Spatiotemporal models highlight influence of oceanographic conditions on common dolphin bycatch risk in the Bay of Biscay

Lola Gilbert

Gilbert Lola, Rouby Etienne, Tew-Kaï Emilie, Spitz Jérôme, Peltier Hélène, Quilfen Victor, Authier Matthieu

CONTEXT – BYCATCH THREAT

- Bycatch on the rise

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- Represent a potent threat for the population

Mannocci et al. 2012

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Mannocci et al. 2012

CONTEXT – BYCATCH THREAT

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- Represent a potent threat for the population

- 1000 individuals / year ⇒ extinction in a 100 years

- Estimation for 4 months in 2019 : 11 300 individuals (IC95% : [7550; 18 530])

Mannocci et al. 2012, Peltier et al. 2019

CONTEXT – STRANDING DATA

- In the Bay of Biscay, stranding data have been instrumental to study the issue

Peltier et al. 2016

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CONTEXT – STRANDING DATA

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→ Estimations of its magnitude

→ Spatio-temporal patterns

→ possible association with dolphin preys

Peltier et al. 2016, Peltier et al. 2020, Spitz et al. 2013

QUESTION RAISED

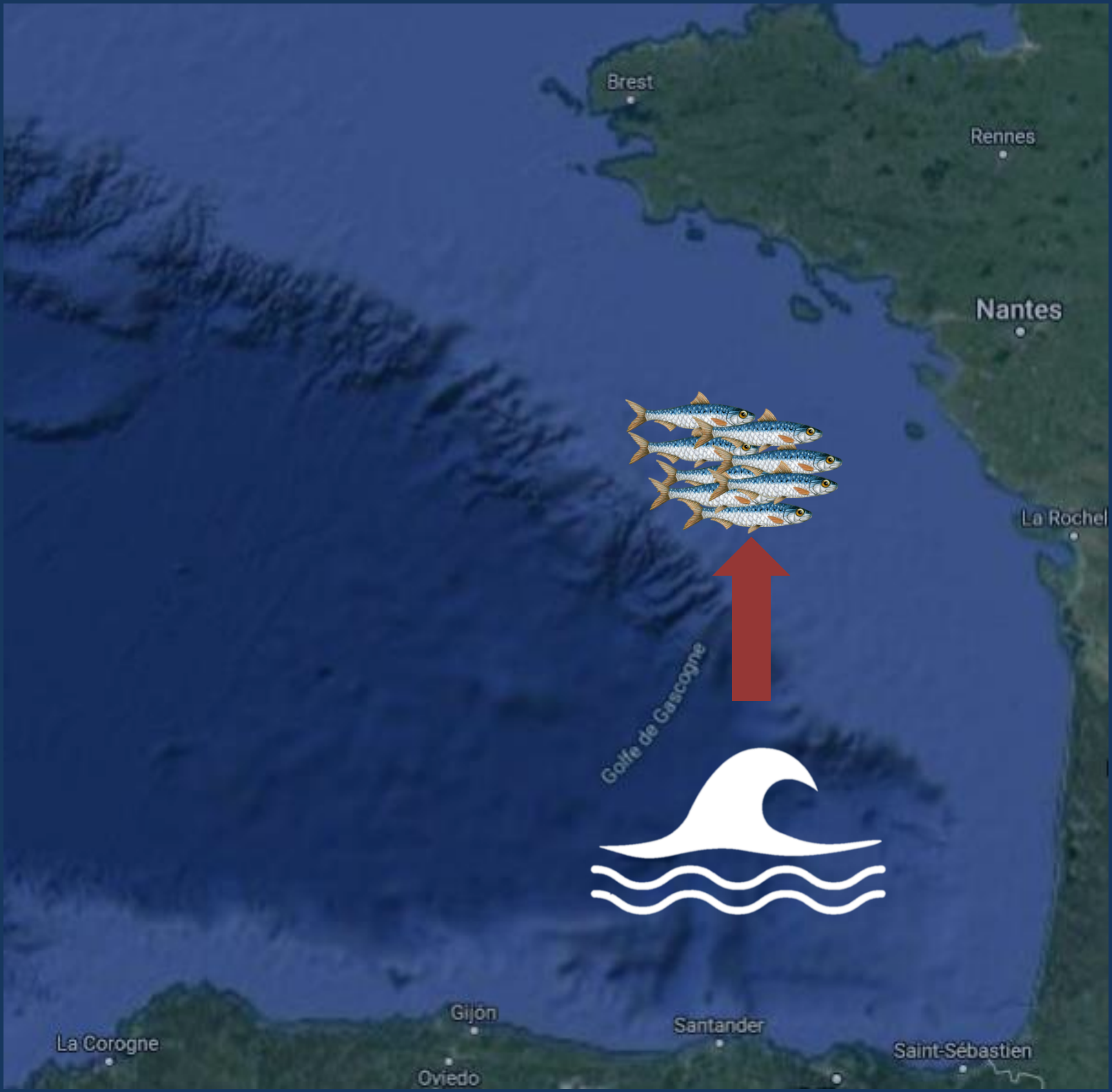
Is there an influence of oceanographic processes on the cooccurrence of

and

?

HYPOTHESIS

Oceanographic processes structure the availibility of preys



HYPOTHESIS

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Spatial

Temporal

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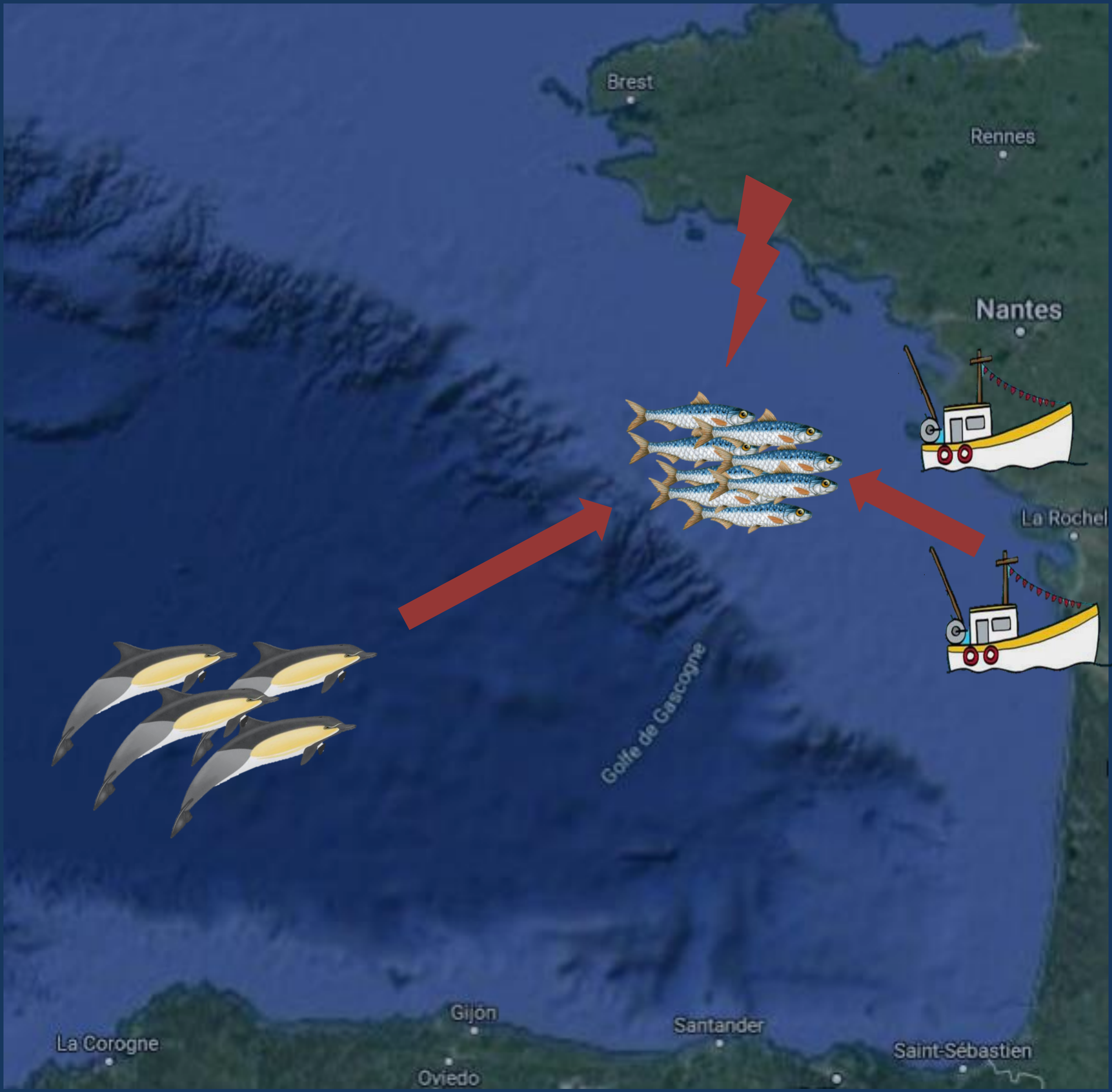

M & M - DATASET

OCEANOGRAPHIC

- Circulation model

García-Barón et al. 2020, Tew-Kaï et al. 2020

L'océan en référence

OCEANOGRAPHIC

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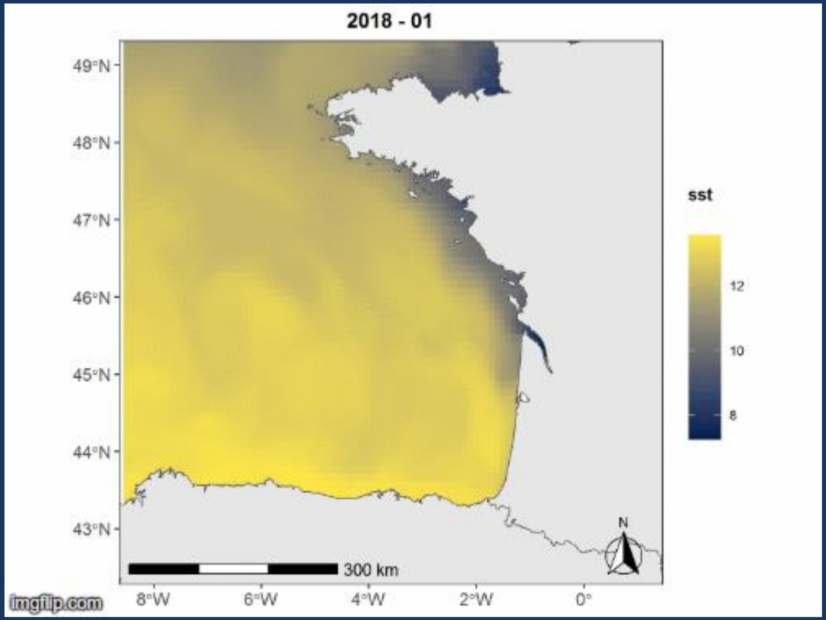

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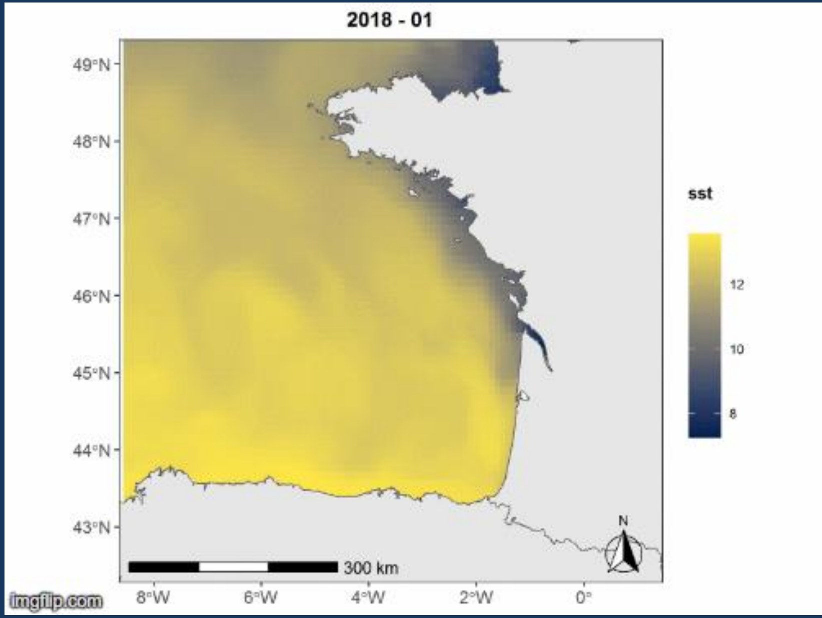

BYCATCH MORTALITY

Réseau National Echouages

PELAGIS UMS 3462 - ULR - CNRS

- Strandings → reverse drift

García-Barón et al. 2020, Tew-Kaï et al. 2020

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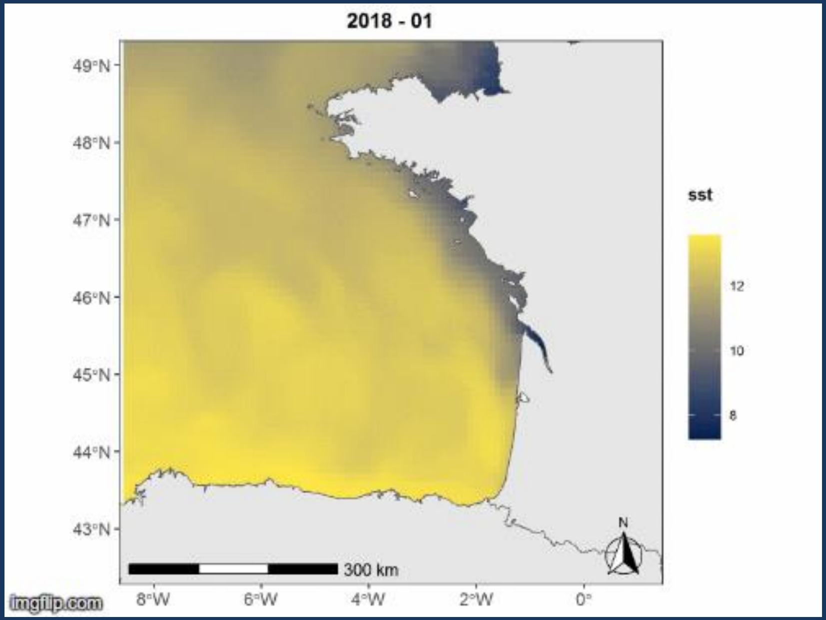

