Sensitivity of upper ocean state to air-sea fluxes (tested with Basilisk's GOTM implementation)

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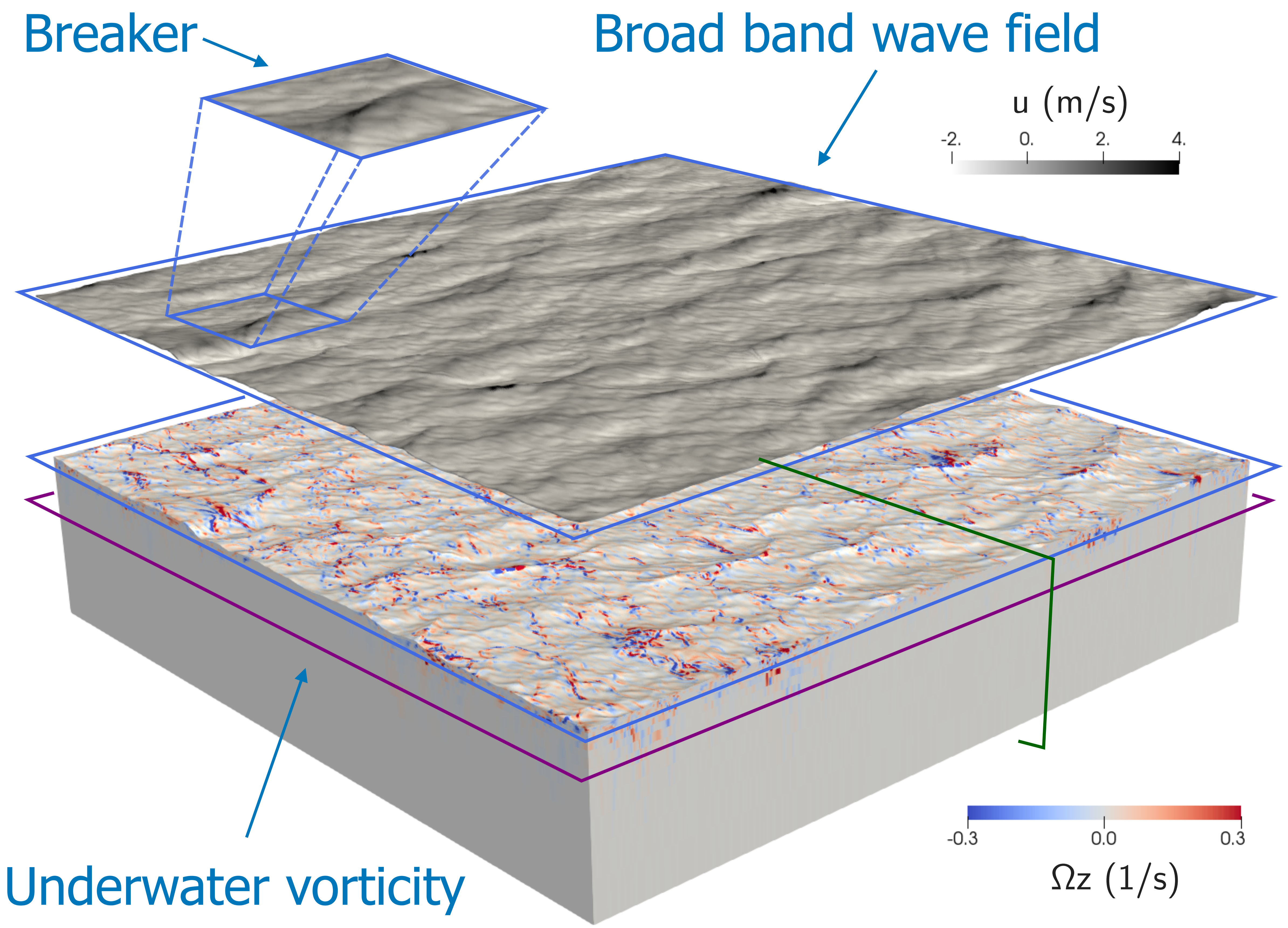
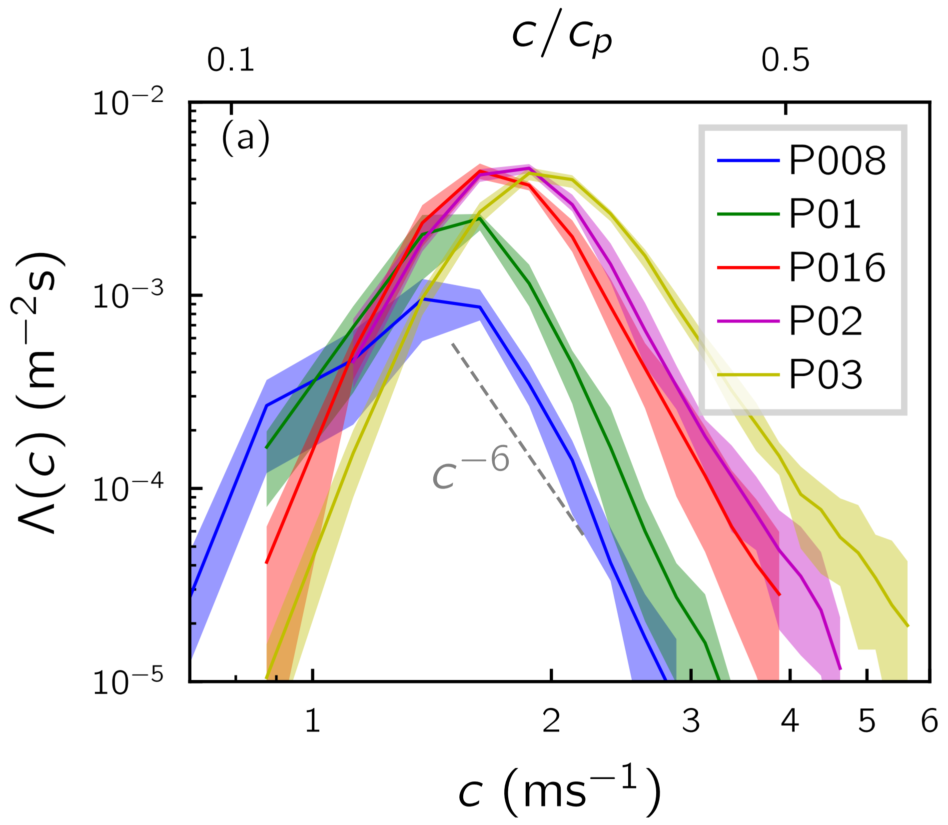
BUGM, Oxford, 2025/07/08

