DLOA 2023

Project session

https://github.com/CIA-Oceanix/DLOA2023/tree/main/projects

Project topics:

- Topic 1: Space-time downscaling/super-resolution of sea surface dynamics:
 - Associated paper: Buongiorno Nardelli et al., 2022 <u>link</u>
- Topic 2: Space-time interpolation of SSH fields from satellite altimetry data
 - Associated paper: Barth et al., 2022 link
- Topic 3: Short-term weather forecasting
 - Associated paper: Rasp et al., 2020 <u>link</u>
- Topic 4: Space-time segmentation of oceanic eddies from satellite-derived observations
 - Associated paper: Moschos et al., 2023 <u>link</u>
- Topic 5: Classification of metocean processes in SAR-derived observations
 - Associated paper: C. Wang et al., 2019 <u>link</u>
- Topic 6: Prediction of a summer-cumulated streamflow for electrical production
 - Associated paper: link
 - The choice of this topic must be discussed with a teacher beforehand.
- Topic 7: Data-driven identification and simulation of Lorenz-63 dynamics
 - Associated paper: Ouala et al., 2018 link
- Topic 8: dimension reduction on SSH or Sentinel2 time series

Organisation:

• 2 (independent) groups per project

Topic 1: Space-time downscaling/super-resolution of sea surface dynamics



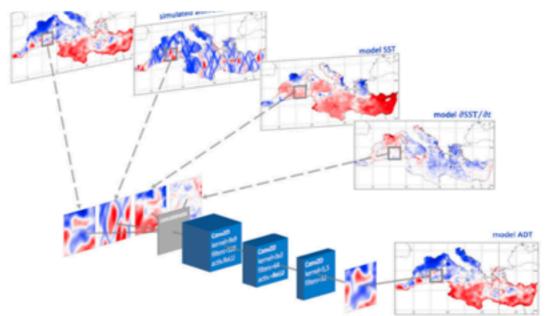


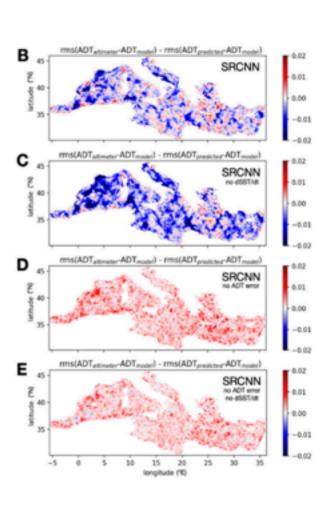
Article

Super-Resolving Ocean Dynamics from Space with Computer Vision Algorithms

Bruno Buongiorno Nardelli 1,*0, Davide Cavaliere 2, Elodie Charles 3 and Daniele Ciani 20

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Topic2: Space-time interpolation of SSH fields from satellite altimetry data

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DINCAE 2.0: multivariate convolutional neural network with error estimates to reconstruct sea surface temperature satellite and altimetry observations

Alexander Barth, Aida Alvera-Azcárate, Charles Troupin, and Jean-Marie Beckers GHER, University of Liège, Liège, Belgium

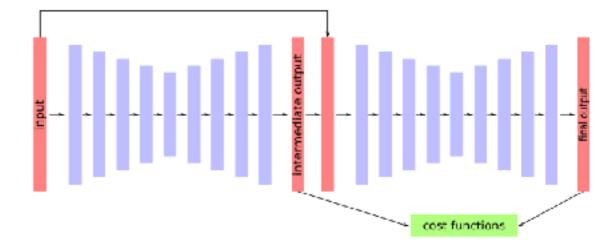


Figure 2. DINCAE with a refinement step composed essentially by two sequential autoencoders coupled such that the second autoencoder uses the output of the first and the input data.

SSH Mapping Data Challenge 2020a

This repository contains codes and sample notebooks for downloading and processing the SSH mapping data challenge.

The quickstart can be run online by clicking here: 8 launch binder



Motivation

The goal is to investigate how to best reconstruct sequences of Sea Surface Height (SSH) maps from partial satellite altimetry observations. This data challenge follows an Observation System Simulation Experiment framework: "Real" full SSH are from a numerical simulation with a realistic, high-resolution ocean circulation model: the reference simulation. Satellite observations are simulated by sampling the reference simulation based on realistic orbits of past, existing or future altimetry satellites. A baseline reconstruction method is provided (see below) and the practical goal of the challenge is to beat this baseline according to scores also described below and in Jupyter notebooks.