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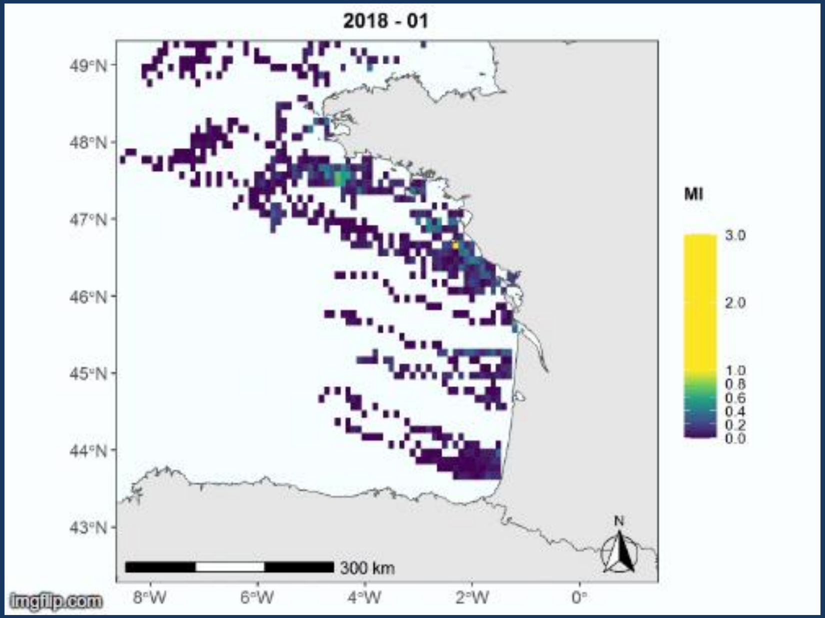

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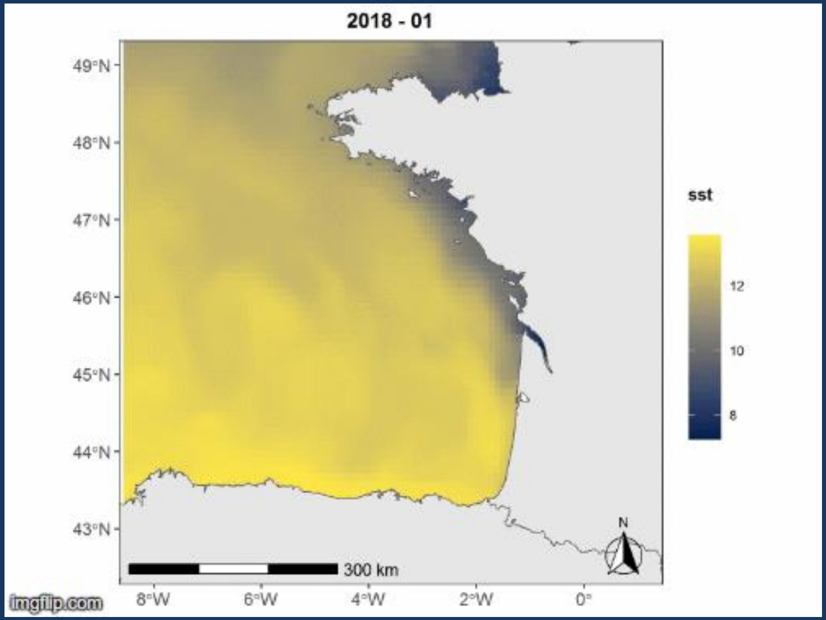

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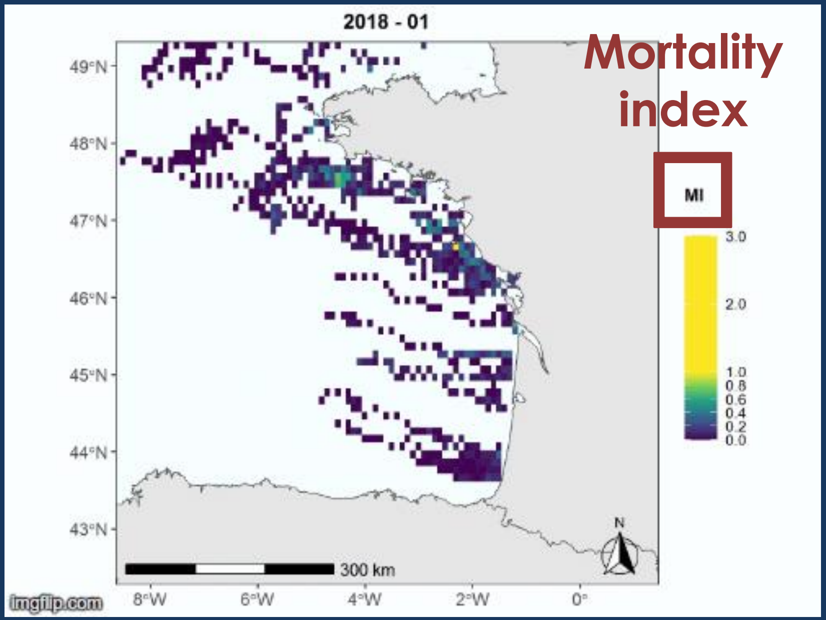

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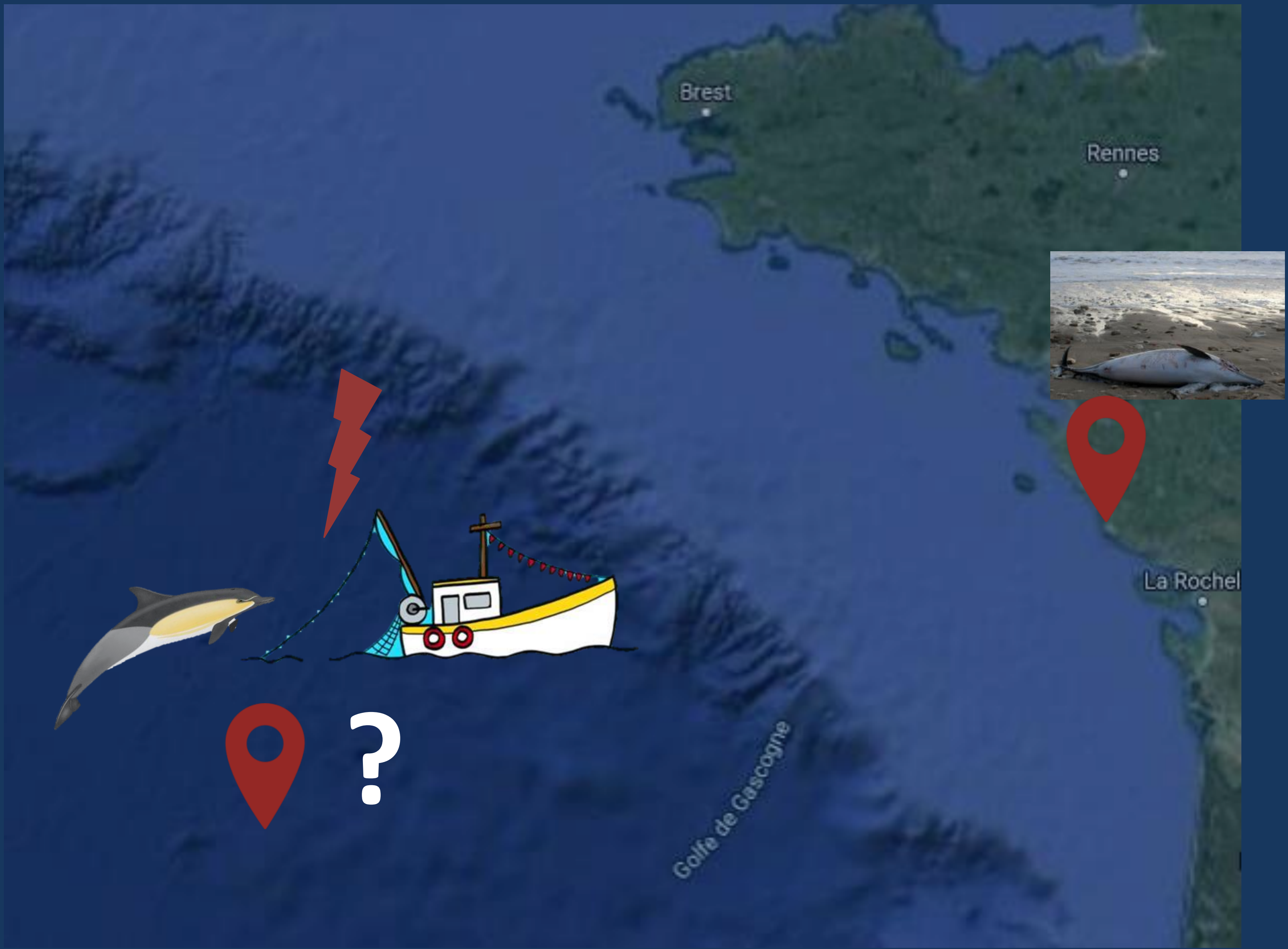
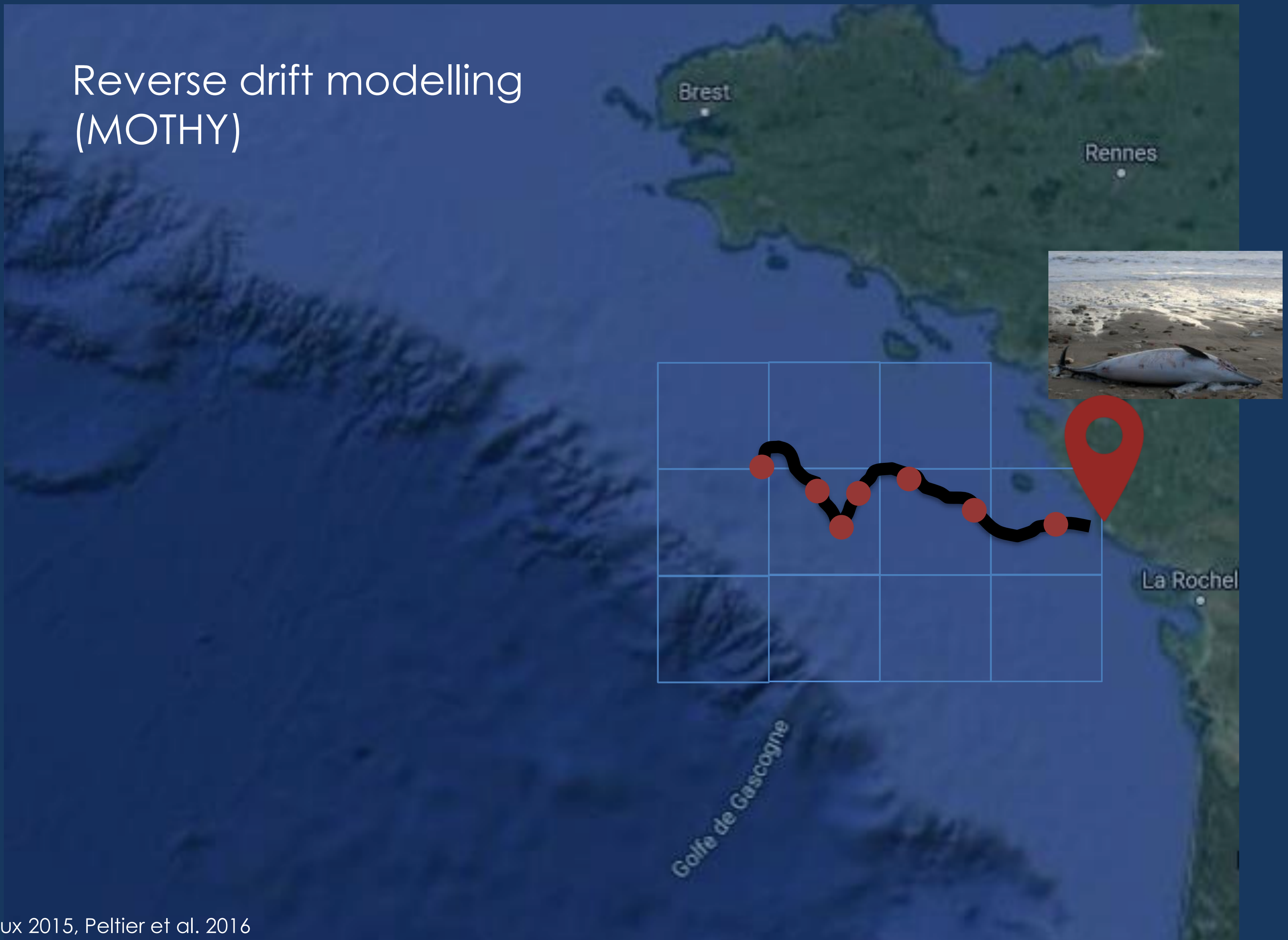
M & M – MORTALITY INDEX (MI)



M & M – MORTALITY INDEX (MI)

Reverse drift modelling (MOTHY)