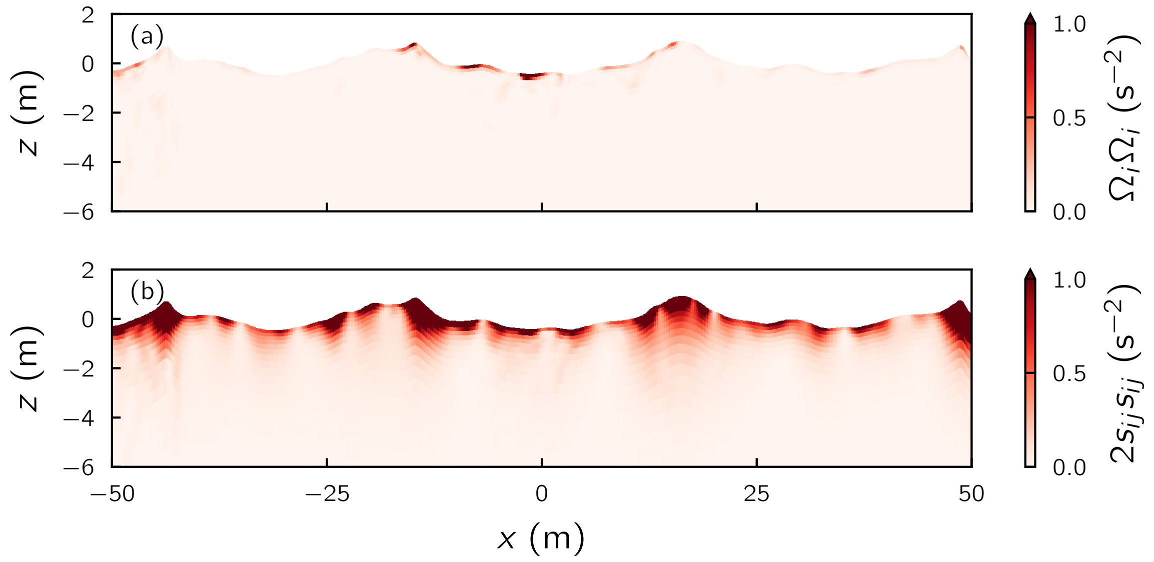
Previous work: broadband breaking waves (multilayer)



