DTO
Marine Heat Waves Prediction

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Objectives of the Digital Twin Ocean Precursor (DTOp)

- Evaluate a complementary method to numerical model based on « heavy classical ocean dynamic approach" in order to forecast oceanic events ➔ in our case Marine Heatwaves : MHWs
- Use massive data approach to exploit the large amount of Earth Observation data (satellite & in-situ)
- Use advanced Machine Learning approach onboard HPC
- Setup a demo on a DIAS infrastructure (feasibility study)
- Identify gaps to reach the target

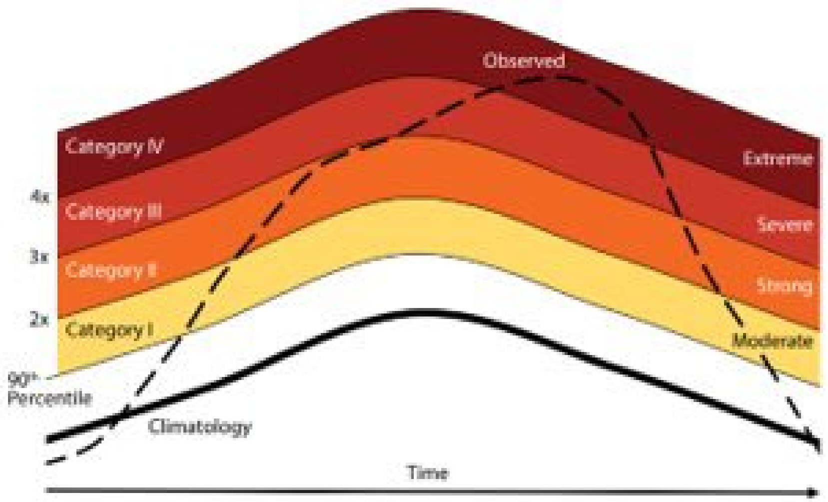
Marine Heatwaves definition

Target: Evaluate the ability of a 2D-CNN model to forecast Marine Heatwaves (MHWs) on the Mediterranean Sea

MHW widespread definition in the community & proposed by Hobday et al. (2016, 2018) :

- "prolonged, anomalously warm water event at a particular location"
- should be defined relative to a 30-year period"
- When upper locally determined threshold [90th, 95th or 98th percentile relative to the local long-term climatology] is exceeded for at least 5 days

MHWs categories I to IV



Approach

Main interest

- **Meteo-marine service [target forecast: several days to 3 months]**

Are we going to have a MHW in a specific region and which category in the short to middle-term?
Potential use cases:

  - Should fish and shellfish farmers plan to collect their fish and shellfish in advance?
  - Should fishing quotas be reviewed? In which regions, at what time?
  - Should MPAs (Marine Protected Areas) organise specific monitoring of their ecosystems to assess the impact of the next planned MHWs?
  - …

- **Extend the current forecasting time frame of ocean models from 10-days to 30, 60... 90 days**

- **To evaluate a method lighter to implement than a complete oceanic numerical model**

Approach

- **Inputs**: Mediterranean Sea Reanalysis (Copernicus Marine Service)

  Data from oceanic regional models = super-interpolator + homogenous dataset + subsurface temperature.

  Not the final target for such future application but useful to fit/test the ML model (objective: use **observations** in future work)

- **incremental scenarios to assess the contribution of the variables added**
  - 1) SST + SSH
  - 2) Add a proxy of the stratification: + Temperature at 40m
  - 3) Add more context: + SST climato + Day of the year + lat/lon

- **Period**: 1992-2019
- **Region**: Mediterranean Sea

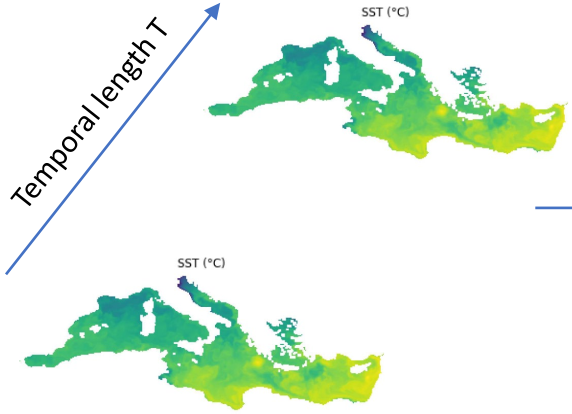
- **Outputs:**
  - SST time-serie of future values
  - Then MHW categories are calculated