Topic 3: Short-term weather forecasting

WeatherBench: A benchmark dataset for data-driven weather forecasting

Stephan Rasp¹, Peter D. Dueben², Sebastian Scher³, Jonathan A. Weyn⁴, Soukayna Mouatadid⁵, and Nils Thuerey1

Correspondence: Stephan Rasp (ste

a) Direct prediction t = 5 days t = 0Channels = Variables x Levels

atitude. Longitude b) Iterative prediction t = 6 hours t = 5 dayst = 0

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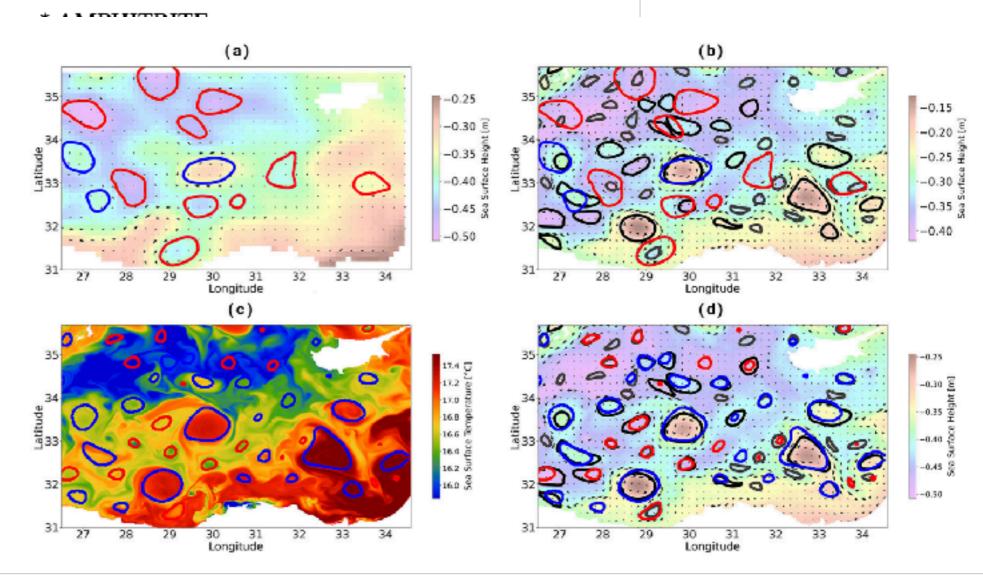
Topic 4: Space-time segmentation of oceanic eddies from satellite-derived observations

Computer Vision for Ocean Eddy Detection in Infrared Imagery

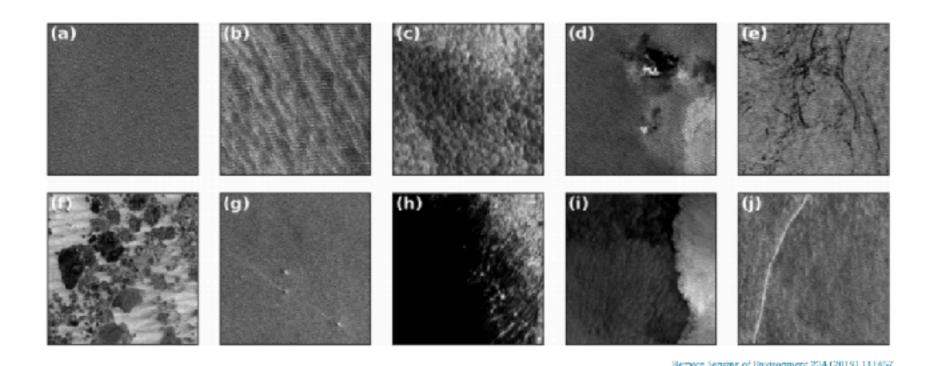
Evangelos Moschos* † Alisa Kugusheva* † Paul Coste* † Alexandre Stegner* †

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Topic 5: Classification of metocean processes in SAR-derived observations



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Contents lists available at ScienceDirect

Remote Sensing of Environment

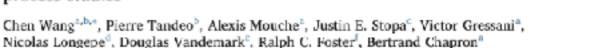
journal homepage: www.elsevier.com/locate/rse



A labelled ocean SAR imagery dataset of ten geophysical phenomena from Sentinel-1 wave mode

Chen Wang^{1,2} | Alexis Mouche¹ | Pierre Tandeo² | Justin E. Stopa³ | Nicolas Longépé⁴ | Guillaume Erhard⁴ | Ralph C. Foster⁵ | Douglas Vandemark⁶ | Bertrand Chapron¹

Classification of the global Sentinel-1 SAR vignettes for ocean surface process studies





Topic 6: Prediction of a summer-cumulated streamflow for electrical production

Hydrol. Earth Syst. Sci., 27, 2283–2299, 2023 https://doi.org/10.5194/hess-27-2283-2023 © Author(s) 2023. This work is distributed under the Creative Commons Attribution 4.0 License.

