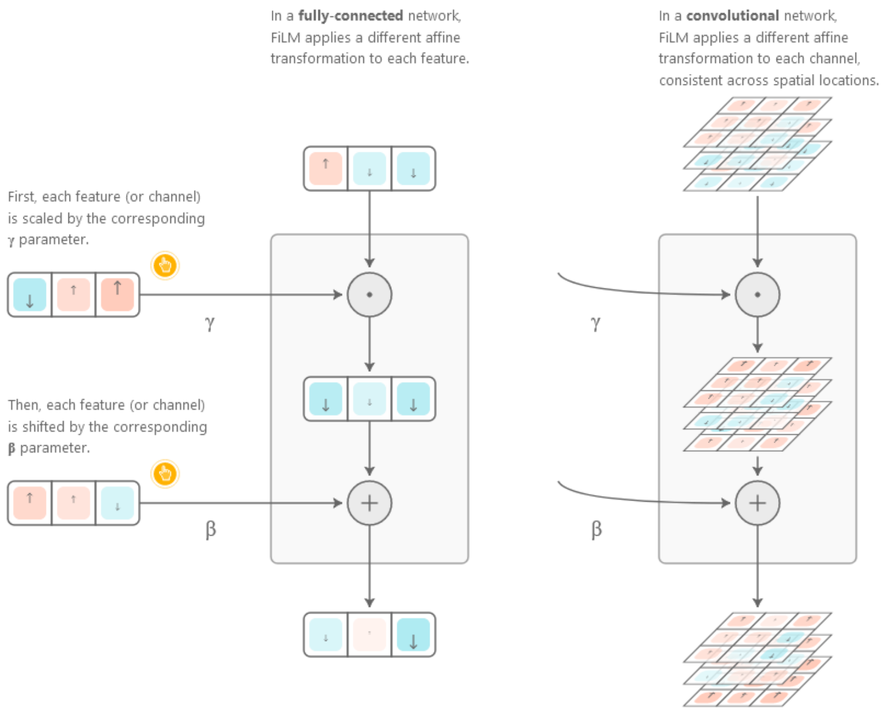
Experimental protocols

a) hyperlocal:
hold-out target gauges are provided within input time series

b) densification:
hold-out target gauges are NOT provided within input time series

Our approach





Network architecture & technicalities

- U-Net backbone, with a lightweight temporal attention module
- temporal conditioning imputes lead time dependency via Feature-wise linear Modulation (FiLM)

Densification

- CONV kernels at the output layer are broadcasting predictions across (un-)labelled pixels
- additionally: input data dropout, supervision on auxiliary output