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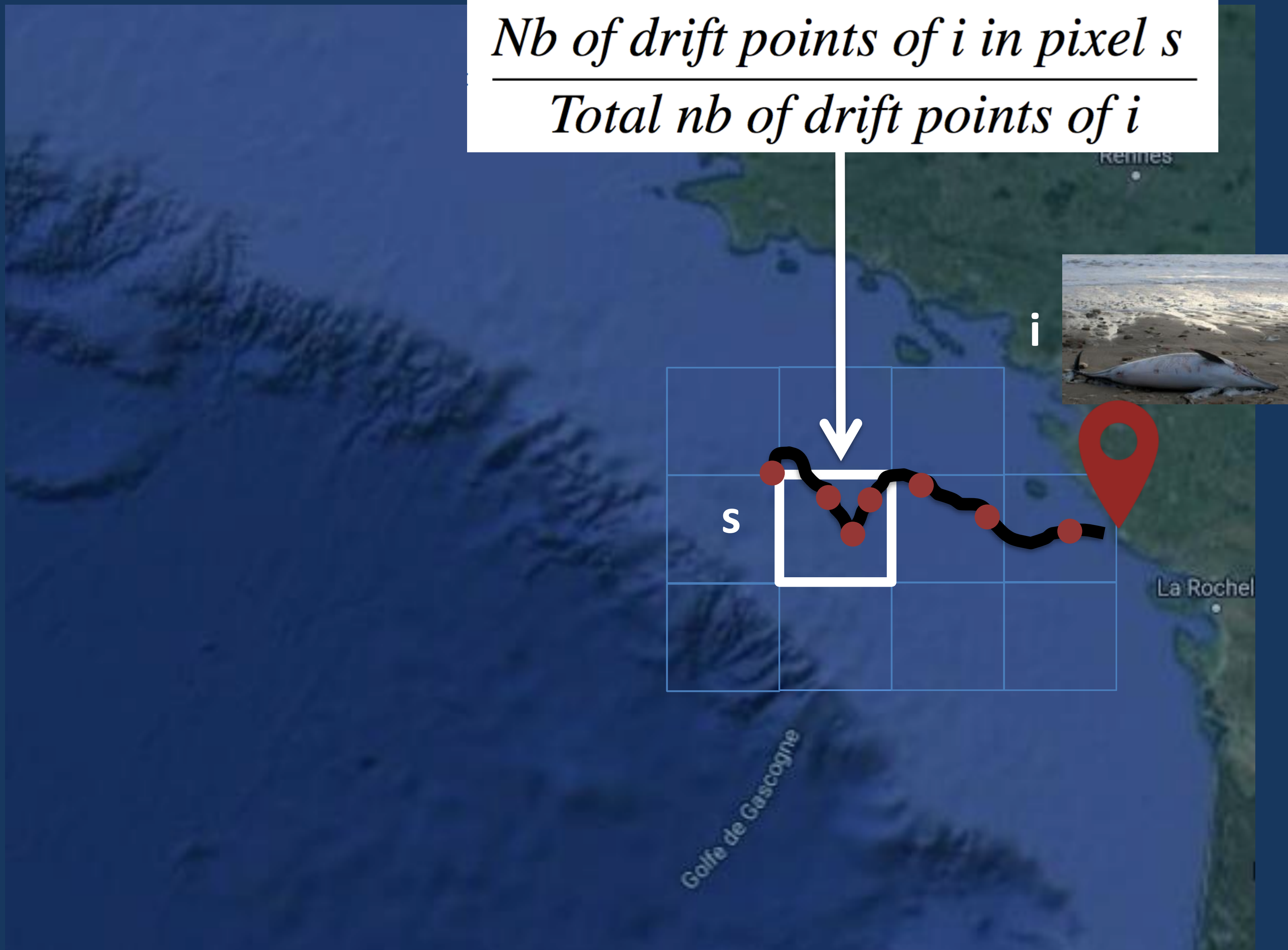

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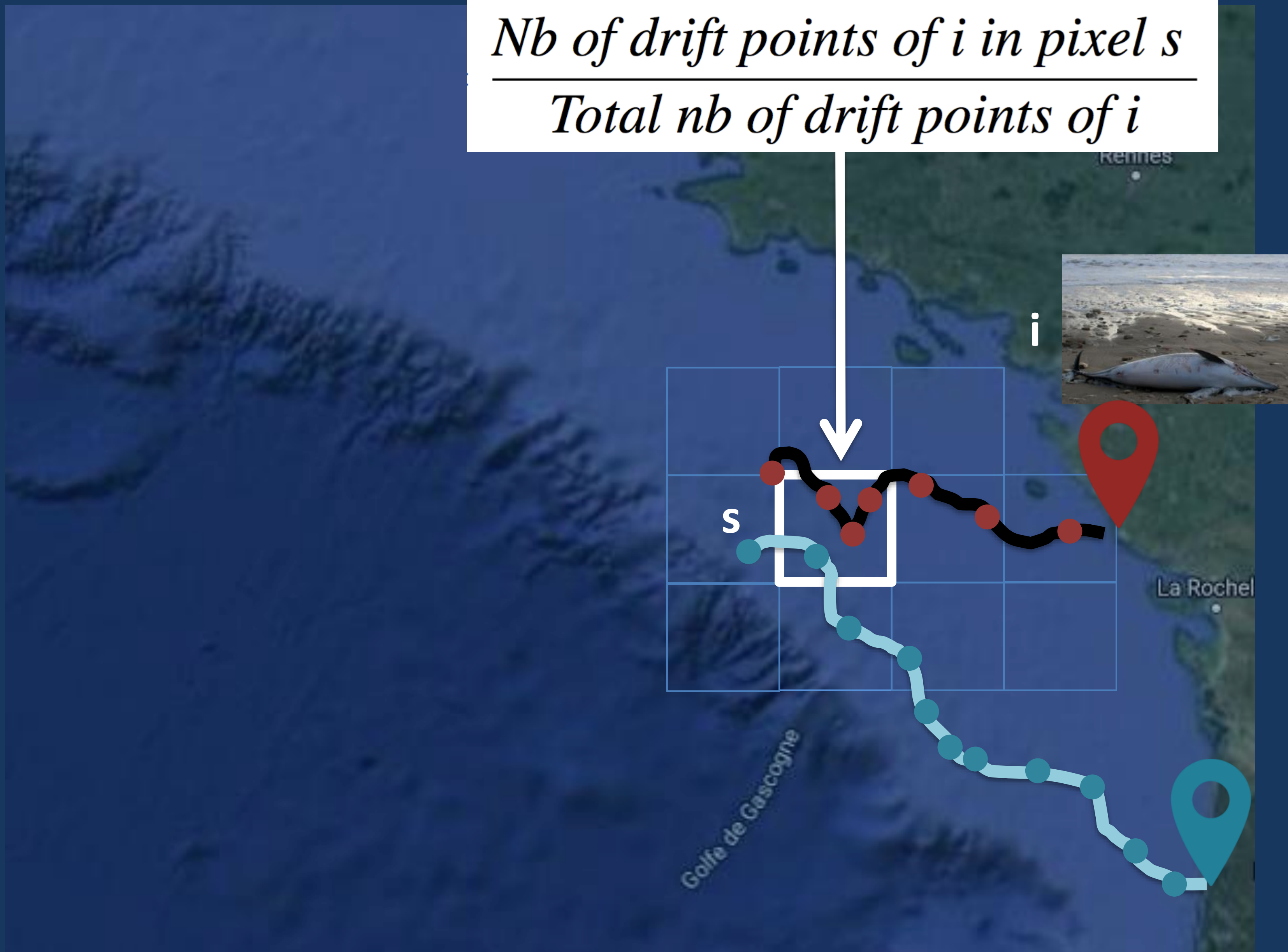

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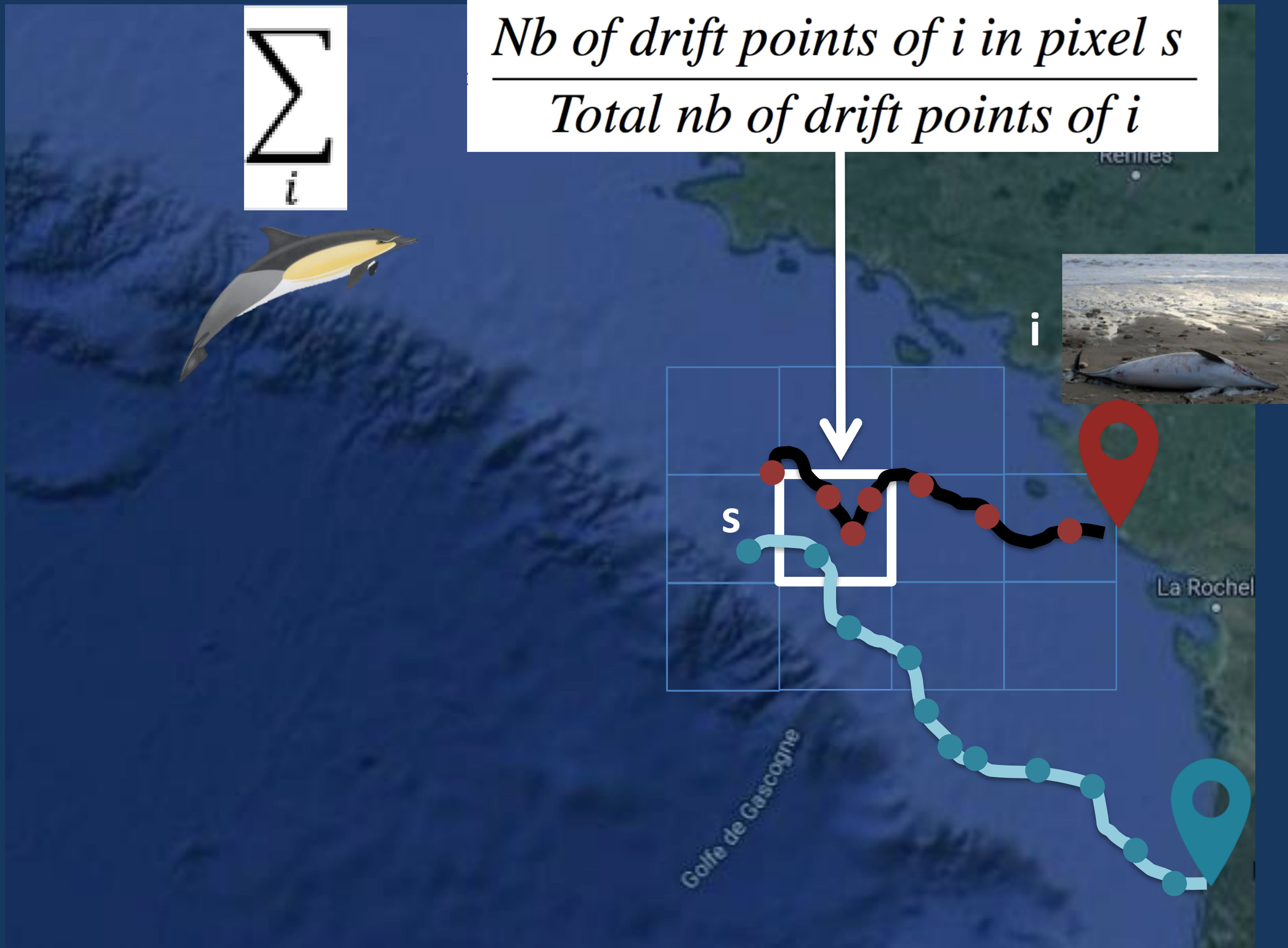
$$\sum_{i} \frac{\text{Nb of drift points of } i \text{ in pixel } s}{\text{Total nb of drift points of } i}$$



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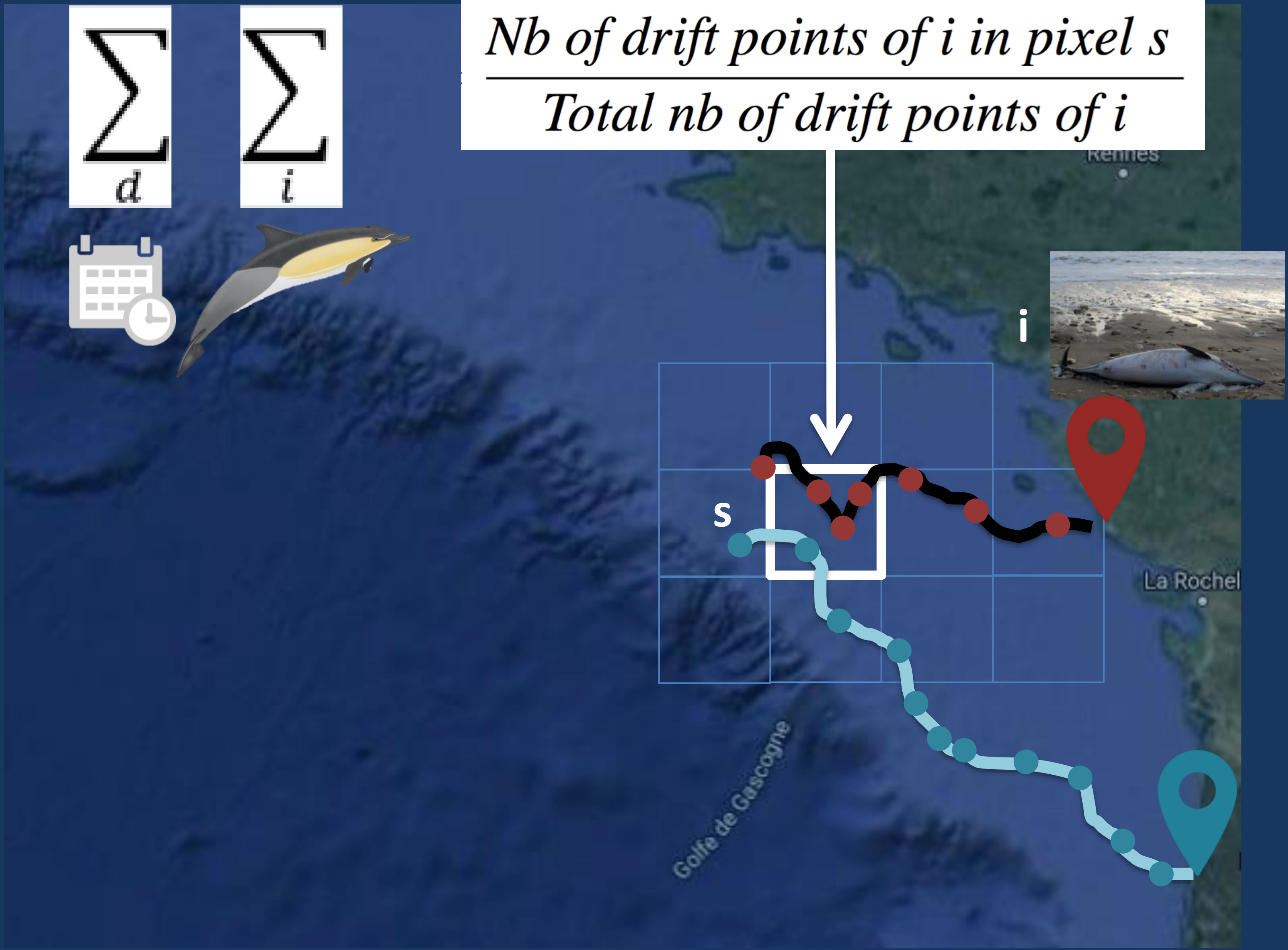