MHW: 2D-CNN model baseline

CNN = Convolutional Neural Network

- Exploitation of each pixel **spatiotemporal context through temporal stacking and 2D convolutions**

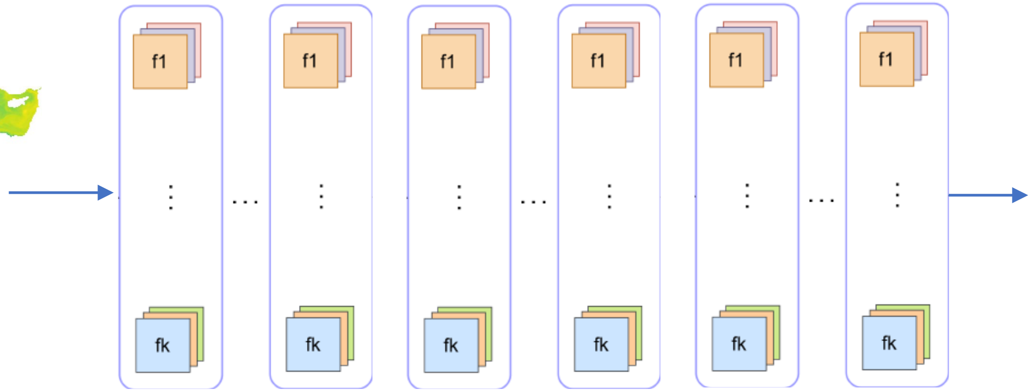
Past data maps [SST, SSH, T40m, …] time series t0 – T days



Inputs : Tensor (N, T, LON, LAT)

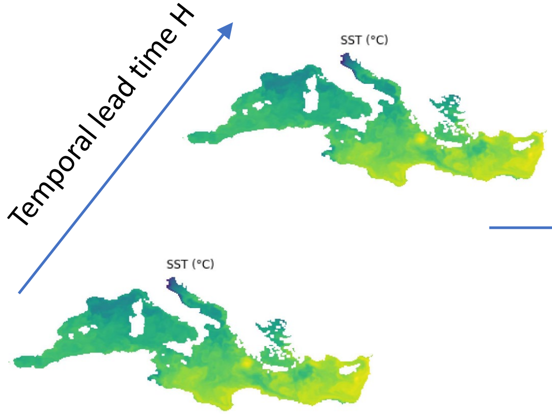
N = number of input variables
T = length of time series

Forward Pass



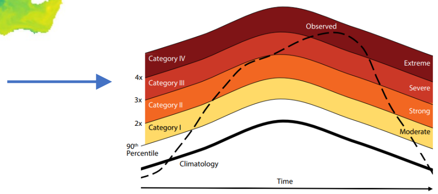
6 layers [conv2d – BN – ReLU – Dropout]

Future SST regression [t0, …, t0 + H] days



Output : Tensor (H, LON, LAT)
H : temporal horizon / lead time

MHW Classification



Hobday et al. (2018)

MHW: long-term SST forecasts

- **Resampling** daily to n-day averaged T°
  - reduced noise and memory size, faster training + temporal context ==> to **improve** long-term forecast capabilities

- **Input data :** e.g with 5-day mean resampling and 20 points: input sequences of 100 past days

- **30-day SST forecasts : resampling to 5-day averaged input**
  - output forecast [d+5, d+10, d+15, d+20, d+25, d+30]

- **60-day SST forecasts : resampling to 10-day averaged input**
  - output forecast [d+10, d+20, d+30, d+40, d+50, d+60]

- **90-day SST forecasts : resampling to 10-day averaged input**
  - output forecast [d+10, d+20, d+30, d+40, d+50, d+60, d+70, d+80, d+90]