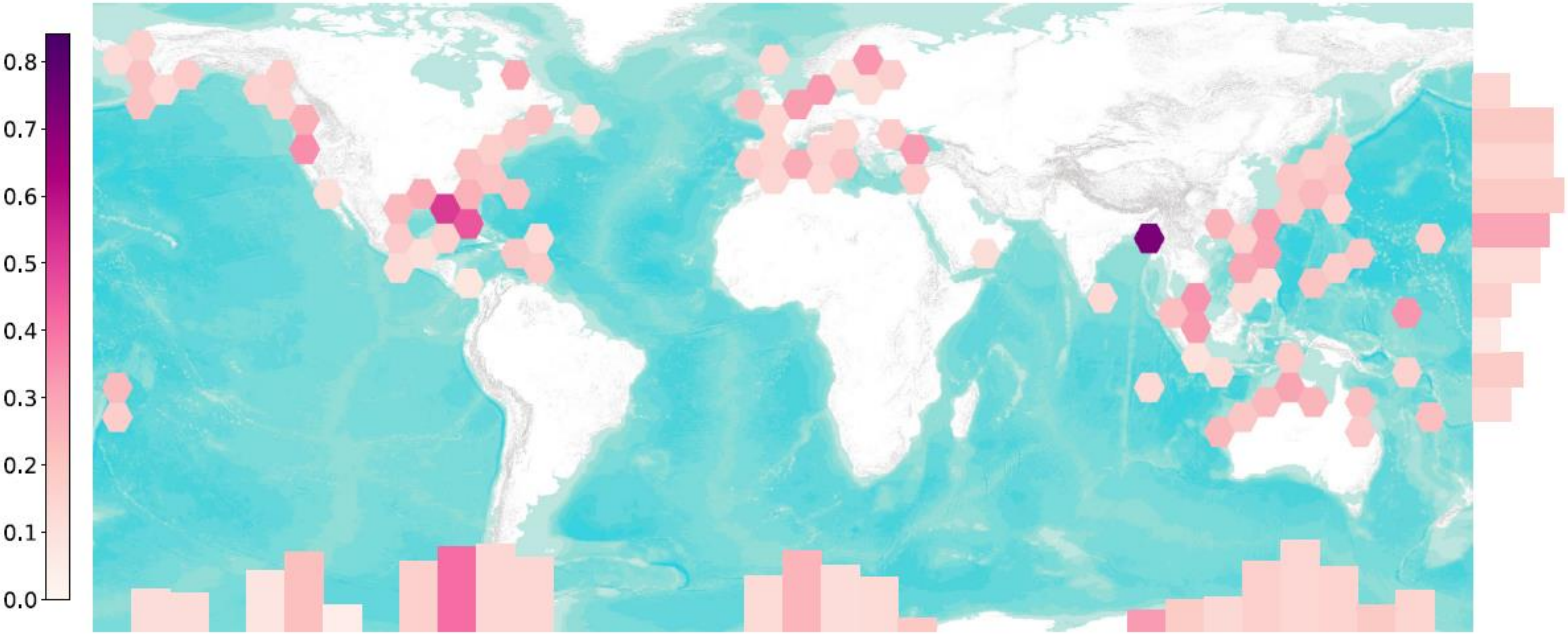
Outcomes: Main results

Model	Hyperlocal		Densification	
	↓ MAE (std)	↓ MSE (std)	↓ MAE (std)	↓ MSE (std)
seasonal average	0.281 (0.313)	0.177 (0.539)	—	—
input average	0.267 (0.295)	0.158 (0.452)	—	—
input extrapolation	0.182 (0.239)	0.090 (0.342)	—	—
GTSM extrapolation [23]	—	—	0.351 (0.643)	0.536 (4.744)
LSTM [11, 37]	0.166 (0.282)	0.107 (0.759)	—	—
ConvLSTM [33, 37]	0.162 (0.267)	0.098 (0.691)	—	—
FiLM U-TAE [7, 27]	**0.158 (0.209)**	**0.069 (0.248)**	0.190 (0.260)	**0.104 (0.535)**
MaxVIT U-Net [1, 38]	0.160 (0.212)	0.070 (0.263)	**0.178 (0.273)**	0.106 (0.587)

Results

- the hyperlocal setting is easier than the densification setting
  -> input gauges are informative
- all deep learning approaches outperform conventional approaches, transformers outperform LSTM models
- FiLM U-TAE outperforms MaxVIT U-Net
  -> temporal attention is more beneficial than spatial attention

Outcomes: Errors as a function of location



Outcomes: Ablation experiments

Table 2. **Repeated Measures.** Evaluation of FiLM U-TAE with varying numbers of input time points T, flexibly accommodated for via temporal self-attention. Longer inputs tend to be beneficial.

input length T	↓ MAE (std)	↓ MSE (std)	↑ NNSE
6	0.194 (0.282)	0.115 (0.587)	0.551
12	0.190 (0.260)	0.104 (0.535)	0.556
18	**0.180 (0.230)**	**0.085 (0.510)**	**0.573**
24	**0.180 (0.230)**	**0.085 (0.510)**	0.571

Table 3. **Lead Time.** Evaluation of FiLM U-TAE with varying lead time offset L, modifiable thanks to lead time conditioning. Storm surge forecasts become more challenging the larger L gets.

lead time t	↓ MAE (std)	↓ MSE (std)	↑ NNSE
4	**0.169 (0.254)**	**0.093 (0.543)**	**0.583**
6	0.182 (0.269)	0.106 (0.551)	0.552
8	0.190 (0.260)	0.104 (0.535)	0.556
10	0.191 (0.273)	0.111 (0.553)	0.540
12	0.196 (0.273)	0.113 (0.539)	0.536

Table 4. **Input ablations.** Evaluation of our models with varying inputs. The outcomes underline the relevance of each modality.

input ablation	↓ MAE (std)	↓ MSE (std)	↑ NNSE
full model	0.190 (0.260)	**0.104 (0.535)**	**0.556**
no GTSM input	0.207 (0.284)	0.124 (0.543)	0.513
no ERA5 input	0.189 (0.273)	0.110 (0.545)	0.542
no data dropout	0.217 (0.289)	0.130 (0.539)	0.500
no FiLM, $L = 8$ fixed	**0.183 (0.273)**	0.108 (0.567)	0.547