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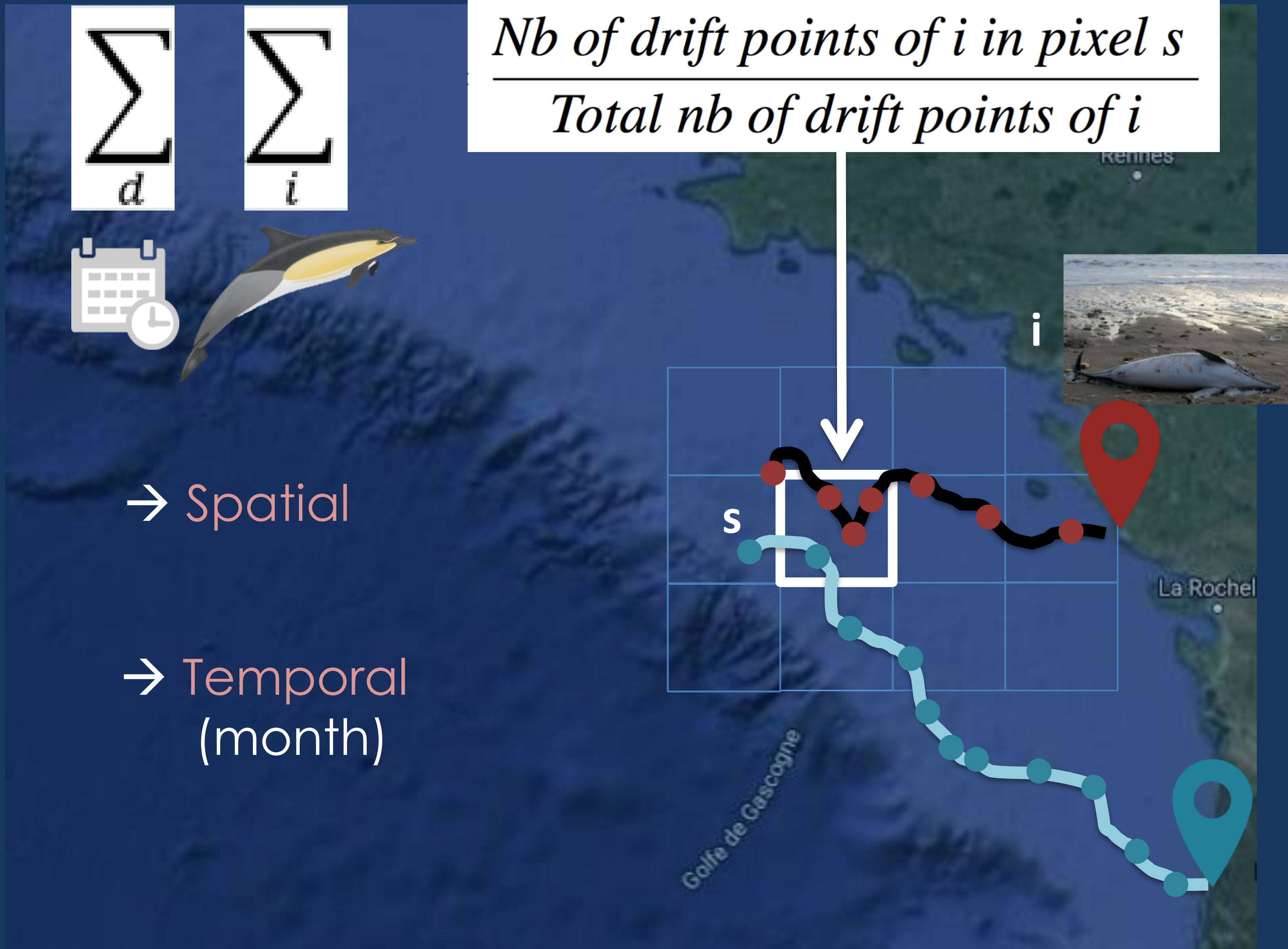
→ Spatial

→ Temporal (month)



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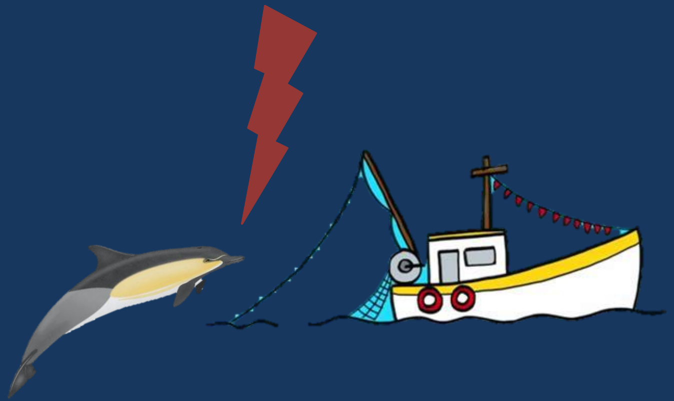
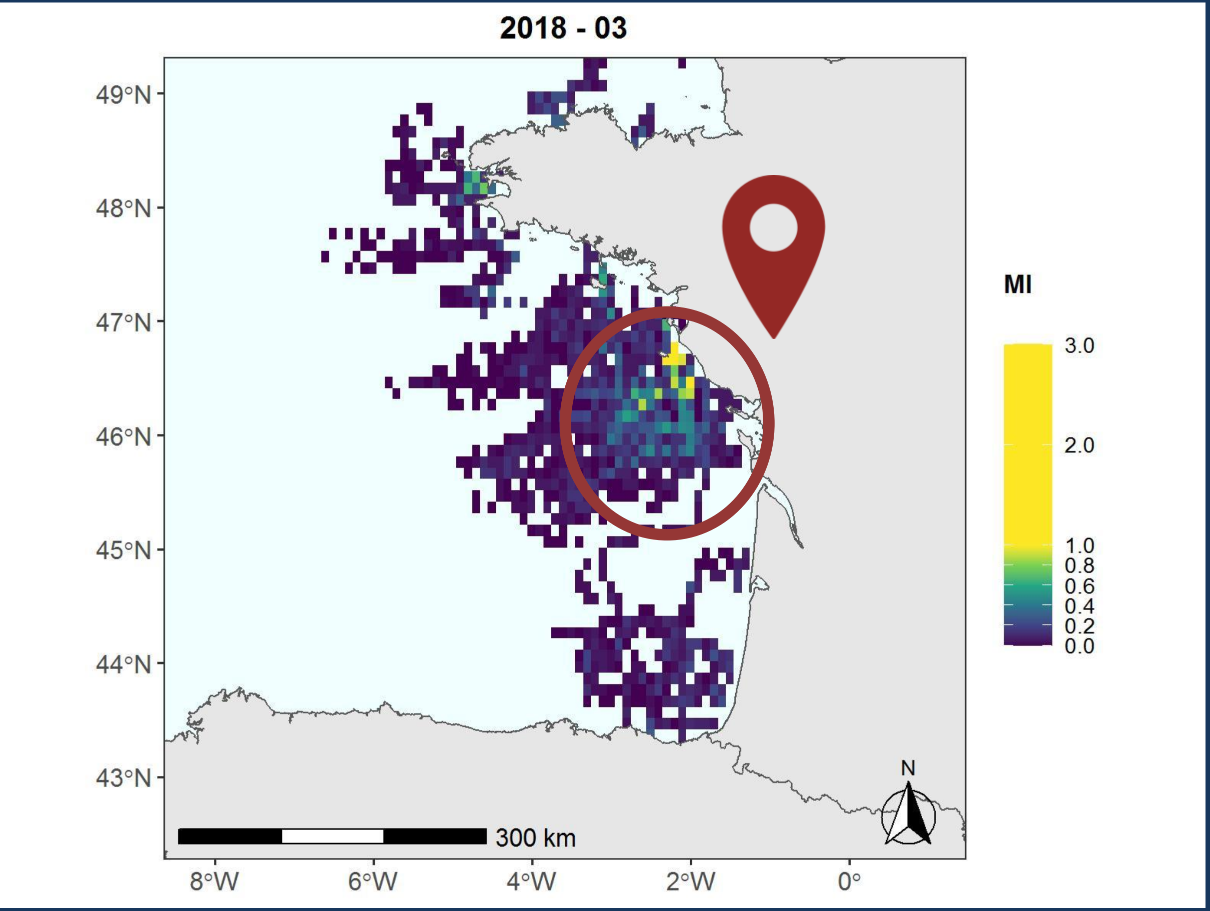


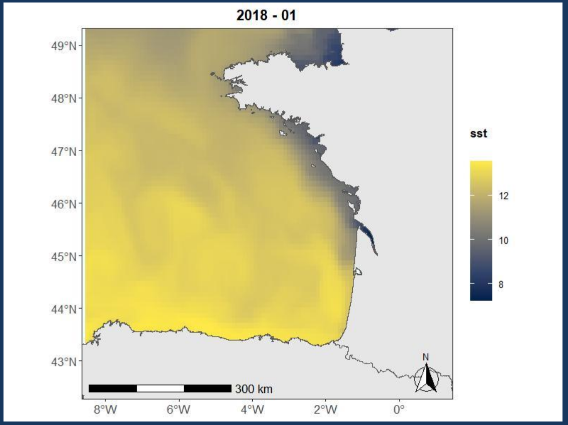
→ Mortality areas

→ Intensity of mortality events



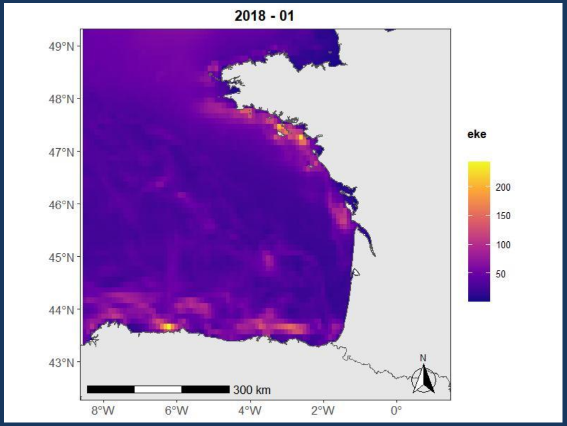
M & M – OCEANOGRAPHIC COVARIATES

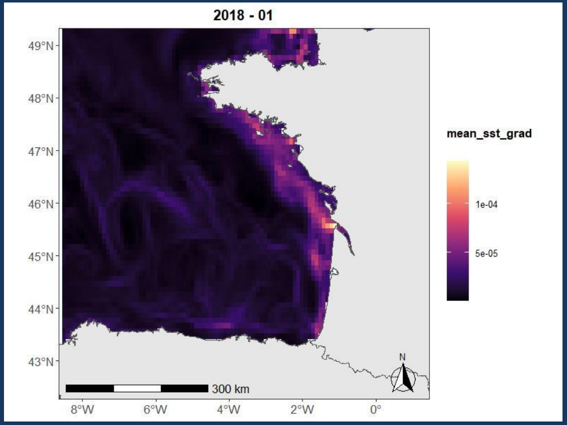
- 3 oceanographic variables



Sea surface temperature (*sst*)

Eddy kinetic energy (*eke*)





Mean sea surface temperature gradient (*mean_sst_grad*)

MODELLING – HBMs WITH INLA

- Spatiotemporal hierarchical bayesian model

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- 1 model per month, each with 7 years

2012 → ... → 2018

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$$log(MI_{s,t} + 1) \sim \mathbb{N}(\pi_{s,t}, \sigma)$$

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Yearly linear coefficients
(random slopes)

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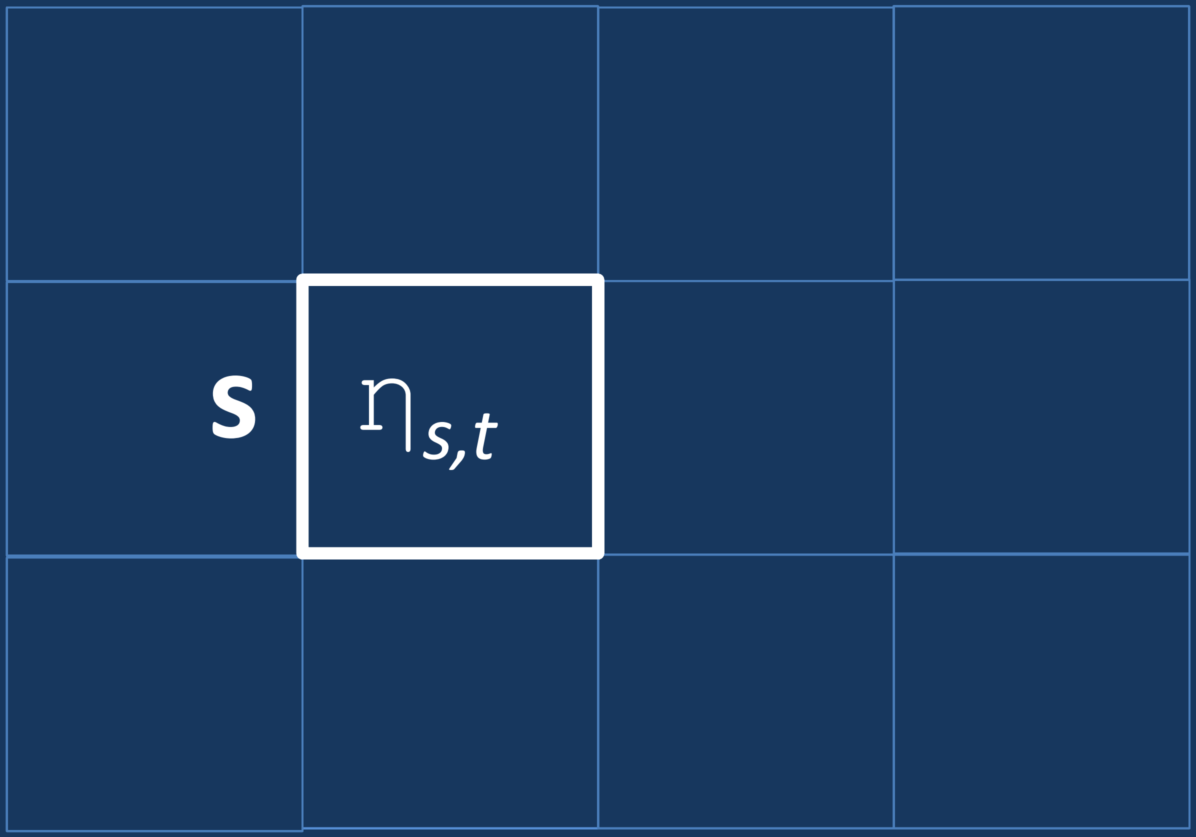
Spatial field