constrained prediction
up to d + lead time

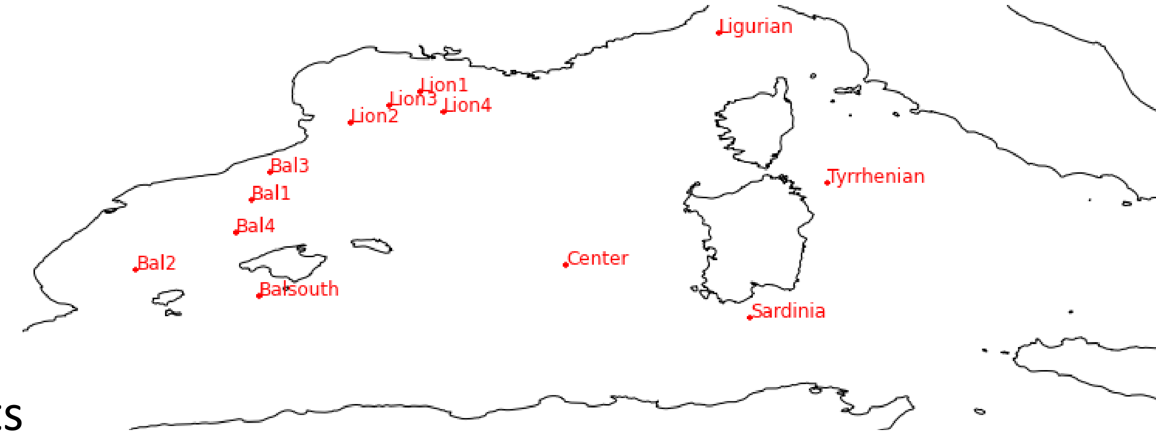
=> forcing forecast coherence
in the model

MHW: training – validation – test sets

- Full data period : 1992 - 2019

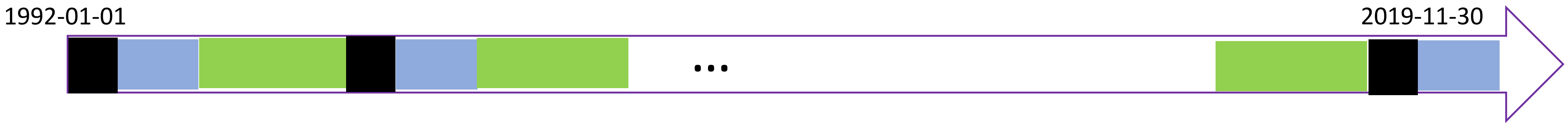
Training period	~ 5 years each – Total = 17 years
Validation period	2 years each – Total = 8 years
Test period	1 year each – Total = 4 years

- Focus on special **test sites** where MHWs are frequent



- **Full** spatial domain for training, validation and test sets

- **Split** temporal domain btw training, validation and test sets



MHW: Long-term SST forecasts – results

SST forecasts - Validation set (all med, 8 years) | **Test set (all med, 4 years)**

Input variables	Lead time	Resampling	RMSE at lead time (°C) – Validation set	RMSE at lead time (°C) – Test set
SST SSH	up to 30 days	5 days	1.06	1.15
	up to 60 days	10 days	1.22	1.24
	up to 90 days	10 days	1.95	2.21
SST T40m SSH	up to 30 days	5 days	**1.02**	**1.09**
	up to 60 days	10 days	**1.14**	**1.14**
	up to 90 days	10 days	**1.23**	**1.32**
SST T40m SSH SST climato Day of year Lat / lon	up to 30 days	5 days	**0.82**	**0.91**

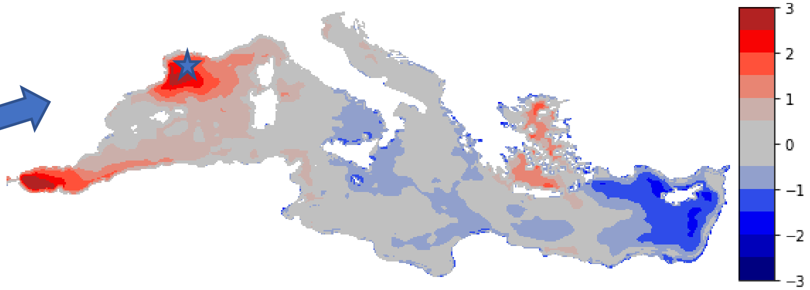
- SST, SLA and T40m depth are key components. By adding the T40m, the mean error at 30 days is reduced and becomes similar to the one at 10 days
- RMSE similar to model forecast skill
- ML method are able to predict SST with reasonable error

