Electronic Supplemental Material

Manuscript title

Blue mussels (*Mytilus edulis*) improve light conditions in a downstream eelgrass (*Zostera marina*) meadow in the Limfjorden, Denmark

Journal name

Estuaries and Coasts

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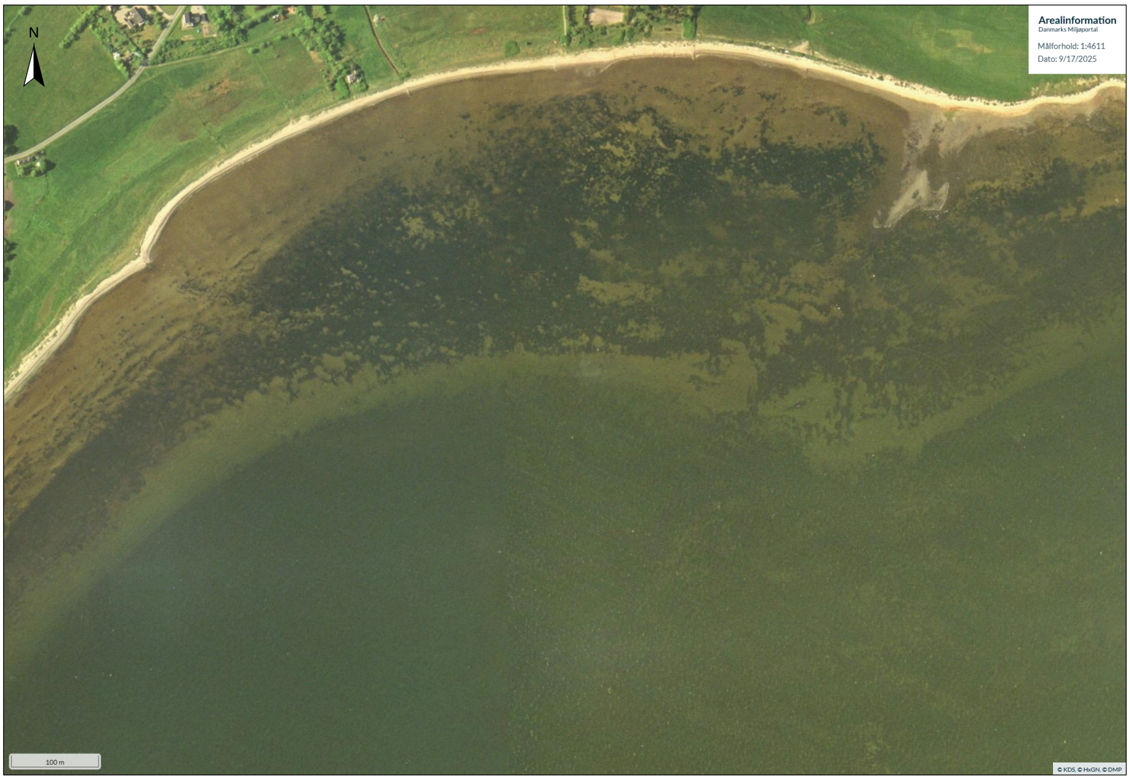
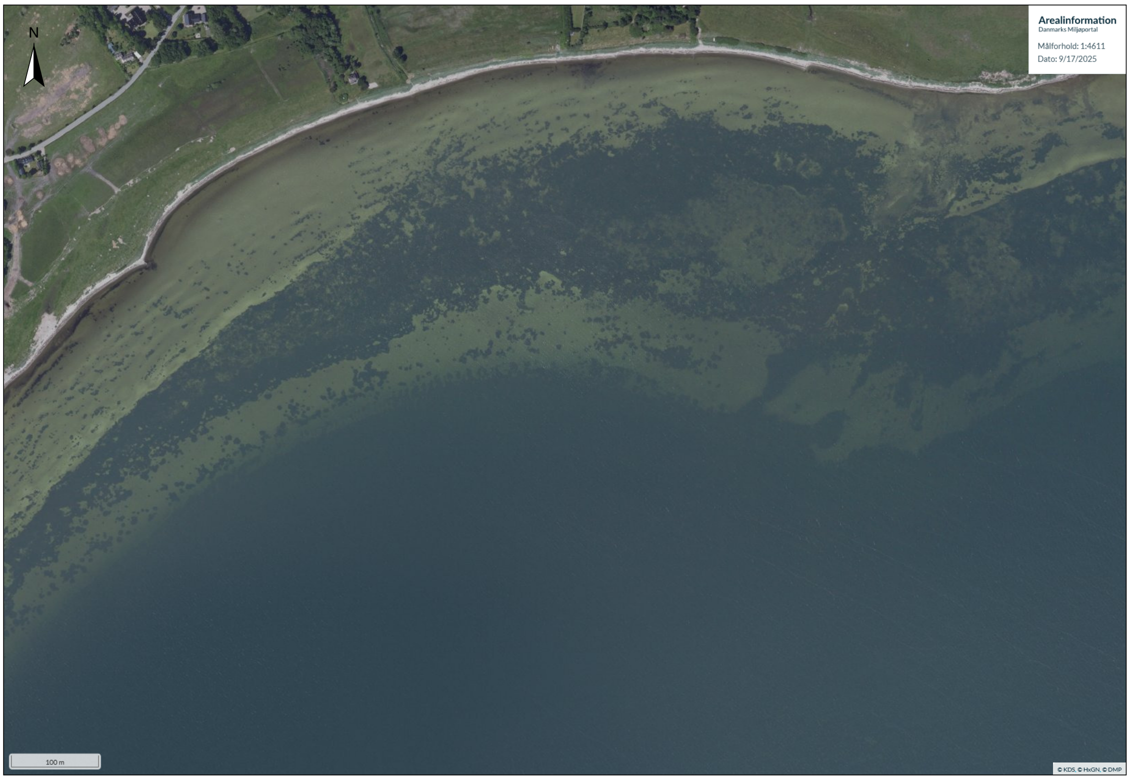