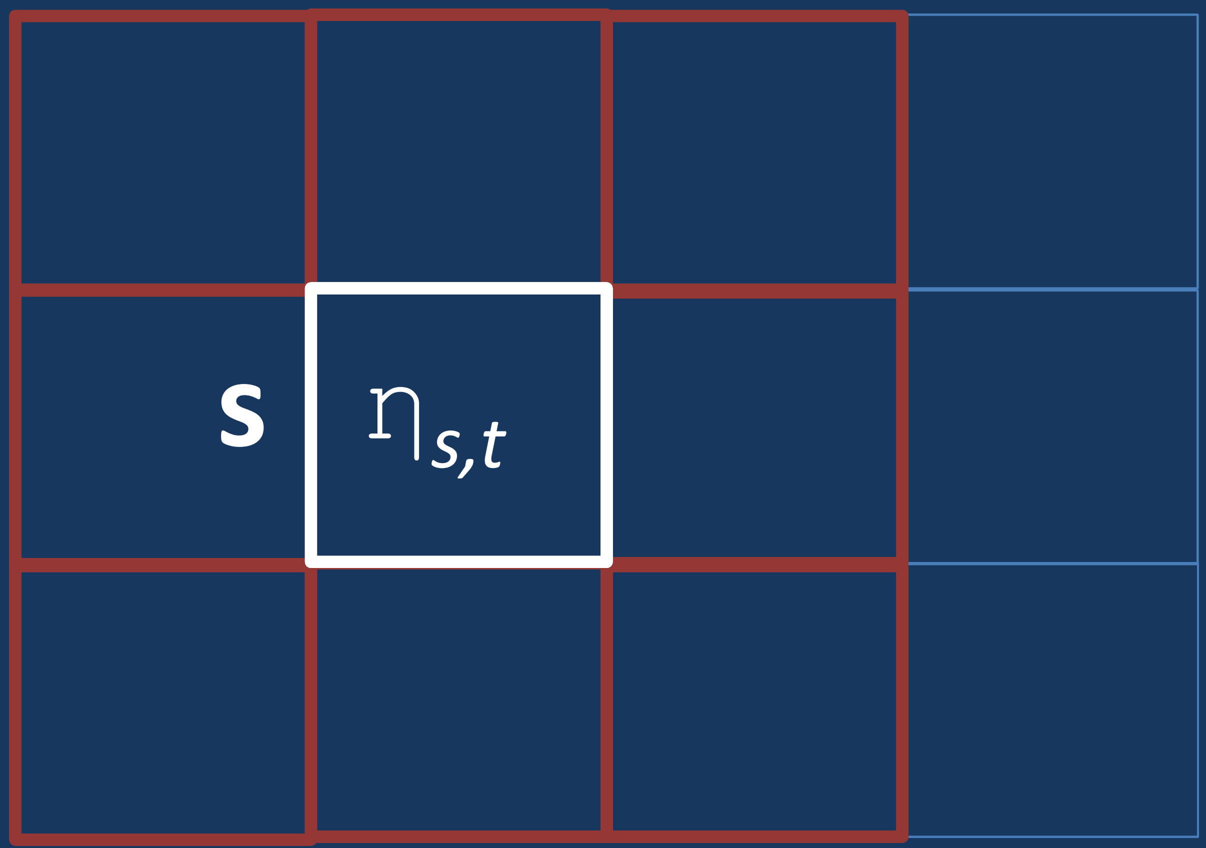
- Conditional autoregressive spatial field (CAR)



Besag et al. 1991, Besag & Kooperberg 1995

- Conditional autoregressive spatial field (CAR)

Spatial dependance between adjacent pixels



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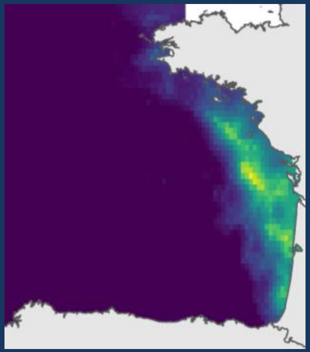

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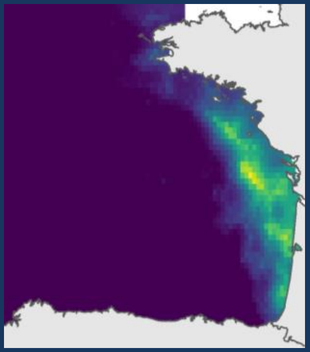

→ **INLA**

Integrated
Nested
Laplace
Approximations

Rue et al. 2009, Martins et al. 2013, www.r-inla.org

MODELLING – HBMs WITH INLA

- Model selection based on WAIC

Wanatabe 2010, Gelman et al. 2013

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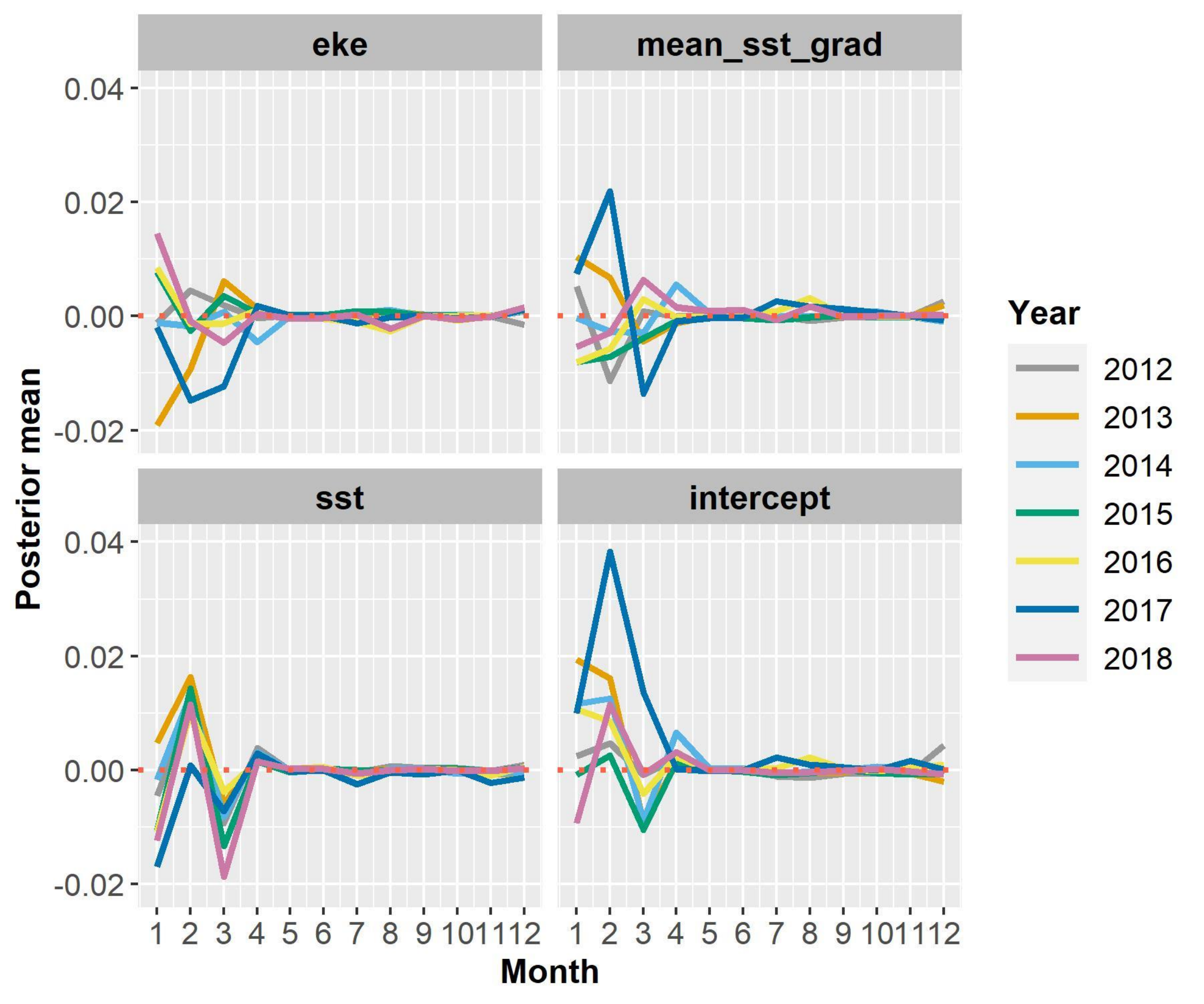
Could oceanographic processes' effect on bycatch mortality help explain observed mortality of 2019 ?