MHW: Long-term SST forecasts – results

Prediction using
only SST, SSH and T40m

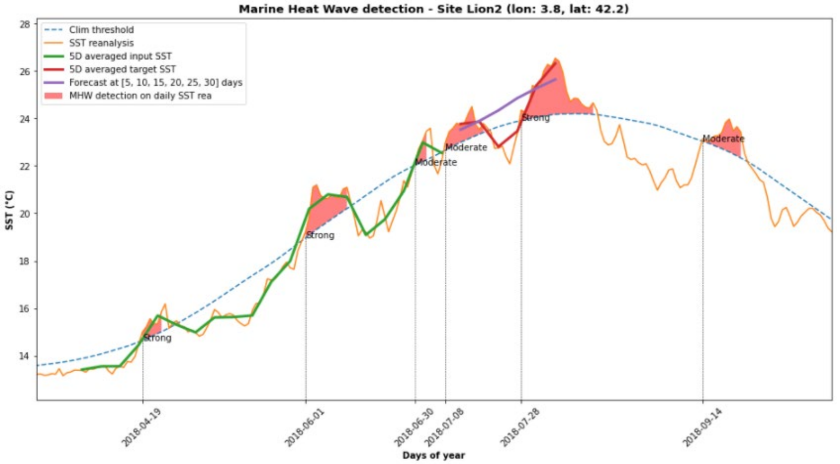
Mean prediction and target maps estimated at 90 days

Predicted minus Target SST



Some areas are harder to predict:
Complex area chosen (Med Sea), with sub-basin characteristics and specificities, local, sub-basin, basin scale of variabilities + large scale.

Detection of MHW on Lion2 site (1° x 1° patches)



Good in RMSD but extreme events not well represented ➔ Change loss function to better optimize towards fitting variability and extreme values in ML learning (MSE is indeed not appropriate) + direct classification approach

Test period : 2016-01-01 – 2018-01-01
Examples of sites

Site name (lat, lon)	RMSE at 30 days (°C)
Ligurian	1.07
Lion 1	1.44
Lion 2	1.42
Lion 3	1.45
Lion 4	1.44
Bal 1	0.88
Bal 2	0.84
Tyrrhenian	0.93
Sardinia	0.87
Center	0.97
Balsouth	0.84

Conclusions

What have we achieved ?

- We demonstrated the feasibilty to predict SST & MHWs based on ML and massive "observed data“
- By using about 20 years of data, ML approach allowed to develop a method than can forecast SST up to 30 to 90 days in the future (validated mainly at 30 days)!
- The mean errors are ~1°C
- Innovative work: New approach, not a lot scientific publications on the topic. Tropical Cyclones, Atmospheric Rivers and Weather Fronts with CNN classification (2016, https://arxiv.org/abs/1605.01156) + CSIRO initiative (monthly SST, averaged on several regions around Australia are forecasting. Strong interannual signals dominate in this region).
- The operational ML method requires only CPUs to run and the computing time to make a 30 days forecast on the MED is less than 30 sec on local laptop << classical oceanic model
- Ready to use and make some tests

Conclusions

Possible improvement

- For practical reasons (no gaps in data, data in depth), we have used Copernicus Marine Service numerical outputs to access SST, SSH and temperature @ 40m
  - → We would like to use Earth **Observations** from satellite/in-situ rather than/in addition with **numerical model** data (but some work must be done to "prepare & calibrate" the data for ML ingestion)
  - → The observations monitor all the complexity of the ocean (complement with numerical model)
- Improve our approach: add atmospheric variables, another loss function (extremes are more difficult to catch), change to CNN classification or other algorithms (LSTM, other advanced statistical methods [analogs, ..]))
- Skills inhomogeneous on the domain (sub-basin specificities) => Strengthening upstream work is essential to identify the right variables and identify the necessary pre-processing. Work on **drivers** identification started (European climate Indices from Meteo-France and Sea Level Pressure from ERA5) → first conclusions: the link with SST on MED is not straightforward…
- link with CareHeat (drivers, …)


THANK YOU !
CLS
COLLECTE LOCALISATION SATELLITES

Summary

- ML CNN model developed and allowing some improvements rather quickly (flexible) /data pre-processed (including to allow possible tests with CNN model + classification with labelled data)
- Identification of the weaknesses of a first version of the ML model. Estimation of the errors and identification of the points of improvement (add atmospheric variables, another loss function, change to CNN classification or other algorithms (LSTM, other advanced statistical methods [analogs, ..]))
- SST, SSH but also subsurface temperature are key variables to forecast MHWs.
- Skills inhomogeneous on the domain (sub-basin specificities) => Strengthening upstream work is essential to identify the right variables and identify the necessary pre-processing. Work on drivers identification started. Recovery of European climate Indices from Meteo-France and Sea Level Pressure from ERA5 (Not shown) ➔ first conclusions: the link with SST on MED is not straightforward… (link with CareHeat)
- Complex area chosen (Med Sea), with sub-basin characteristics and specificities, local, sub-basin, basin scale of variabilities + large scale.
- Innovative work: New approach, without many scientific publications (2-3) on the topic. Tropical Cyclones, Atmospheric Rivers and Weather Fronts with CNN classification (2016, https://arxiv.org/abs/1605.01156). + CSIRO initiative (monthly SST, averaged on several regions around Australia are forecasting. Strong interannual signals dominate in this region). Promising results but extremes are complicated to catch.