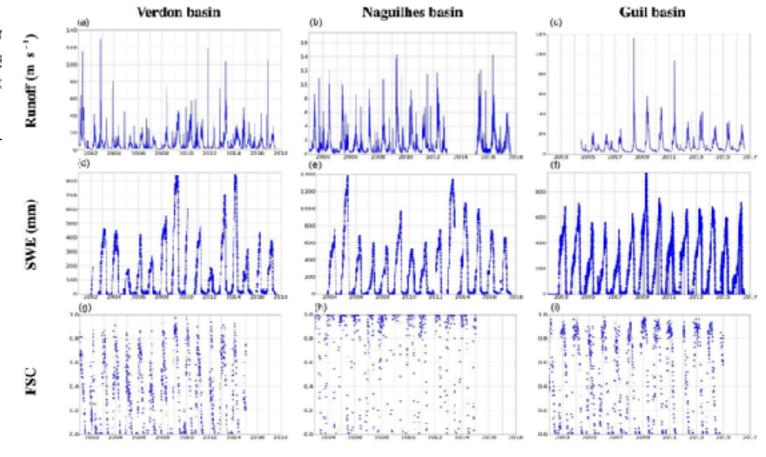




Snow data assimilation for seasonal streamflow supply prediction in mountainous basins

Sammy Metref^{1,2}, Emmanuel Cosme¹, Matthieu Le Lay³, and Joël Gailhar

³Électricité de France – Division Technique Générale, Saint-Martin-le-Vinoux,



¹Centre National de la Recherche Scientifique, Institut de Recherche pour le Dé Institut des Géosciences de l'Environnement, Université Grenoble Alpes, Greno ²Datlas, Grenoble, France

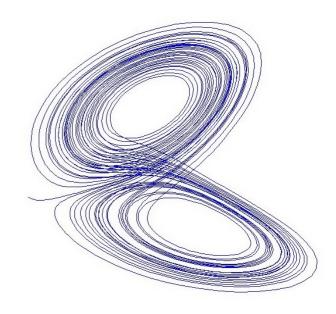
Topic 7: Data-driven identification and simulation of Lorenz-63 dynamics

2018 26th European Signal Processing Conference (EUSIPCO)

Bilinear Residual Neural Network for the Identification and Forecasting of Geophysical Dynamics

Ronan Fablet 1, Said Ouala 1, Cédric Herzet 1,2

IMT Atlantique; Lab-STICC, Brest, France
 INRIA Bretagne-Atlantique, Fluminance, Rennes, France



$$\frac{\mathrm{d}x(t)}{\mathrm{d}t} = \sigma\left(y(t) - x(t)\right)$$

$$\frac{\mathrm{d}y(t)}{\mathrm{d}t} = x(t)\left(\rho - z(t)\right) - y(t)$$

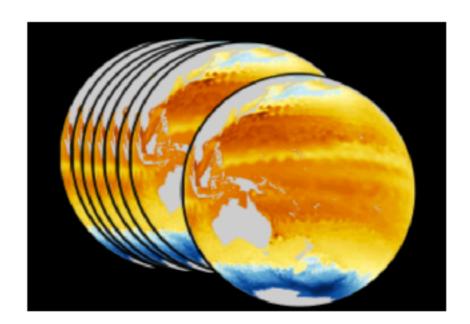
$$\frac{\mathrm{d}z(t)}{\mathrm{d}t} = x(t)y(t) - \beta z(t)$$
Lorenz-63 equations

$$X_t$$
 $\hat{\mathbf{F}}(X_t)$
 $\hat{\mathbf{F}}(X_t)$
 $\hat{\mathbf{F}}(X_{t+1})$

Topic 8: Dimension reduction and forecast of image time series (SSH and Sentinel-2 data)

Blind Hyperspectral Unmixing Using Autoencoders: A Critical Comparison

Burkni Palsson , Student Member, IEEE, Johannes R. Sveinsson, Senior Member, IEEE, and Magnus O. Ulfarsson, Senior Member, IEEE

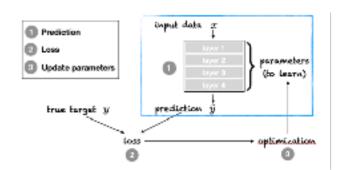


Ocean Chaos - Impacts, Structures, predicability

Project Session #1

- Problem formulation
 - Which inputs/ouputs?
 - Which datasets?
 - Performance metrics?
- Review of available dataset (basic statistics/visualisation)
- Searching for related reference/code on the web
- 3-slide presentation of the project :
 - What? (Inputs/outputs)
 - Dataset
 - Performance metrics / loss ?
- 10' Wrap-up with the 2 groups for each project topic

Guidelines to implement Deep Learning schemes



- 1. Problem formulation (inputs/outputs)
- 2. Data collection (cf. supervised vs. non-supervised)
- 3. Definition of performance metrics
- 4. Selection of neural architectures (at least 2 models)
- 5. Selection of a training loss
- 6. Split dataset into training / validation / test datasets
- 7. Train the selected models from the training dataset and save the best models onto the validation dataset
- 8. Benchmark the performance of the trained models onto the test dataset
- 9. Update/iterate 4-5-6-7-8

Project Session #2

Data preparation

- Dataloader
 - input/ouput tensors for the model to be trained
- Definition of neural architectures
 - at least two competing architectures/models

Project Session #2/3

Data preparation

- Dataloader
 - input/ouput tensors for the model to be trained

- Definition of neural architectures
 - at least two competing architectures/models