S1: Orthophoto of northern study site in 1999



S2: Orthophoto of northern study site in 2022

Supplementary Information: State-space model of daily Kd to account for missing speed and Chl observations

2026-04-22

Methods

Our state-space model assumes that Kd at each station s on each day d follows

$log(Kd_{s,d}) = \beta_0 + \beta_{mussel} + \beta_{Chl} * log(\hat{Chl}_{s,d}) + \beta_{speed} * \hat{speed}_{s,d} + \varepsilon_s + \alpha_{s,d}$

where β_0 is an overall intercept, β_{mussel} is a contrast of how mussel habitat differs from eelgrass habitat, β_{Chl} is a coefficient for the continuous effect of $log(Chl)$, and β_{speed} is a coefficient for the continuous effect of speed. The term ε_s is a random effect of station which is independent and identically distributed $N(0, \sigma_s^2)$. Preliminarily, we tried models with AR(1) random error within each station, but the models rarely converged probably due to overparameterization, so we simplified it to intercept-only station effects. The resisual error $\alpha_{s,d}$ is assumed to be normally distributed with mean 0.

In this model above, Chl and speed are not the observed values, but instead they are the estimated values from a random walk model, used to fill in the missing values with uncertainty (Auger-Méthé et al. 2021). The model assumes the estimated process is this random walk:

$log(\hat{Chl}_{s,d}) = log(\hat{Chl}_{s,d-1}) + \eta_{Chl,s,d}$ with $\eta_{Chl} \sim N(0, \phi_{Chl}^2)$.