The operational ML model requires only CPUs to run and the computing time to make a 30 days forecast on the **MED is less than 30 sec on local laptop<< classical oceanic model**

Conclusions

- General remarks for DTOp & MHWs:
  - •DTE for Ocean must address the difficulties we have to predict MHWs with existing predicting facilities ("classical numerical models")
  - •Indeed, for specific ocean phenomena, interactions within the ocean, interactions between ocean and atmosphere, interactions between small scales and large scale in space & time, are too numerous and too complex to be modelled by "classical physics"
  - •It is moreover complex for extreme phenomena like MHW in a context of climate change / global warming
  - •We need to explore new approaches that ML/DL methods can handle because, today, we access quite easily tremendous quantity of data (EO observations, in situ, numerical model outputs…) and IT facilities for massive computations.
  - •DTO should support data-driven strategy and EO satellites are key-components of this strategy.
  - •We have to keep in mind that CMEMS provide numerical models of the ocean, models that ingest (assimilate) lots of EO and in situ observations, to optimally combine physical equations with observations. In my view it's a good deal between math & physics 😉 that can be enhanced by a DTO approach.

Conclusions

For the Marine Heat Waves, the main messages are (B. Chapron):

- Operational models, already assimilating satellite and in situ observations offer data-cube facilities to help apply ML techniques, i.e. the operational model perform a consistent dynamical space-time gridded interpolation of the different variables. Still, models do not always carry all the multiple interactions between variables, e.g. upper ocean biology. The model-data cubes are to be combined with direct observations.
- More advanced methodologies are necessary to help reduce the dimension of the system to improve the mid- to long-term forecast skills.

For the high-dimensional Earth dynamical system, observables may only capture part of the complex nonlinear interactions. Among observables at global scale, we can now rely on satellite estimates, i.e the sea surface height, temperature, salinity, wind, waves, color, and on numerical simulations, for operational or process sensitivity assessments. Today, major drawbacks are : the time-space sampling and length of homogenous satellite observations (SSH is 25 years, SST is 35 years, SSS is 10 years, …), and lack of absolute well-posedness knowledge of the different numerical simulations. Both aspects preclude full understanding of the horizon of predictability (days, weeks, to months of useful predictability) of present models (data-driven, model-driven). It also precludes our ability to fully understand how to best optimize the use of observations and numerical models, e.g. how many more data shall be necessary, which parameters to look for, what should be their time-space resolution to largely improve numerical models, …