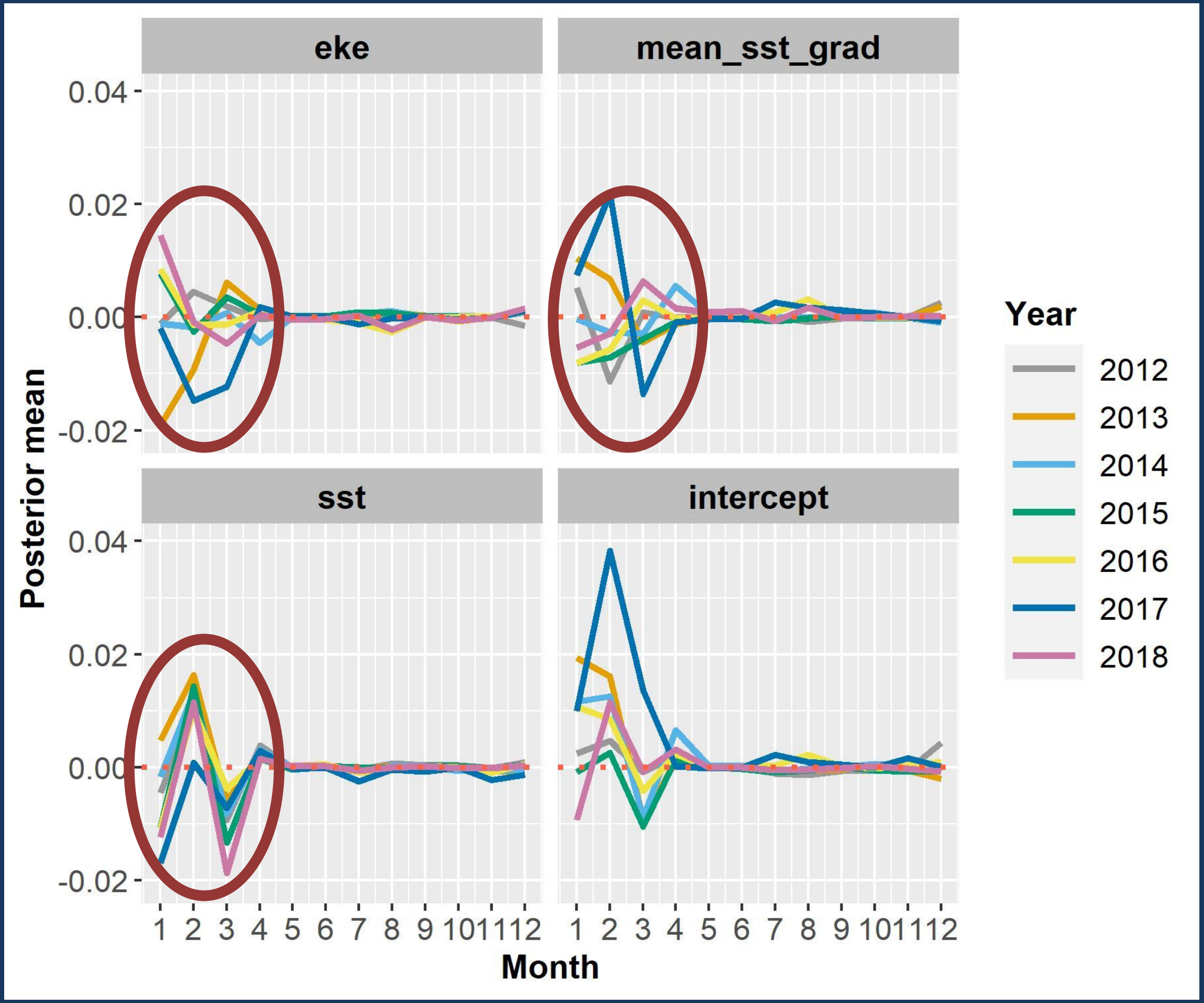
Wanatabe 2010, Gelman et al. 2013

RESULTS – COVARIATES



RESULTS – COVARIATES

- Seasonality



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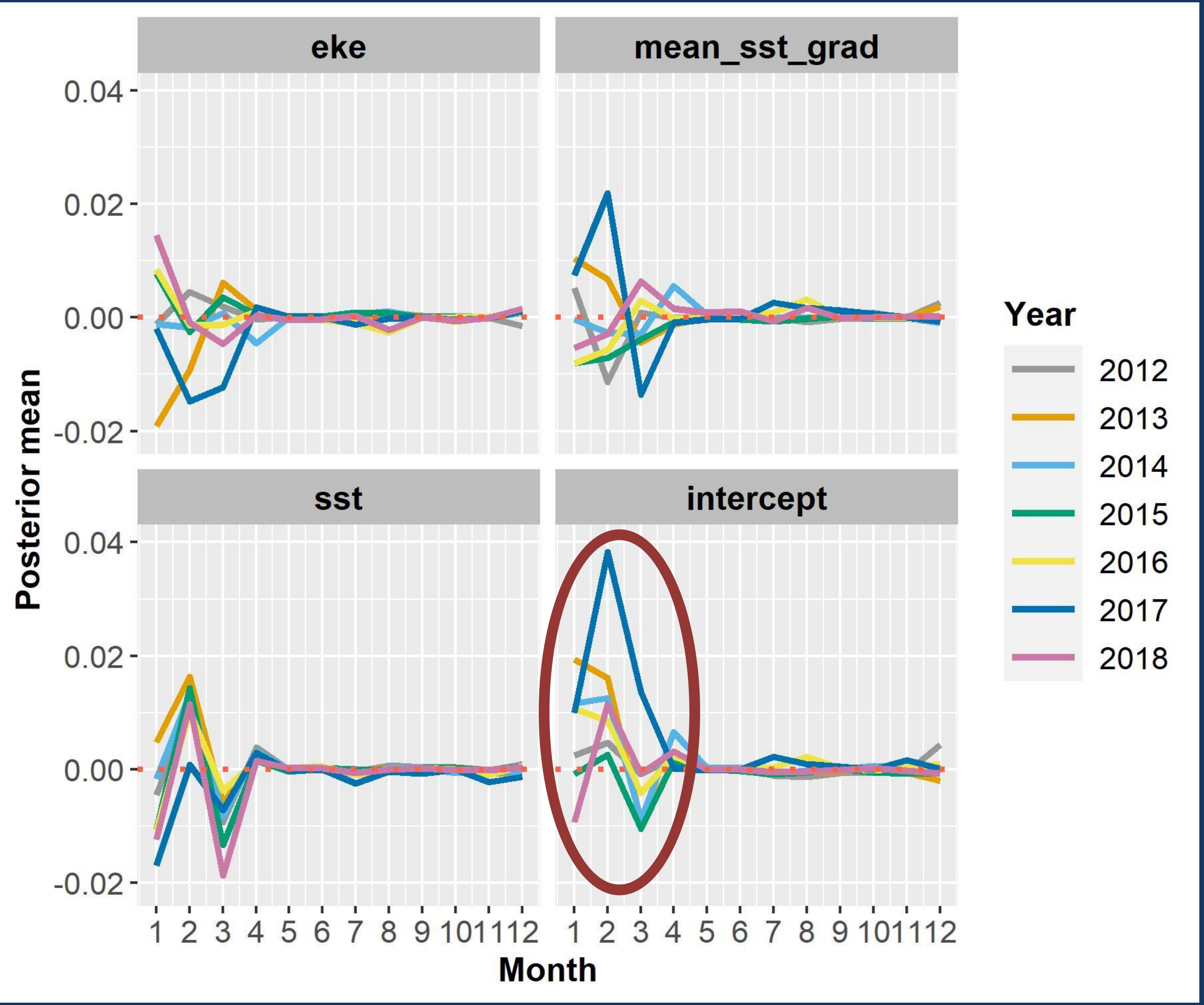
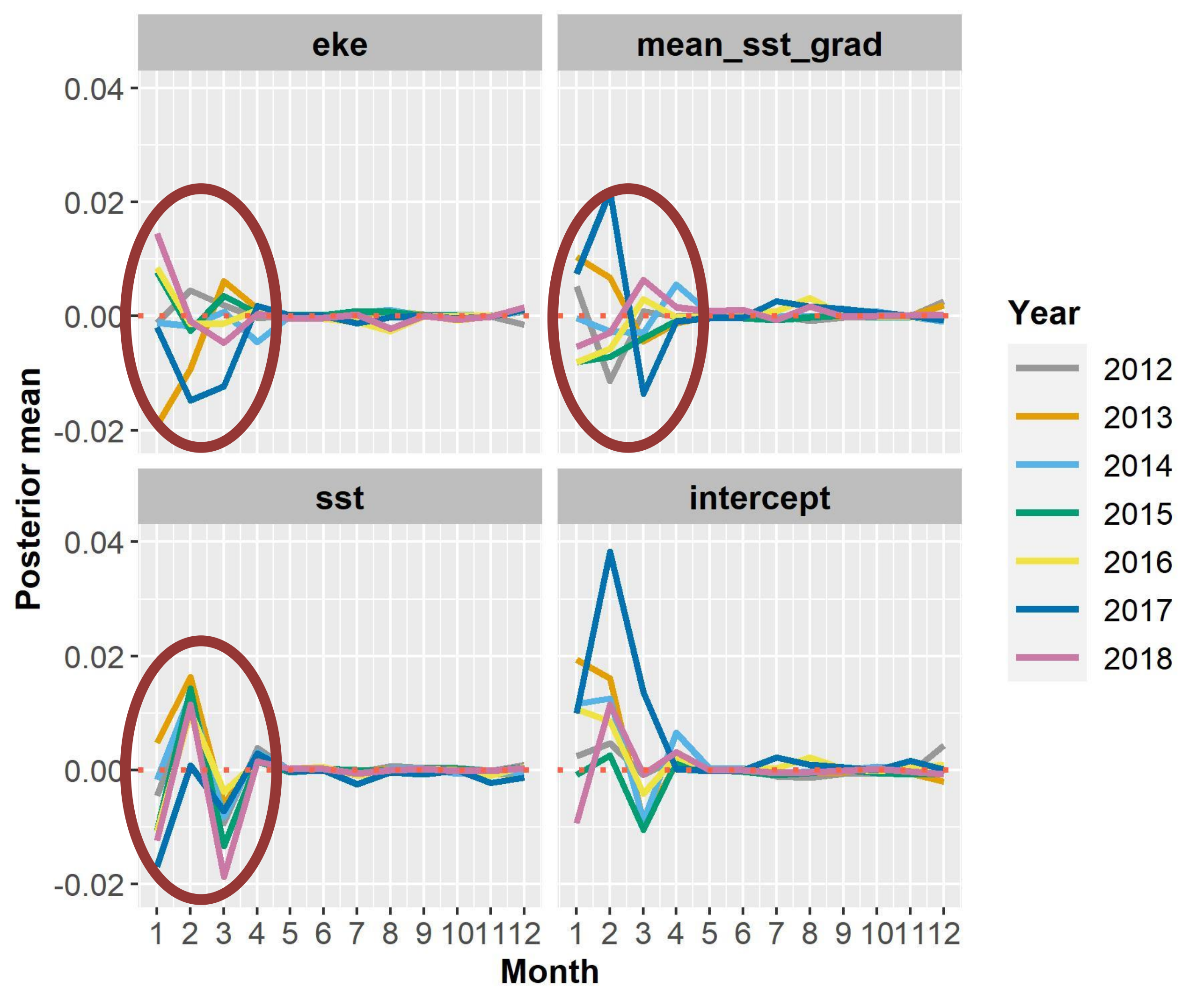


RESULTS – COVARIATES

- Inter-annual variability



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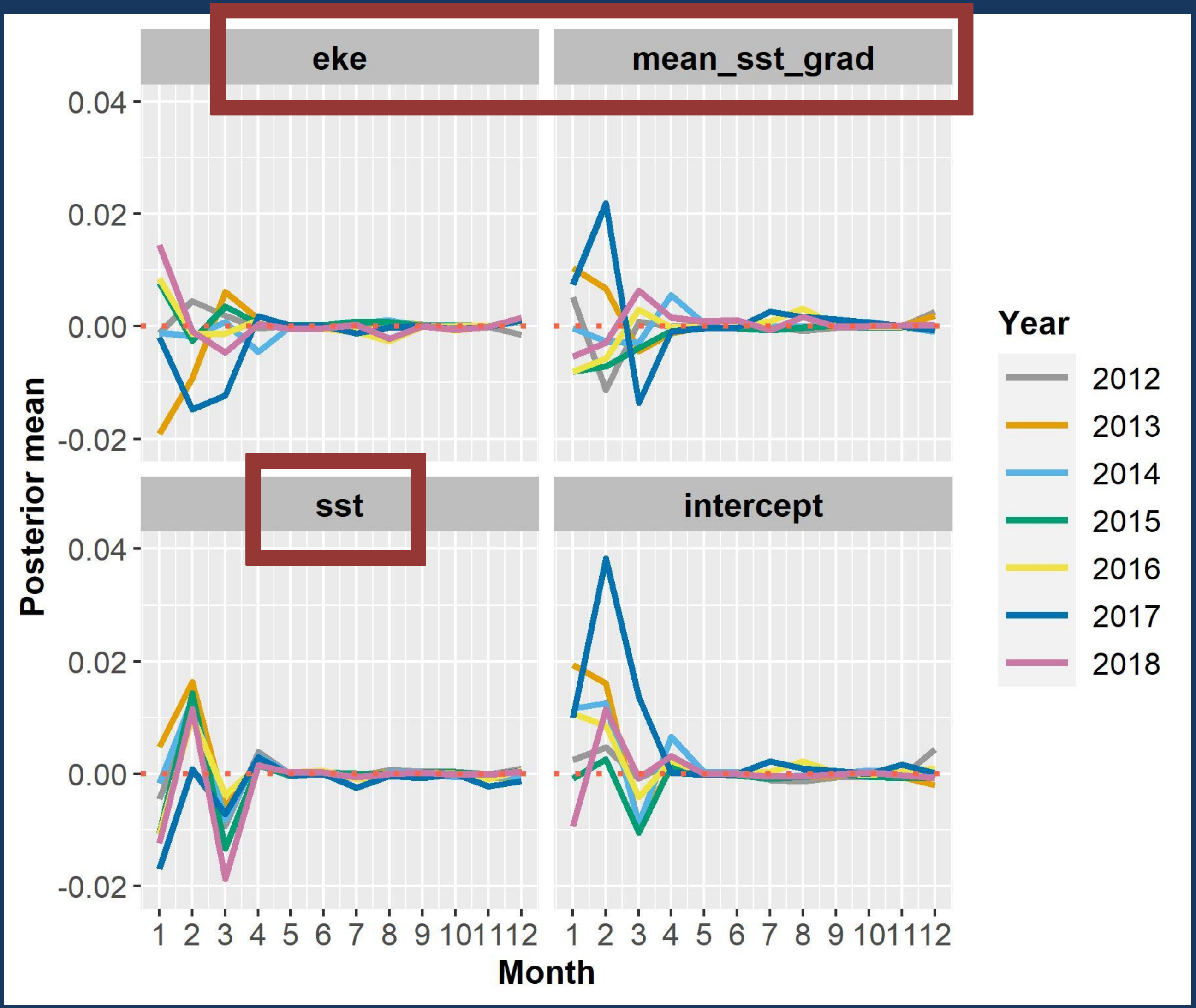
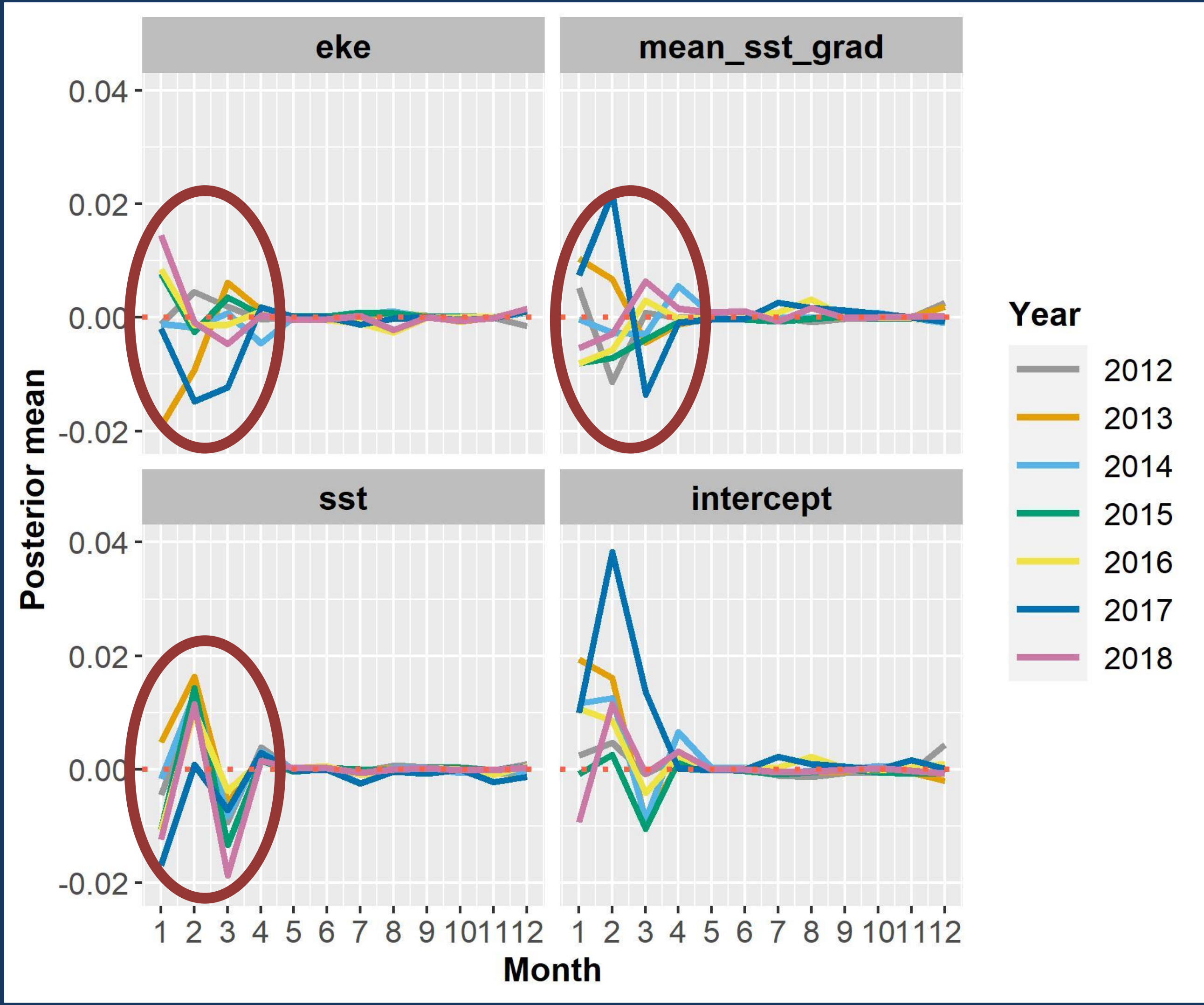
High–frequency processes