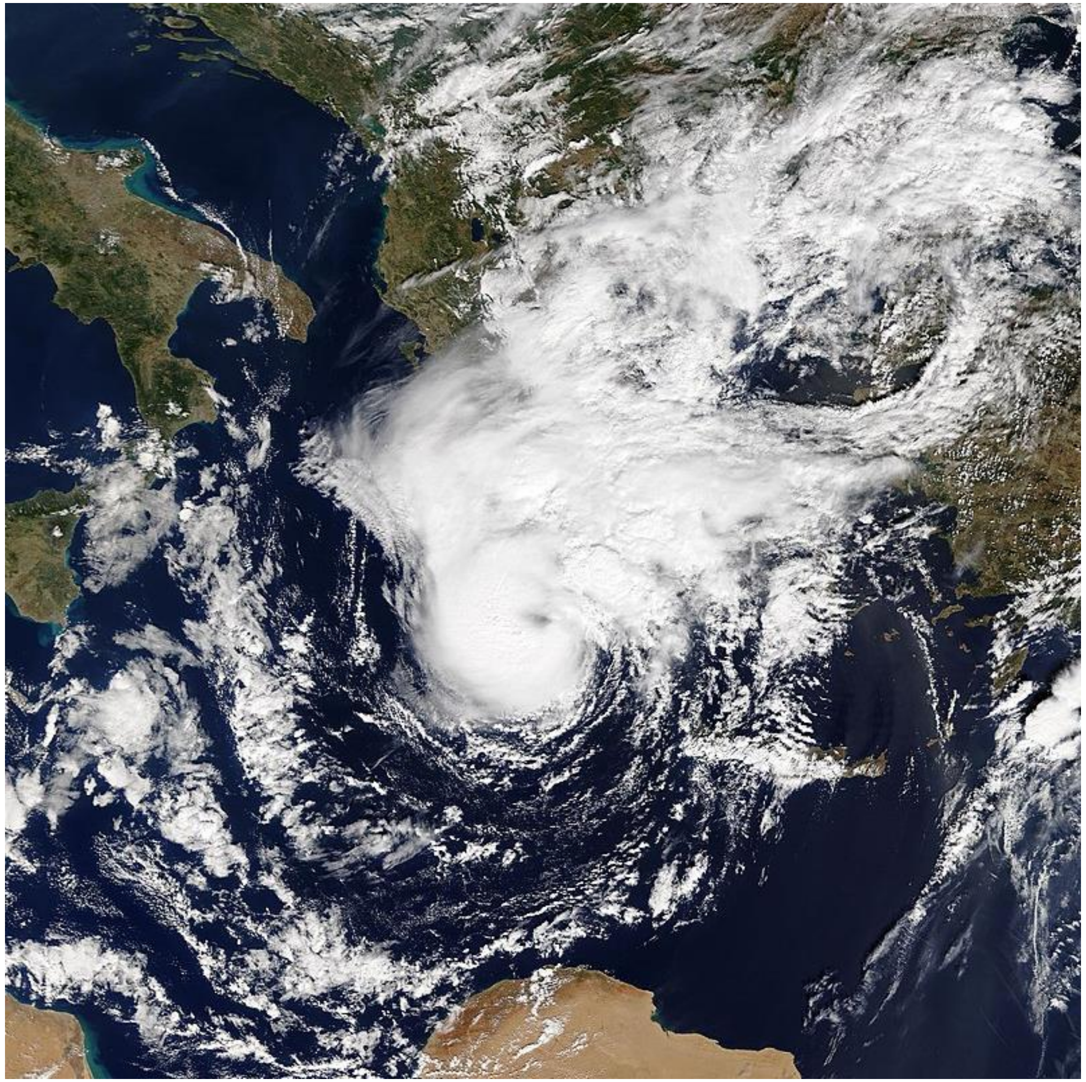
Table 5. **Output ablations.** Evaluation of FiLM U-TAE with varying output channels. Ablations show all outputs' significance.

output ablation	↓ MAE (std)	↓ MSE (std)	↑ NNSE
full model	**0.190 (0.260)**	**0.104 (0.535)**	**0.556**
no GTSM supervision	0.194 (0.276)	0.114 (0.544)	0.534
GTSM, instead of densification	0.210 (0.246)	0.105 (0.536)	0.554

Results

- more input time points are more informative
- the longer the lead time, the more challenging the forecasting
- all input and output modalities are meaningful and informative

Application to MedCyclones



Goal:

- model storm surge in the MedSea

Challenge:

- fewer data: cyclones, storm surge & monitoring
- this is problematic for data-driven approaches!