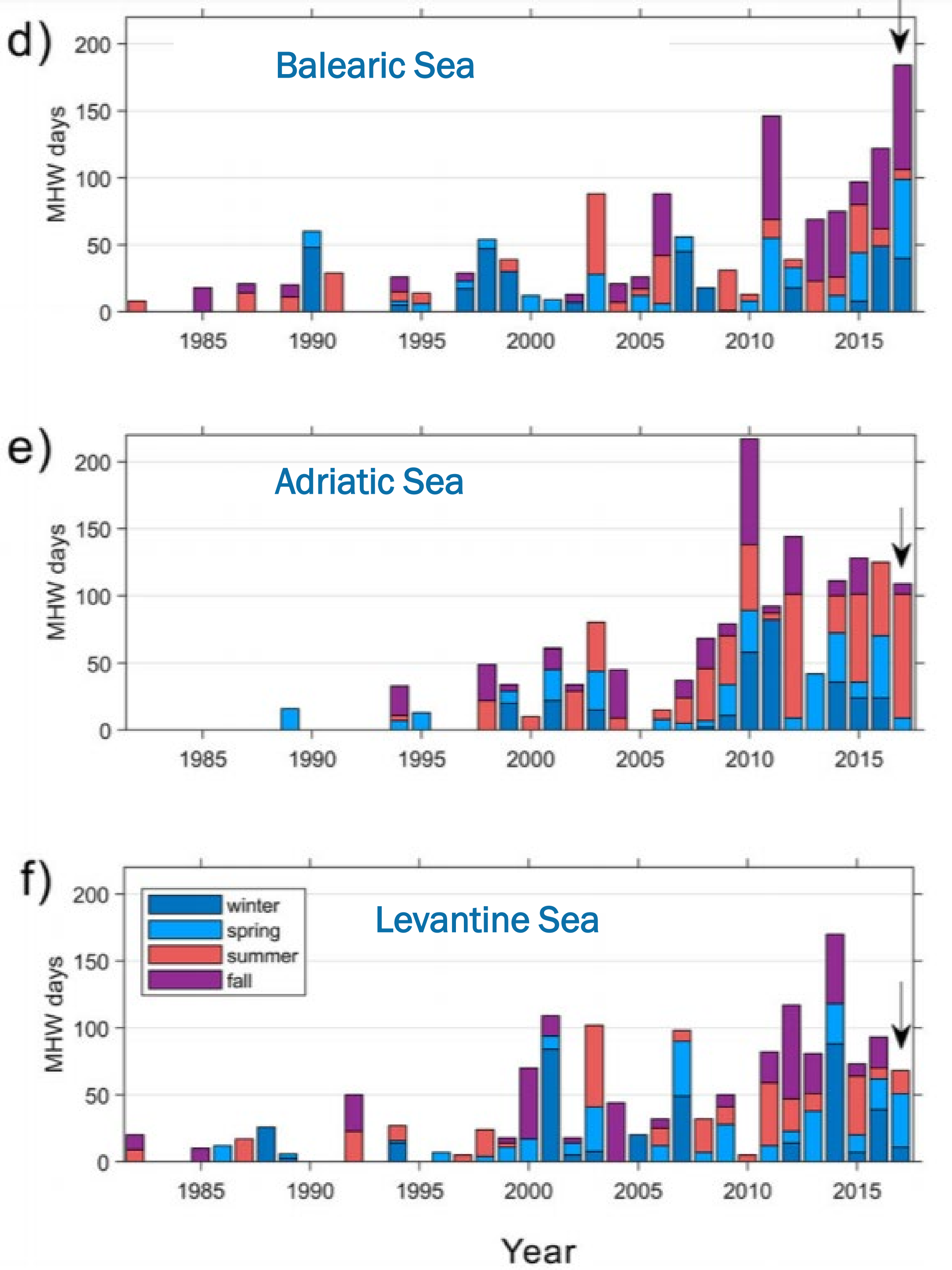
In this context, the ESA DTOp main motivation is to first advance and test new possible and generic strategies to help improve data-driven and/or model-driven developments. On one side, i.e. the Arctic Amplification question, the goal is to question how a very highly resolved (and costly) numerical model can be best reduced to be efficiently incorporated within coarse operational models. On the other side, i.e. the predictability of Marine Heat Waves in a particular region (Med. Sea), it is to question if available data sets can help best reduce the dimension of the problem. Given these two examples, one main objective is to refine the necessary architecture, from a dynamical data-lake for rapid emulators to perform what-if simulations, such that to ensure the best combined use of data-driven and model-driven capabilities.

Past tendency in different MED regions
Bensoussan et al. CMEMS OSR3

A long-term increasing trend in annual Marine Heatwave duration is obvious over the 1982–2017 period

Preferred period: June to September. But on 1982-2017, period and duration differ. **MHW can be in summer but not only and not systematic…**

Since late nineties, Marine Heatwave events have occurred every year in at least one season (except in 2005 in the N-Adriatic) and they last longer. (reference clim: 1982-2011)



Evolution expected in MED

Darmaraki : Climate Dynamics in February 2019 entitled ”Future Evolution of Marine Heatwaves in the Mediterranean Sea”

❑ Climate Scenario

➔ Marine heatwaves will become stronger and more intense, especially towards the end of the century

➔ Under the high-end scenario of climate change, model simulations project at least one long-lasting marine heat wave event every year by 2100, that lasts **up to three months longer**, is about **4 times more intense and 42 times more severe than present-day events.**

➔ They are expected to occur from **June-October** and to affect at peak **the entire Mediterranean basin.**

➔ The observed exceptional 2003 event seem to become the new standard already in the period 2021 – 2050. Same strong impact on the Mediterranean ecosystems.