Low frequency process



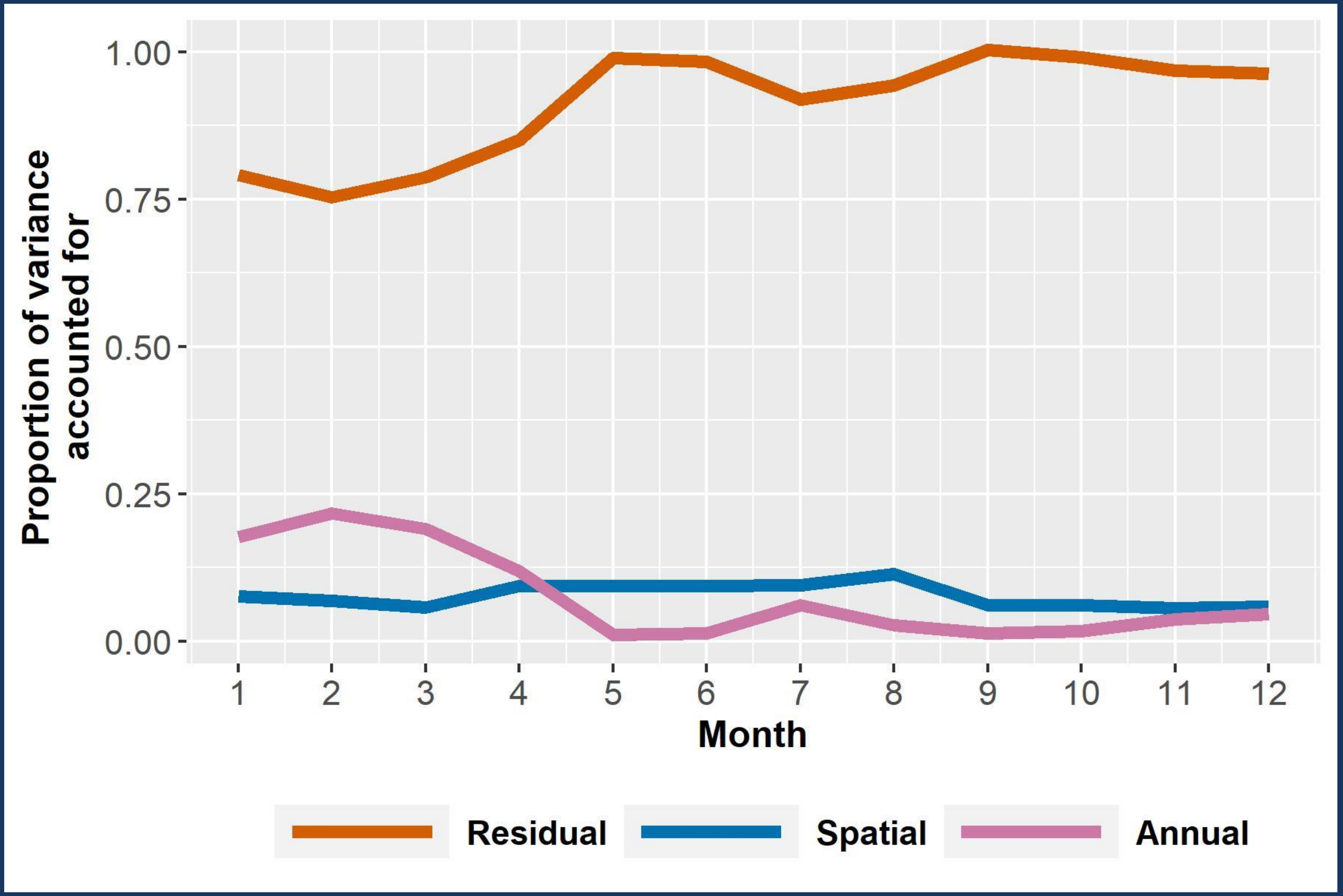
RESULTS – COVARIATES

- Between month variability



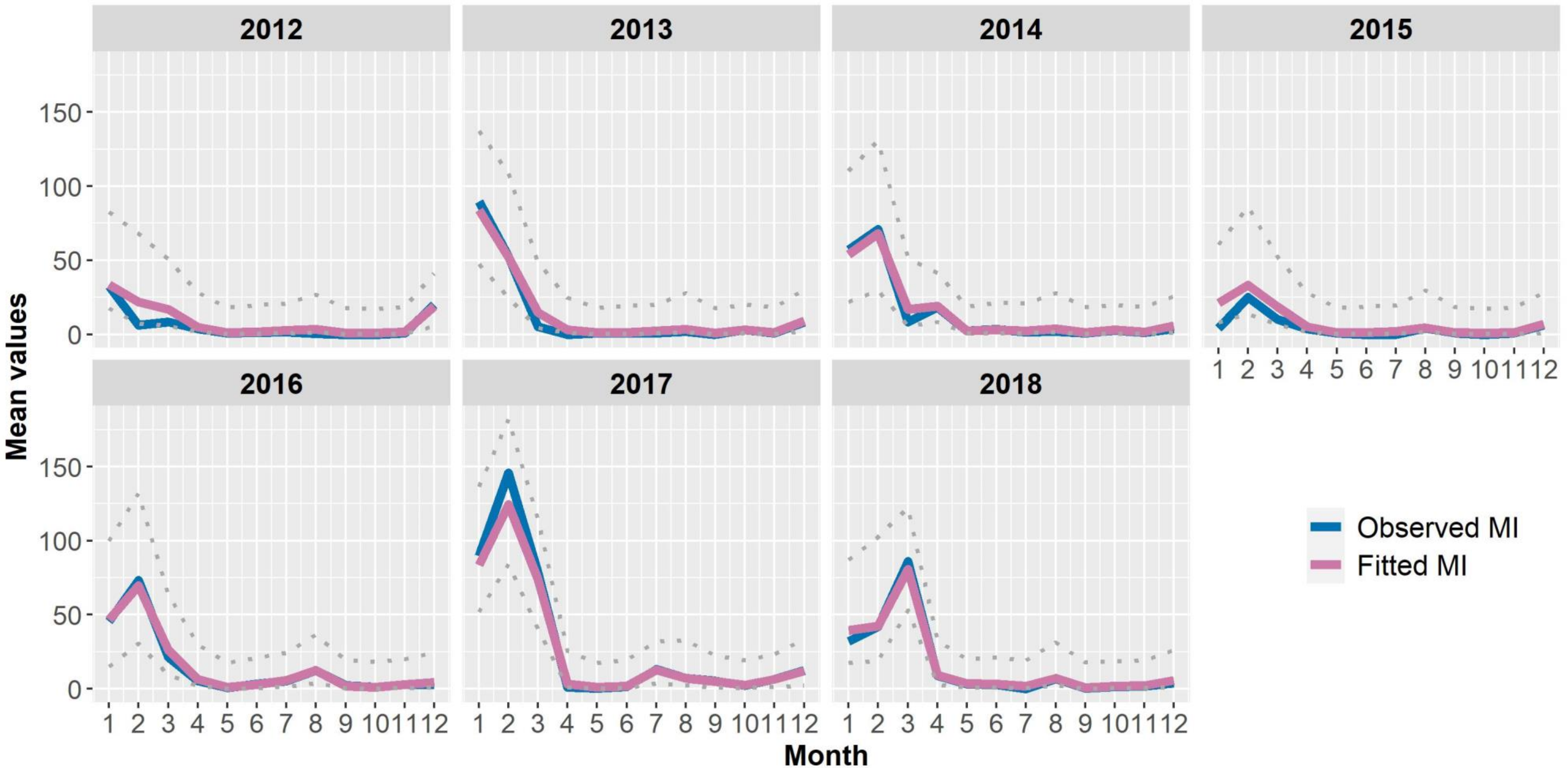
RESULTS – VARIANCE

- Variance taken into account by the different components of the models



RESULTS – FITTED VS OBSERVED TOTAL MI

- $\sum_s MI_s$ = total nb of stranded carcasses for a month



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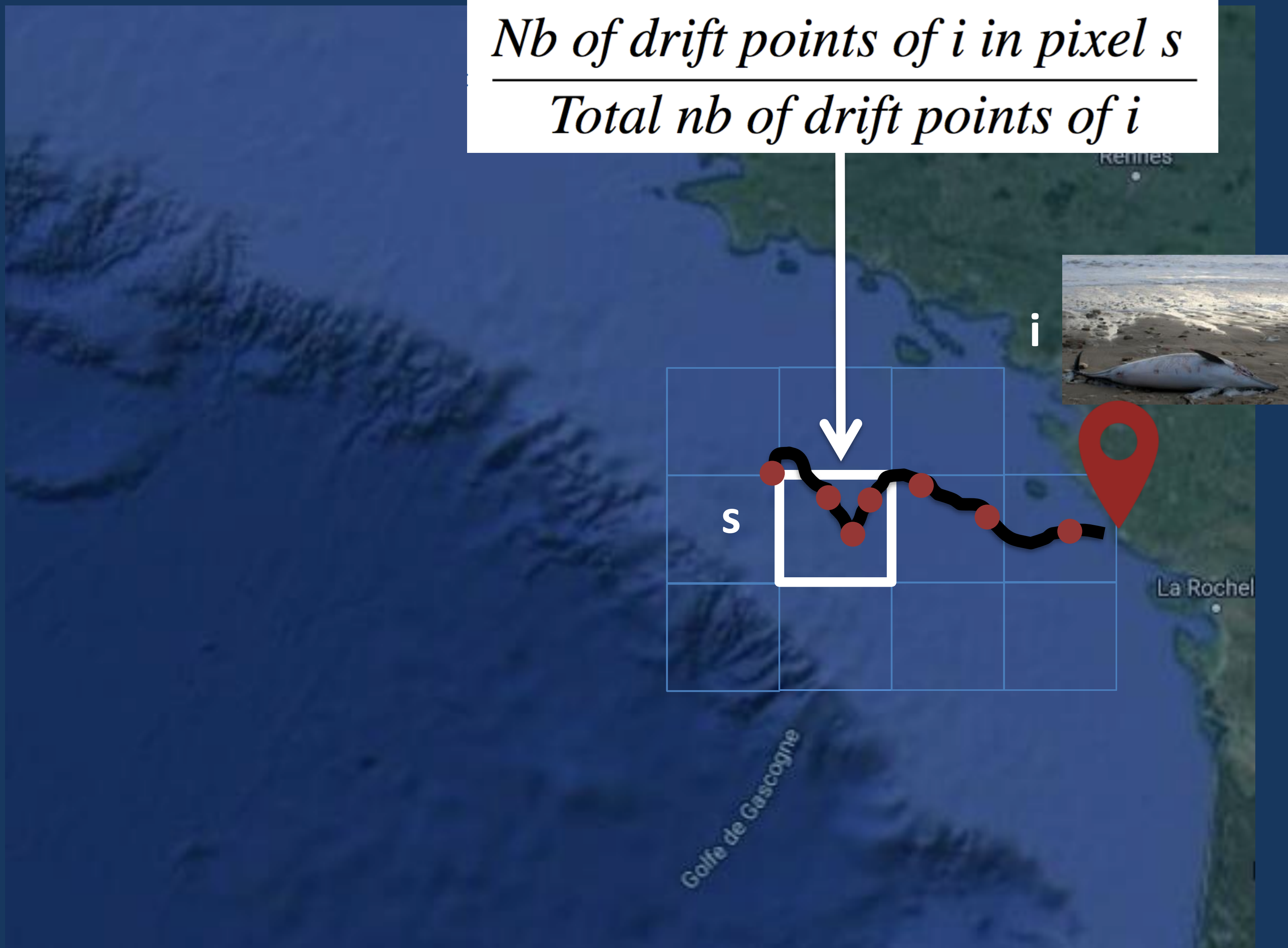

