# Pre-processing of sea turtle biologging observations using a clustering algorithm SynObs Workshop 

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## STORM-IO Overview

## STORM-IO

- Sea Turtles for Ocean Research and Monitoring
- Contribution of biologging technology using sea turtles equipped with ARGOS transmitters


## Collaboration based on la Réunion Island

- LACy (Météo France) : Better understanding and modelling of the tropical cyclones on the SWIO. Part research, part operational.
- Kelonia : Sea turtle care center based in la Réunion. Animals caught in fisher nets or hurt by boat are here hosted, healed then released in the ocean $\rightsquigarrow 25$ turtles/year


## STORM-IO Context

## South Western Indian Ocean

- Strong cyclonic activity from January to May
- Operational forecasting system (AROME-Réunion), 3D-Var DA system
- Very poorly instrumented, need of in situ observations

Sea turtles as oceanographic auxiliaries

- Autonomous sampling platforms
- Travel thousands of $\mathbf{k m}$ in several months within the ocean mixed layers
- Might be trapped inside cyclonic structures



## STORM-IO Main objectives

## Sea turtle ecology

- Navigation corrected using surface currents
- Diving patterns

Physical Oceanography \& Meteorology

- Sample the ocean mixed layers (even deeper layers)
- Verify the satellite-derived ocean surface products
- Analyse the AROME-Réunion forecasting performances
- Improve climate forecast during cyclonic emergence focused on the SWIO


## STORM-IO Material

## Sea turtles profiles

- 93 sea turtles equipped : 38 juveniles, 54 nesting females, 1 male
- From Jan 2019 to Apr 2022
- 7 initial locations: Moheli, Aldabra, Seychelles, Réunion Island, Europa, Tromelin, SA
- North global migration for juveniles, $500 \mathrm{~km} /$ month on average



## Tags description

|  | LRGOS | Temperature sensor <br> $\left(0.05^{\circ} \mathrm{C}\right.$ res $)$ | Depth sensor <br> $(0.5 \mathrm{~m}$ res $)$ | Internal <br> memory | Perpetual acquisition of temp. <br> series data (5min rate) |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Loc. |  |  |  |  |  |

## Raw data characteristics

## ARGOS transmitters

- Transmits periodic short duration messages to ARGOS instruments on satellites
- Polar orbiting satellites at an altitude of 850 km
- Transmission only possible when the turtle is close to the surface and a satellite is passing overhead (Max. 14 messages per day)


## Raw data characteristics

- Location of the ST is computed during transmissions only
- Based on Doppler effect : received frequency differs from the transmitting one, due to the satellite being mobile



## STORM-IO - Oceanography Objectives

## Objectives of STORM-IO - Oceanography

- Elaborate a methodology allowing the assimilation of ST environmental biologging time series in an operational meteorologic and oceanic forecasting system
- Produce monitorings to check data quality, compare to model forecasts, verify satellite-derived ocean surface products
- Run several reanalysis experiences for cross-validation


## Data Assimilation global overview

## The Variational Approach

- Evaluate the discrepancy between the model predicted trajectory and the observation data using a cost function :

$$
J\left(\mathbf{x}^{\mathbf{o}}\right)=\underbrace{\frac{1}{2}\left(\mathbf{x}^{\mathbf{o}}-\mathbf{x}^{\mathbf{b}}\right)^{T} \mathbf{P}^{-1}\left(\mathbf{x}^{\mathbf{o}}-\mathbf{x}^{\mathbf{b}}\right)}_{J^{b}: \text { background }}+\underbrace{\frac{1}{2}\left(H\left(\mathbf{x}^{\mathbf{o}}\right)-\mathbf{y}\right)^{T} \mathbf{R}^{-1}\left(H\left(\mathbf{x}^{\mathbf{o}}\right)-\mathbf{y}\right)}_{J^{0}: \text { obs }}
$$

With $\mathbf{x}^{\mathbf{0}}$ the initial state, $\mathbf{x}^{\mathbf{b}}$ the background, $\mathbf{H}$ the observation operator, $\mathbf{P}$ the covariance matrix of the background error, $\mathbf{R}$ the covariance matrix of the observation error.

- Minimize $\mathbf{J}$ over all the possible $\mathbf{x}^{\mathbf{0}}$ to find the optimal state $\mathbf{x}^{\mathbf{a}}$

$$
x^{\mathbf{a}}=\min _{x^{0}} J\left(\mathbf{x}^{\mathbf{o}}\right)
$$

## Pre-processing of ST biologging observations

## Need to pre-process ST observation time series

- DA requires to compute an error covariance matrix $\mathbf{R}$, that gathers all the "inter-dependencies" of the observations $\rightarrow$ Huge matrix that needs to be inverted !
- Data acquisition frequency rate is very high here (every 5 min ) $\rightarrow$ Large profusion of data, obs cannot be considered as non dependant without pre-processing
- Two approaches to reduce the number of information to use as observation data : data filtering (pick up a restricted amount of data) or superobs creation (average similar data)