Approach:

- train a model on global data, then run inference on the MedCyclone event of our interest
- future directions: *fine tuning, conditioning etc*

Cyclone Zorbas, 27.09 – 02.10.2018

Zorbas:

- reported surge varies within 0.8 – 1.4 meters

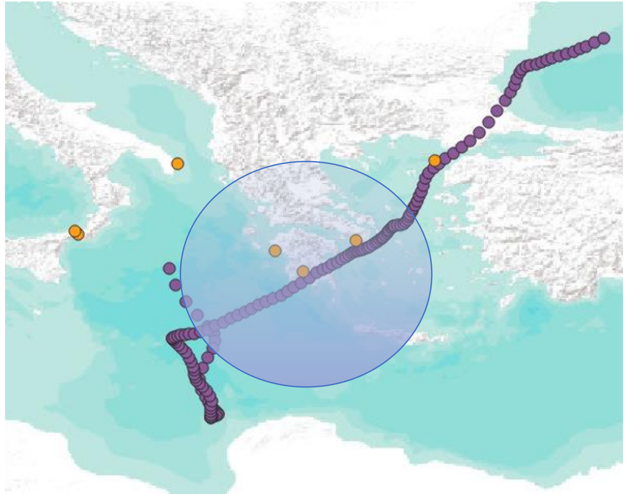
Data:

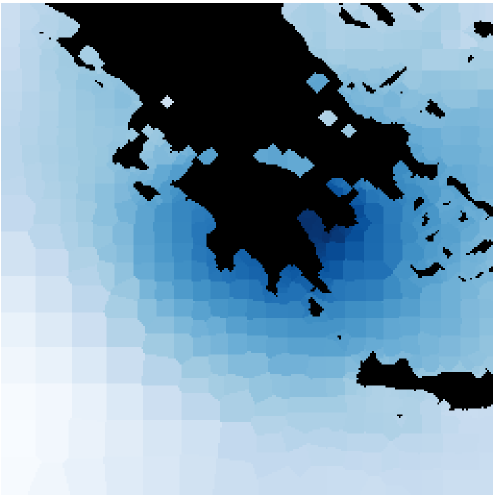
- gauges by [UNESCO/IOC](#) *Sea Level Monitoring*
- track information by *Flaounas et al 2023*

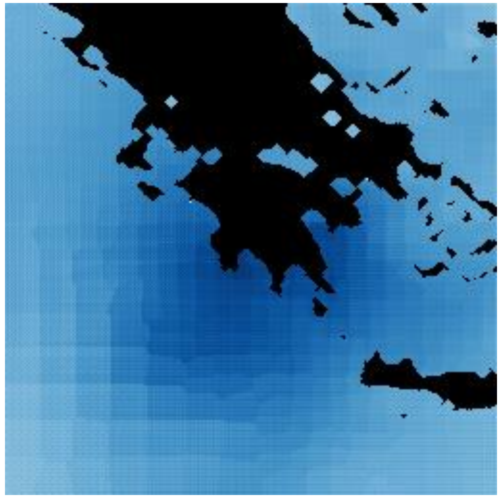
Challenges:

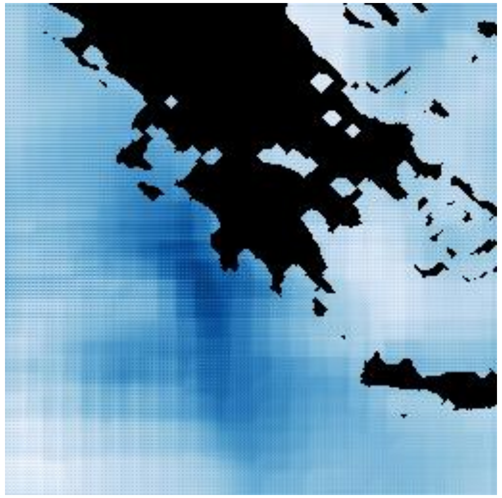
- sparse measurements, 3 gauges within 150 km
- missing data: - *NaN in tidal gauge observations*
  - *for model forcings (GTSM til '18)*