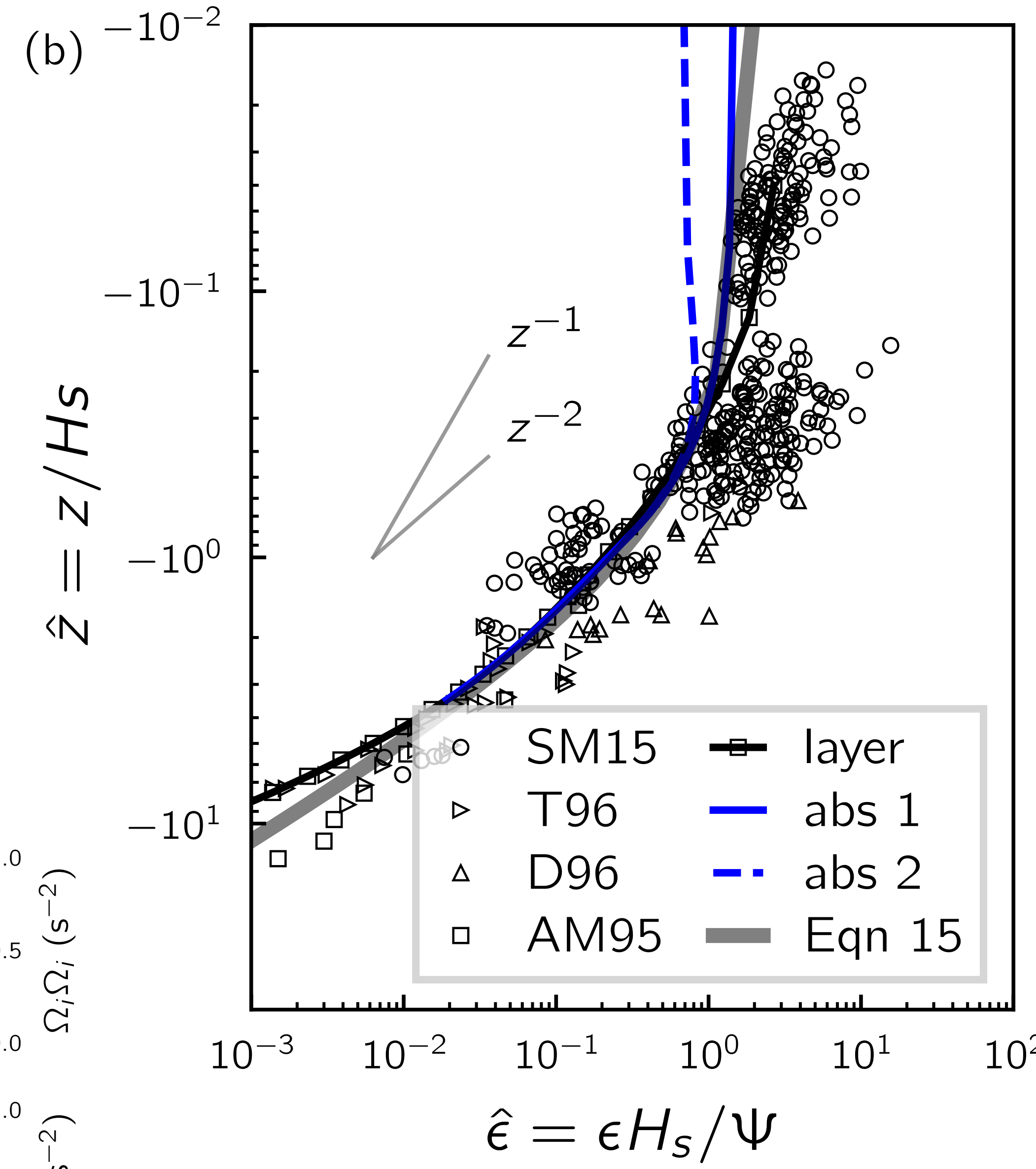
Breaker distribution



Dissipation rate



Dissipation rate profile

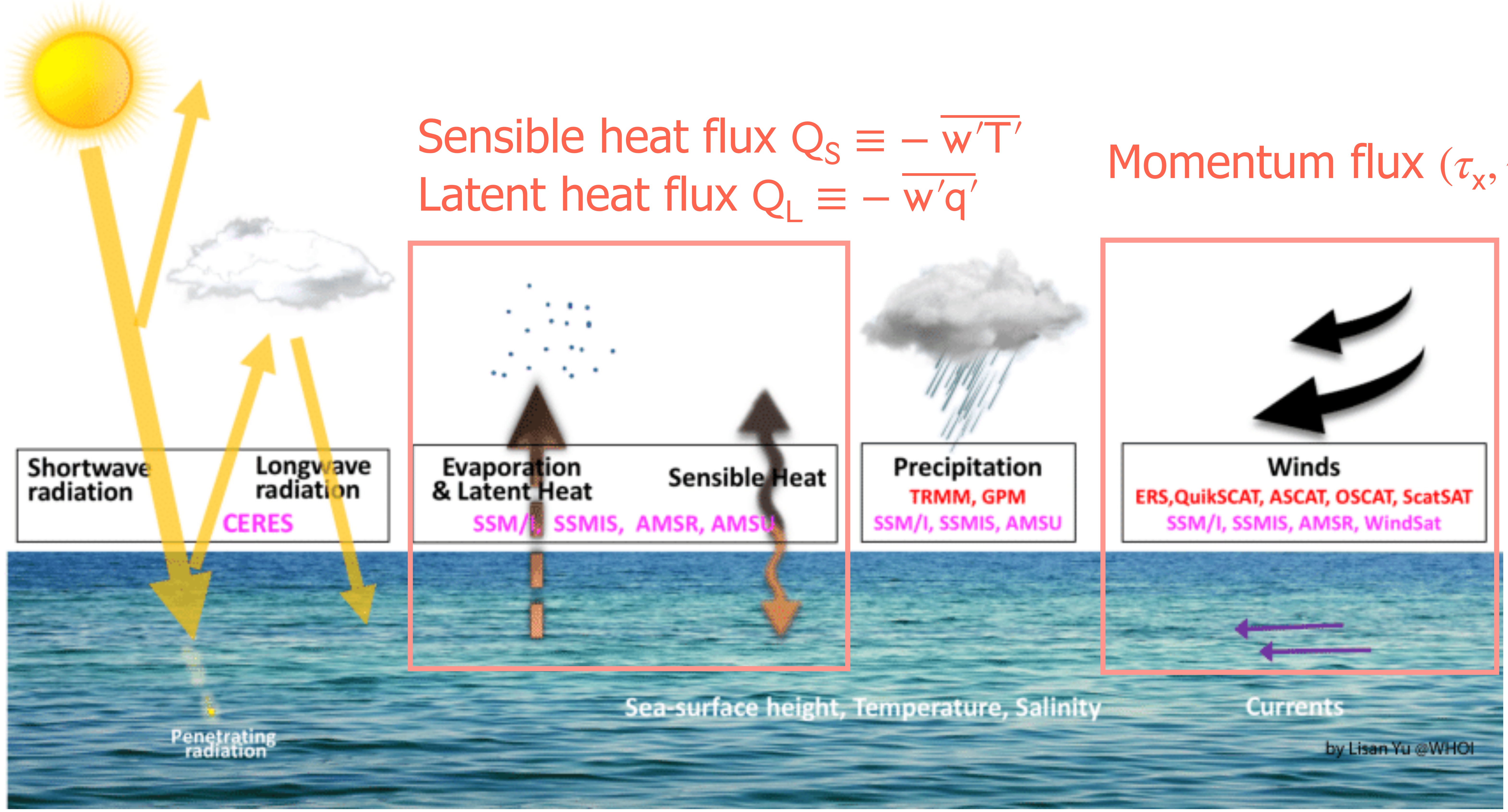


Wu, J., Popinet, S., and Deike, L. (2023). Breaking wave field statistics with a multilayer numerical framework. Journal of Fluid Mechanics.
Wu, J., Popinet, S., Chapron, B., Farrar, J. T., and Deike, L. (2025). Turbulence and energy dissipation from wave breaking. Accepted by Journal of Physical Oceanography.

Air-sea fluxes and their representation

Sensible heat flux $Q_S \equiv -\overline{w'T'}$
Latent heat flux $Q_L \equiv -\overline{w'q'}$

Momentum flux $(\tau_x, \tau_y) \equiv (-\overline{w'u'}, -\overline{w'v'})$



State variables:

Wind speed U_a

Air temp. T_a and humidity q_a

SST T_o

Current speed U_o

…

(At some height e.g. 10m)

We need air-sea flux algorithms in:

- Forced GCM (flux product): observables (in-situ or satellite) -> fluxes (hard to observe)
- Coupled GCM: prognostic variables -> fluxes as boundary conditions

Data-driven probabilistic air-sea flux algorithm

Wind speed U_a
Air temp. T_a
Humidity q_a
SST T_o
Current speed U_o
…

$\xrightarrow{\text{Flux algorithm}}$

Sensible heat flux
$Q_S \equiv -\overline{w'T'}$
Latent heat flux
$Q_L \equiv -\overline{w'q'}$
Momentum flux
$(\tau_x, \tau_y) \equiv (-\overline{w'u'}, -\overline{w'v'})$

Existing bulk air-sea flux algorithms (COARE, ECMWF, etc.):

- Based on Monin-Obukhov similarity theory, with parameters fitted to observations
- Crudely simplified (might have bias)
- Designed to represent the averaged effects

Observation: NOAA PSL ship ~10,000 samples, hourly-averaged covariance $\overline{w'u'}, \overline{w'v'}, \overline{w'T'}, \overline{w'q'}$ + Neural Networks (NN)

No high-fidelity simulation yet.