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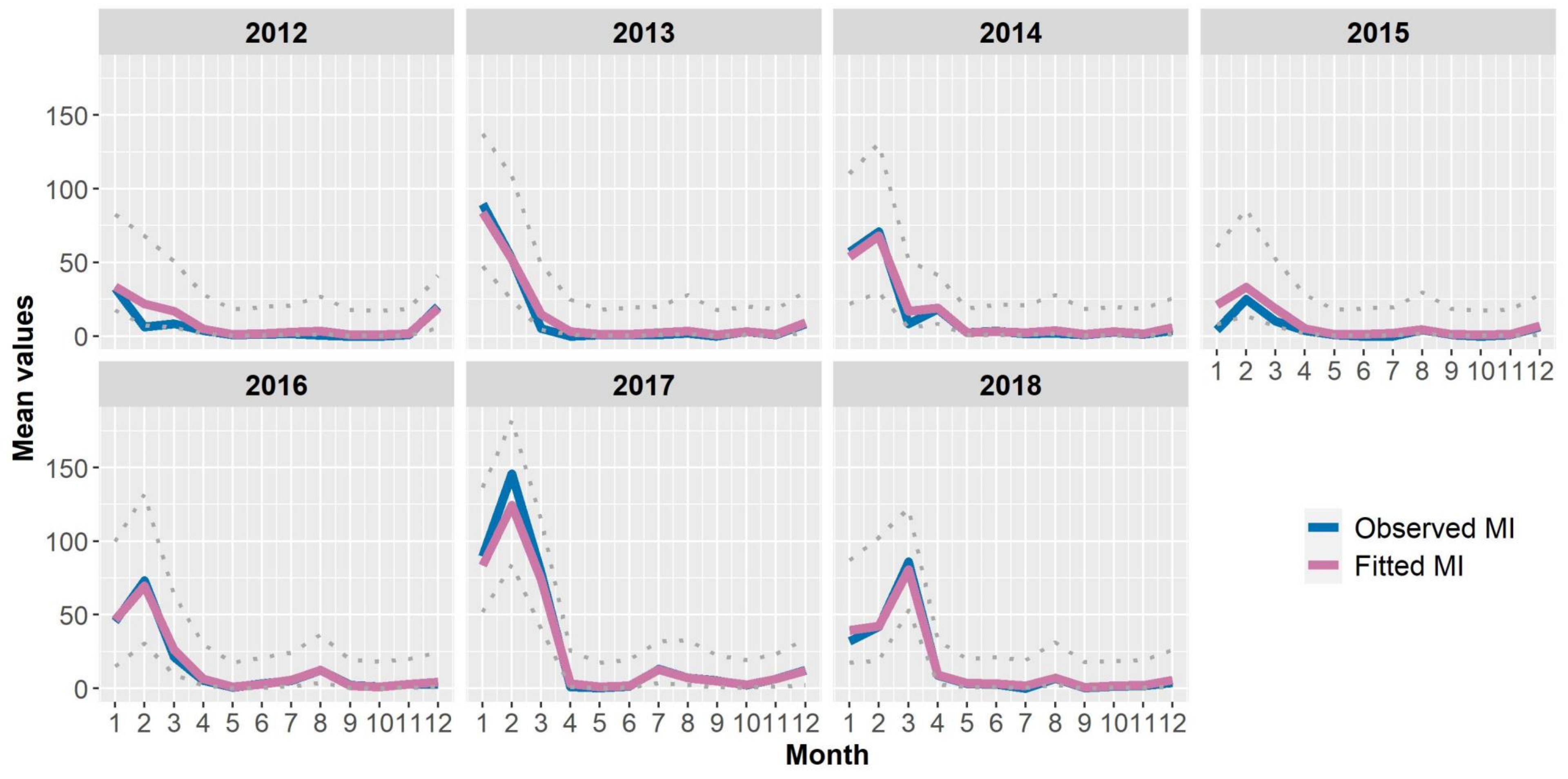
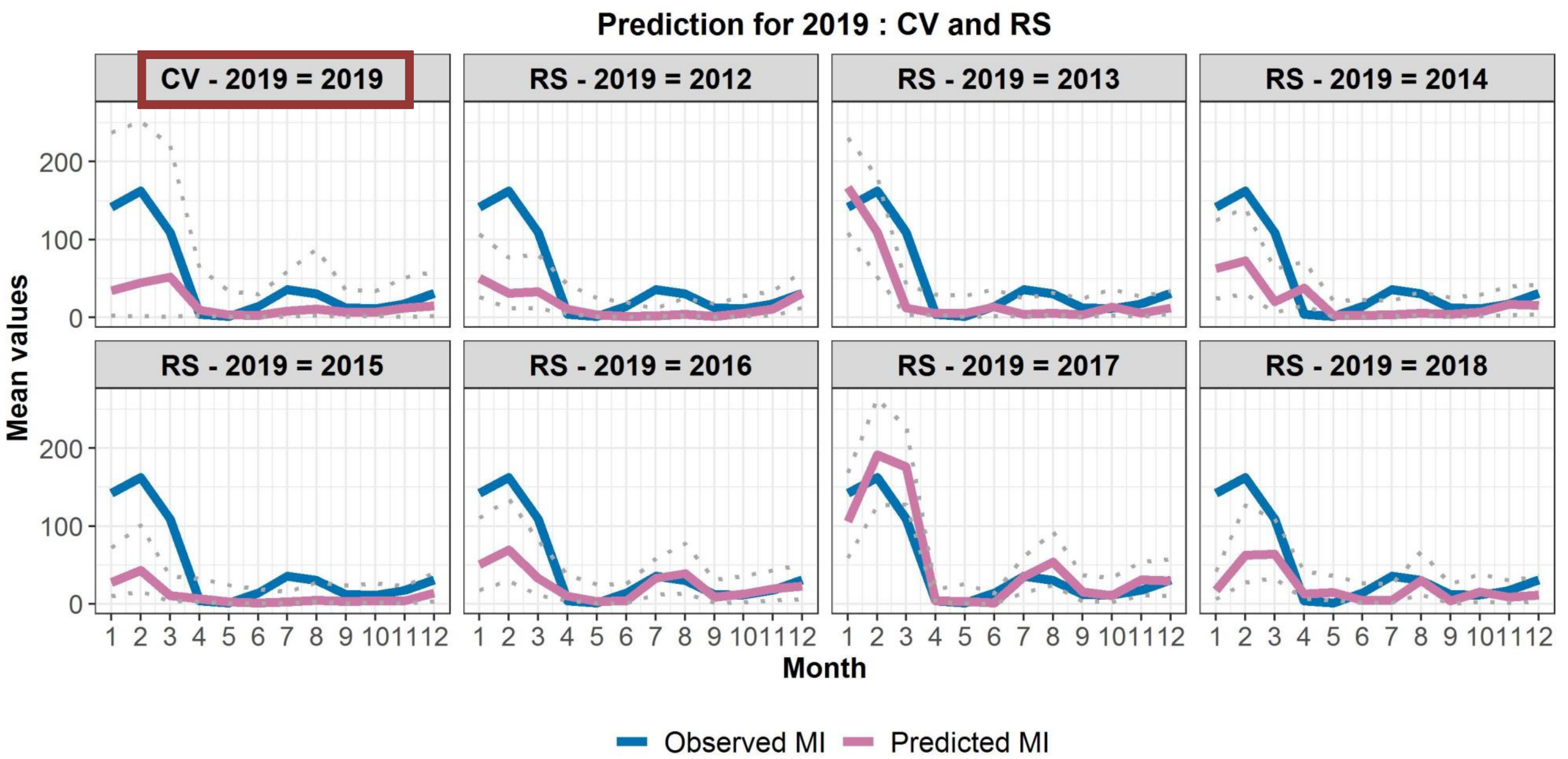


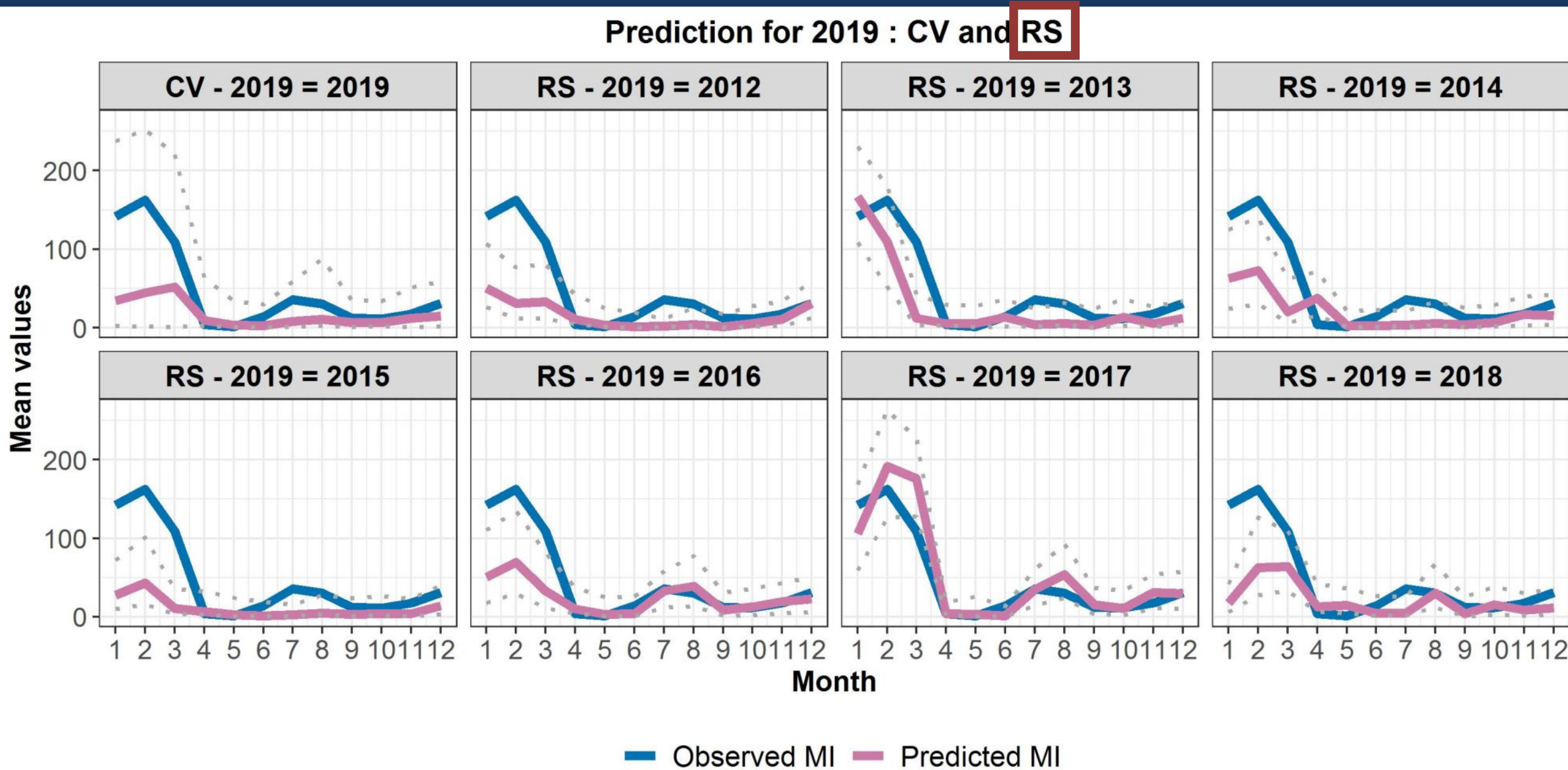
RESULTS – CROSS-VALIDATION & REPETITION SCENARIOS

Cross-validation



RESULTS – CROSS-VALIDATION & REPETITION SCENARIOS

Repetition scenarios



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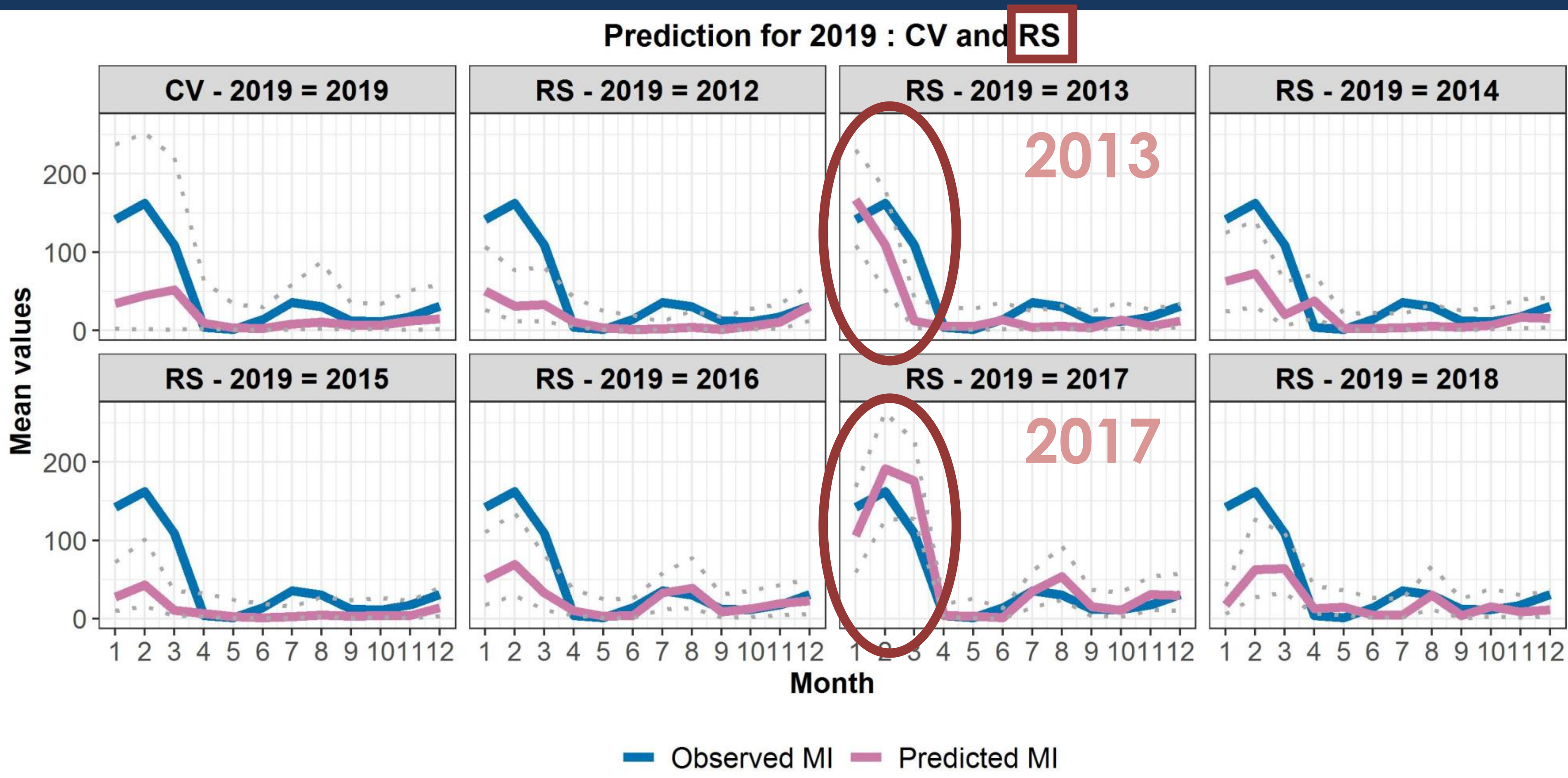

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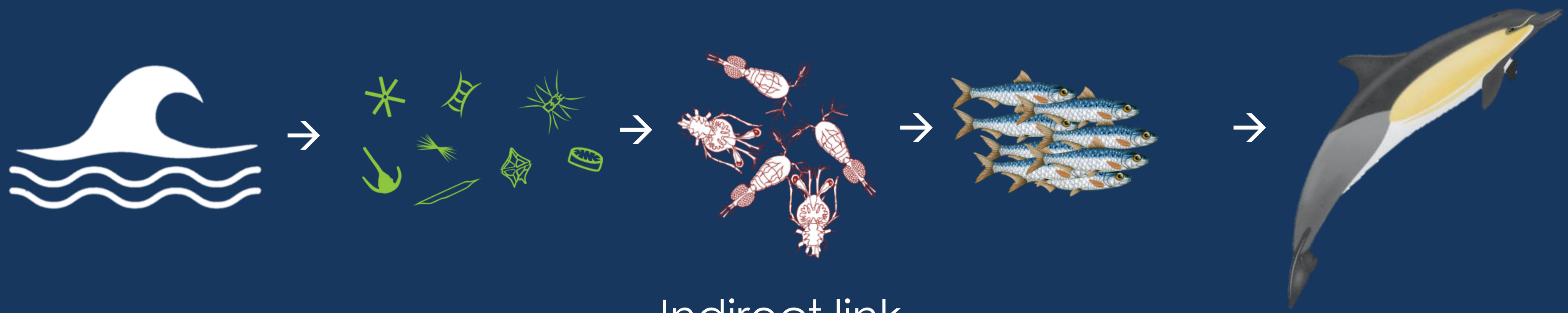

Indirect link

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Spatial

Temporal

Indirect link – complex processes

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DISCUSSION – PROSPECTS OF IMPROVEMENT

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➡ Test shorter time resolution

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- Focus on extreme mortality events

Peltier et al. 2020

REVIEW BY PAIRS – MODELLING FLAWS ?

- Random slopes for  covariates

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Thank you !

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