Outcomes









MaxVit U-Net:

MAE: 0.0526, MSE: 0.0046

U-TAE:

12 h input, 6 h lead

MAE: 0.0329, MSE: 0.0017

24 h input, 6 h lead

MAE: 0.0376, MSE: 0.0022

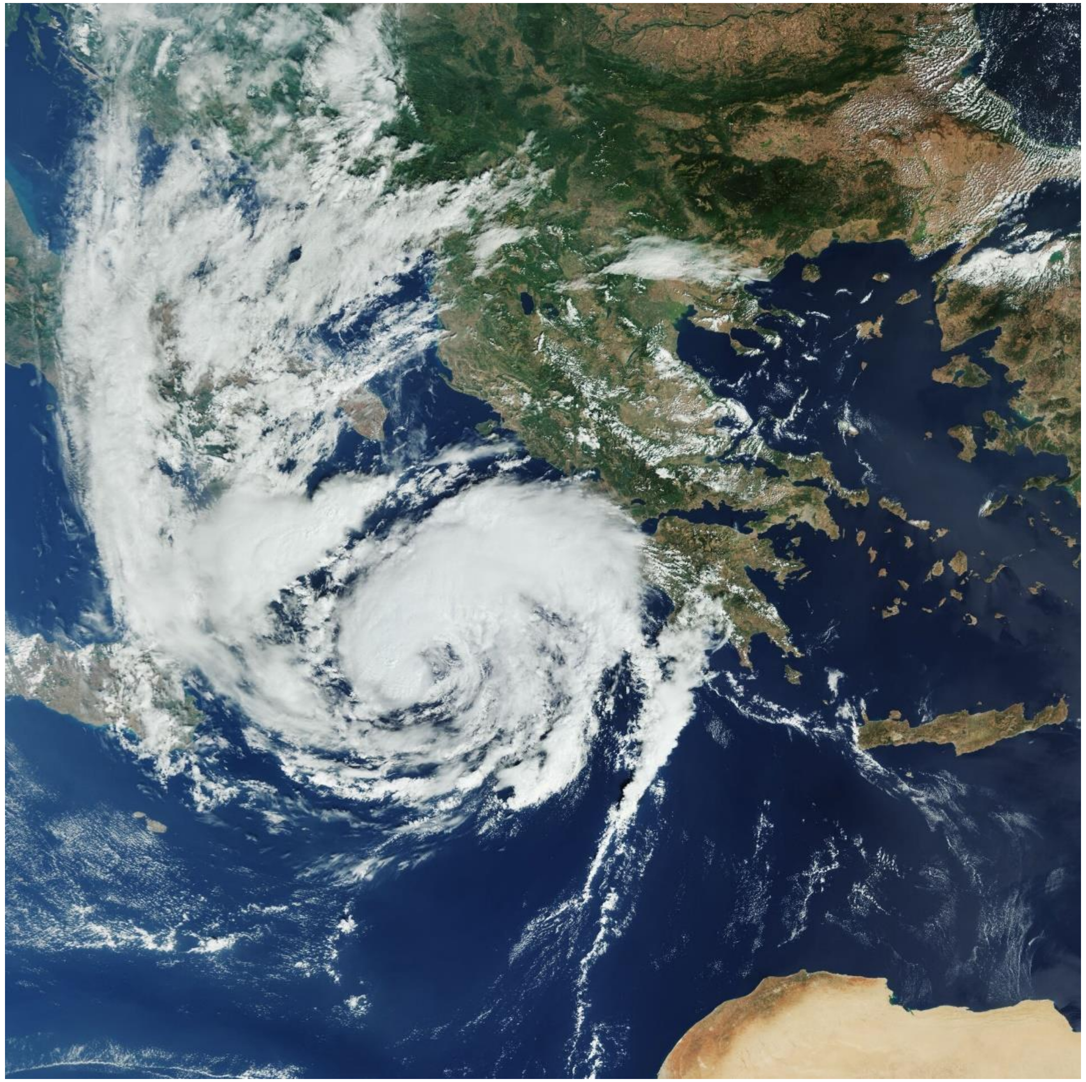
12 h input, 3 h lead

MAE: 0.0310, MSE: 0.0017

12 h input, 9 h lead

MAE: 0.0461, MSE: 0.0032

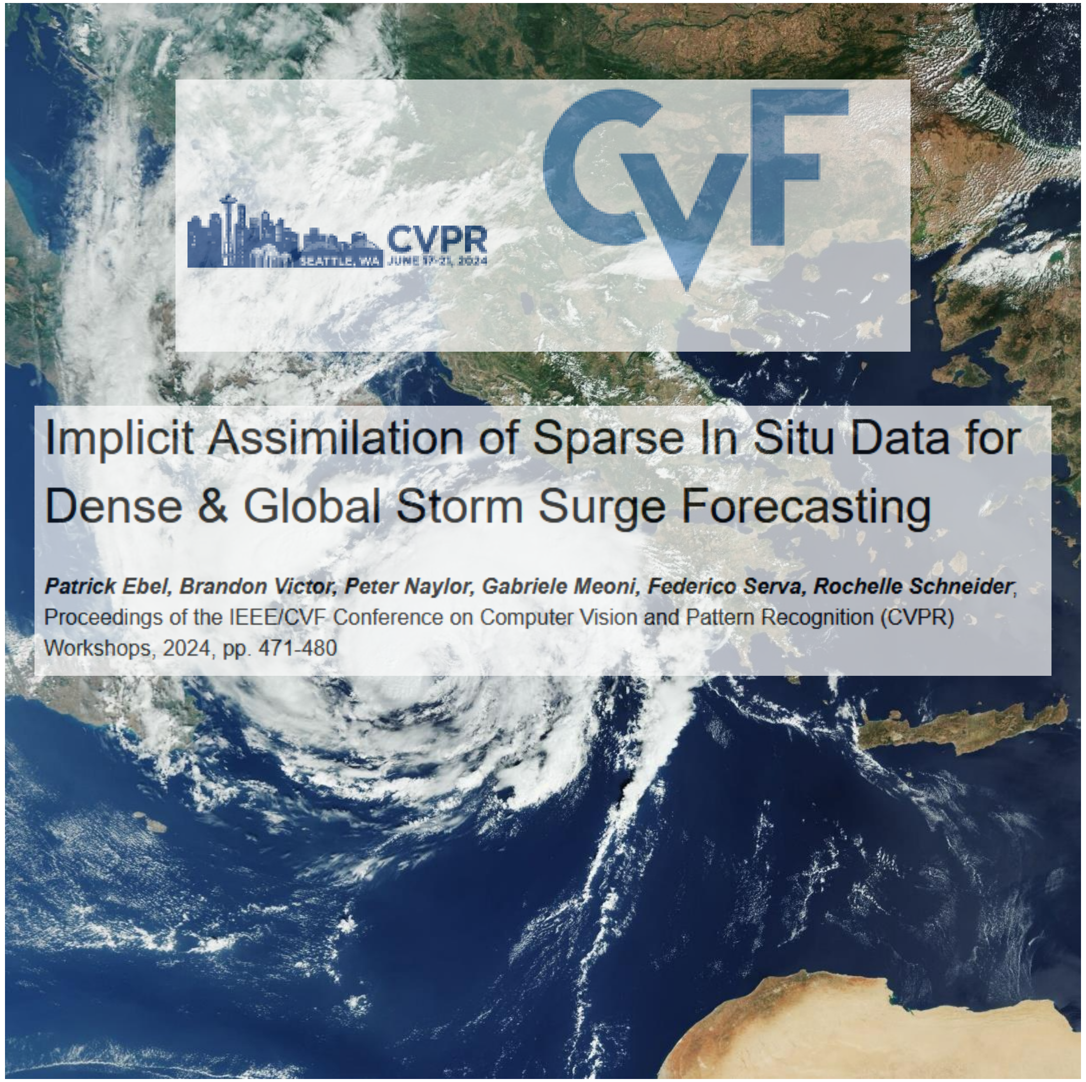
Conclusion



Take-home messages:

- a **new approach** for *short-term* storm surge at <u>ungauged</u> sites is introduced, comprising:
  - a novel multi-modal global <u>dataset</u>
  - a spatio-temporal <u>neural network</u>
- for **regional analysis** over the MedSea:
  - <u>global</u> data facilitate <u>local</u> modelling
  - <u>future research:</u>
    adaptation, conditioning, fine-tuning, …

That’s it!



Thank you.