## Sea turtle observation data pre－processing

## Super－obs creation process

（1）Gather similar environmental data（temperature and depth）within clusters，using a k－means method
（2）Compute the super－obs environmental values and measure errors for each cluster（arithmetic mean），along with the corresponding date
（3）Assign a location to each super－obs using the R package foieGras
（4）Convert the resulting dataset into a feedback file（netcdf）to be used as NEMOVar input




## Step 1 : K-means clustering

## K-means clustering (Non-supervised clustering method)

- Iteration of those steps :
(1) Assign a cluster to each point, based on the distance to the corresponding cluster node
(2) Compute new nodes as the mean of each cluster
- Stopping criterion : Minimizes the intra-class inertia $\rightarrow$ within-cluster variances (squared Euclidian distances)



## Step 1 : K-means clustering

## Regarding the super-obs creation

- Parameters : depth and time only, as temperature is highly correlated to both of them (turtle trajectory). Final within-cluster temperature variance will be used as a verification.
- The final number of clusters should be provided as input $\rightarrow$ Need to define a criterion to determine this value
- Define the final number of clusters $\mathbf{K}$ such that the final intra-class inertia :

$$
\mathbf{I C I}=\frac{1}{N} \sum_{i=1}^{K} \sum_{x \in S_{i}}\left(\left\|Z_{x}-Z_{i}\right\|^{2}+\left\|t_{x}-t_{i}\right\|^{2}\right)<\mathbf{I C} \mathbf{I}_{\max }
$$

With $\mathbf{N}$ points dispatched into $\mathbf{K}$ clusters, $\mathbf{Z}_{\mathbf{i}}$ and $\mathbf{t}_{\mathbf{i}}$ being the cluster node depth and time of the $\mathbf{S}_{\mathbf{i}}$ cluster.

## Step 1 : K-means clustering

## Define $\mathbf{I C l}_{\text {max }}$

- We chose $\mathrm{ICI}_{\max }=\Delta Z_{\max }^{2}+\Delta t_{\max }^{2}$
- $\Delta Z_{\text {max }}$ equals to the size of a NEMO grid cell along the Z-axis
- $\Delta t_{\text {max }}$ is determined using the characteristic autodecorrelation time of the depth time series $\rightarrow$ The goal is to end up with non-correlated super-obs.


Figure: Example of an autocorrelation graph for a loggerhead turtle (26000 points), with an autocorrelation coefficient set to 0.4

## Step 3 : Assign a location to each super-obs

## R package foieGras

- Animal movement is modelled as a continuous-time random walk on velocity $v_{t}$ in two coordinate axes :
- $v_{t}=v_{t-\Delta}+\Sigma_{\Delta}$ where $\Delta$ is the time increment and $\Sigma_{\Delta}$ is a zero-mean, bi-variate Gaussian random variable with variance $2 D \Delta$
- $x_{i}=x_{i-1}+v_{i} \Delta_{i}$ where $x_{i}$ is the true location of the animal at time $t_{i}$
- $y_{i}=x_{i}+\epsilon_{i}, \epsilon_{i} \sim N\left(0, \Omega_{i}\right)$ where $y_{i}$ the location observed at time $t_{i}, \Omega_{i}$ the measurement error-covariance matrix with elements being derived from the ARGOS error ellipses components
- Fit the state-space model, using maximum likelihood to estimate model parameter D (Jonsen et al., 2020 and Kristensen et al., 2016)
- Find the predicted states corresponding to the super-obs dates using the evaluated model


## Obs pre-processing output example

Raw data visualization - Argcs PTT : 224015


Superobs data visualization - Argos PTI : 224015



Figure: Example of obs. pre-processing output : Loggerhead turtle released from South Africa, equipped with Wildlife Computers tag. Final reduction factor: 78\%

## Ocean model monitoring : first results

## Ocean model characteristics

| Model | Config | Spatial res. | Z-levels | Time step | RST | OBC | Forcing |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| NEMO | REUNION12 | $1 / 12^{\circ}$ | 50 | 360 s | PSY4 | PSY4 | $\bullet$ IFS (9km res.), forcing <br> rate $: 3 \mathrm{~h}$ |
| AROME $(2.5 \mathrm{~km}$ res.) <br> forcing rate $: 1 \mathrm{~h}$ |  |  |  |  |  |  |  |

## Monitoring period selection

Superobs environmental data and trajectories within a 83 days-long time window





## Ocean model monitoring : first results


(a) IFS forcing

(b) AROME coupling

Figure: Obs and forecast temp. correlation graphs for a 3 months-long monitoring, starting from a single PSY4 reanalysis. Only Wildlife Computers obs. were processed.

## Future developments

## Monitoring

- Compare AROME forcing, IFS forcing and AROME coupled forecast temp. to the observed ones.
- Run the same monitorings using the LOTEK datasets.


## Reanalysis

- Run a set of $\mathbf{3}$ different reanalysis using the NEMOVar (3DFGAT) system : without obs., with conventional obs., with conventional obs. + STORM obs.


## Conclusion

- The first results reveal a promise of quantifying the ocean mixed layers inside cyclonic eddies, along with the use of additional obs. in the NEMO reanalysis.