Then assume that the observations are normally distributed around the estimates with variance σ_{Chl}^2:

$log(Chl) \sim N(log(\hat{Chl}), \sigma_{Chl}^2)$

Likewise, estimated speed follows a random walk

$log(\hat{speed}_{s,d}) = log(\hat{speed}_{s,d-1}) + \eta_{speed,s,d}$ with $\eta_{speed} \sim N(0, \phi_{speed}^2)$.

and the observations are normally distributed around the estimate with variance σ_{speed}^2:

$log(speed) \sim N(log(\hat{speed}), \sigma_{speed}^2)$

These three processes are combined in the joint negative log-likelihood. The reason why this is preferred over interpolating the covariates and then modelling Kd is that this method includes the uncertainty on the missing covariates, instead of assuming we know the missing values. This allowed us to use 1178 observations of Kd (starting on "2023-04-14"), 127 observations of speed, and 10 observations of Chl.

We compared the full model to submodels using AICc (corrected for small sample size). While there can be complexities of using AICc on state-space models due to counting random effects, all of our submodels contained the same random effects, so their count is inconsequential (Auger-Méthé et al. 2021).

The models were fit using the package `RTMB` version 1.6 in `R` version 4.4.3 (Kristensen et al. 2016, Kristensen 2024, R Core Team 2025).

We verified the best model by examining one step residuals of $log(Kd)$ (Thygesen et al. 2017). These are easier to interpret than standard residuals because they account for correlation in the random effects.

Results

The models were fit with some β coefficients set to zero to simplify the model for Kd. They are ranked according to AICc in the table below.

Table S1. Models ranked by Akaike information criteria corrected for small sample size (AICc). Features of the models other than the Kd formula were kept the same.

Kd formula	delta_AICc
Chl + habitat + speed	0.0
Chl + habitat	1.3
Chl + speed	14.6
Chl	16.0
habitat + speed	78.5
speed	92.8
habitat	670.1
intercept only	685.4

Residuals matched the expected pattern to 2 standard deviations from the mean.

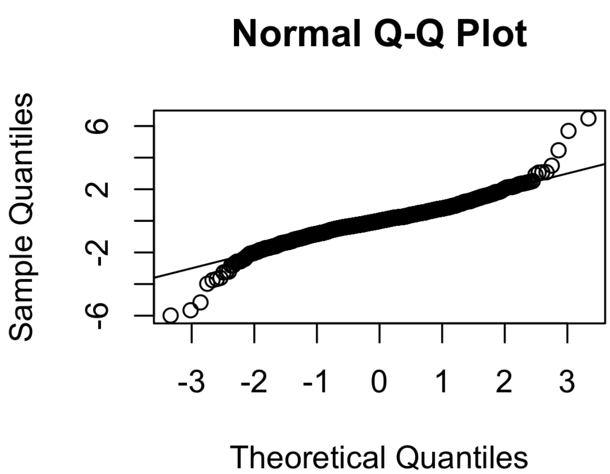


Figure S3. q-q plot of one-step residuals

We compared the observed and estimated values and 95% CI of the random walk variables, Chl and speed. Chl had only 10 observations, so its CI were wider and the estimated random walk was more influenced by the Kd model. The CI of speed were wide in the early part of the time-series when values were missing and then narrow in time periods with many observations.

Availabilty

The R code and data will be available online in a public repository at https://doi.org/10.11583/DTU.31346785

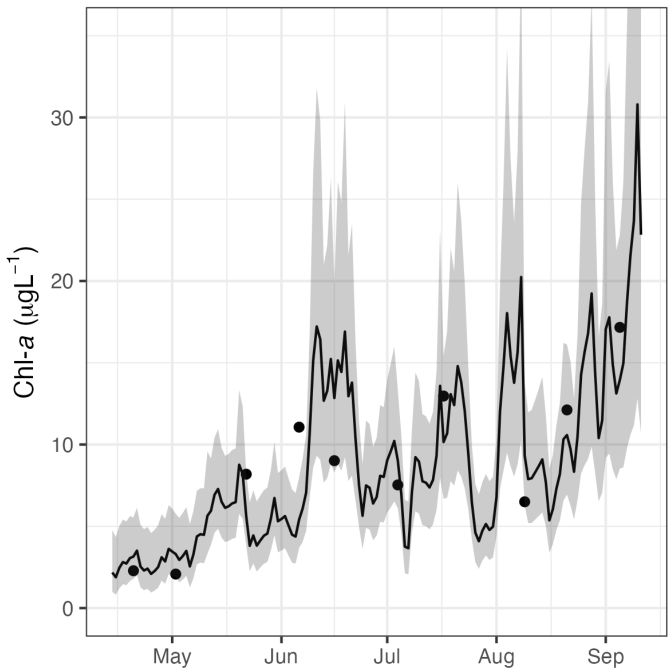


Figure S4. Points are observed values of Chl. The black line is the median estimate from the estimated distribution in the state-space model described in the methods. Grey ribbons are the 95% CI of the estimates.

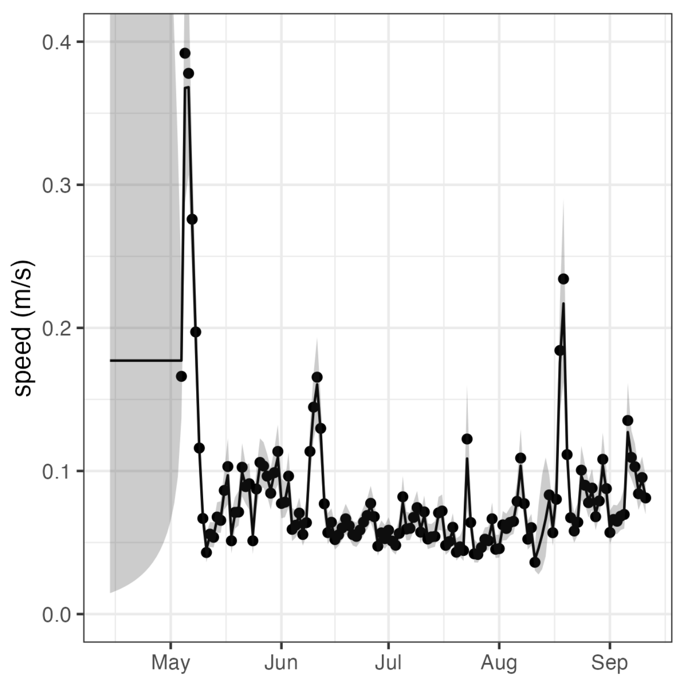


Figure S5 Points are observed values of speed. The black line is the median estimate from the estimated distribution in the state-space modelb described in the methods. Grey ribbons are the 95% CI of the estimates.

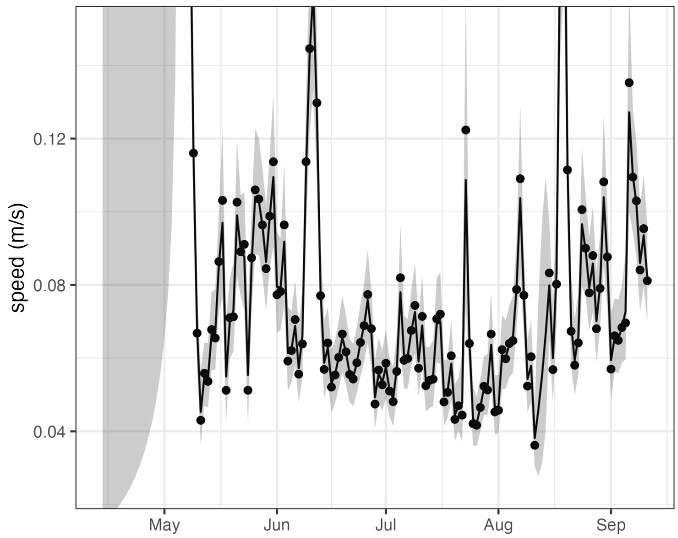


Figure S6. This is a zoomed-in part of figure 3 to show more precision in the time period (from May onwards) with many observations. Again, points are observed values of speed. The black line is the median estimate from the estimated distribution in the state-space modelb described in the methods. Grey ribbons are the 95% CI of the estimates.

References

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