Data-driven probabilistic air-sea flux algorithm

Wind speed U_a
Air temp. T_a
Humidity q_a
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Current speed U_o
…

Flux algorithm $\longrightarrow$

Sensible heat flux
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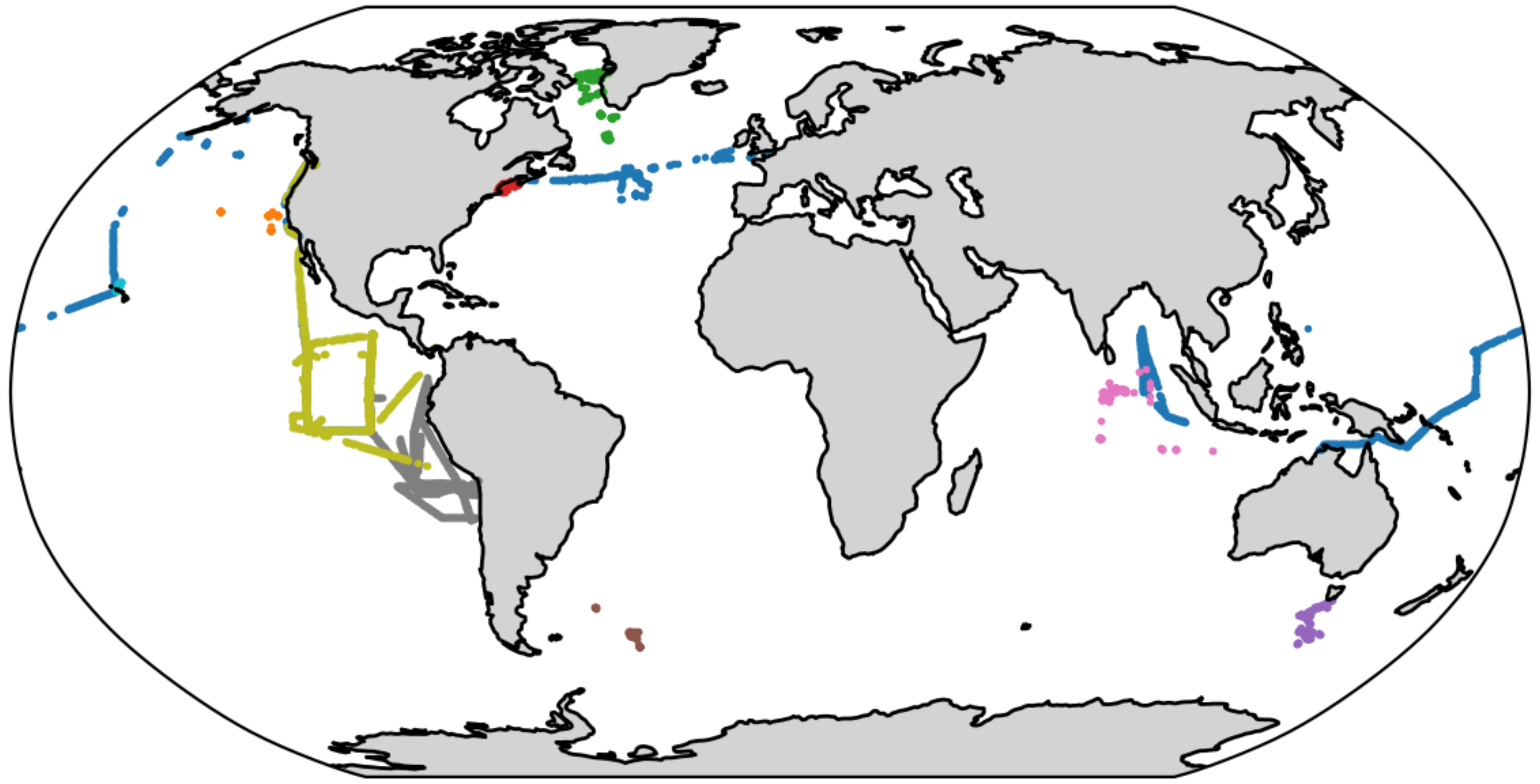
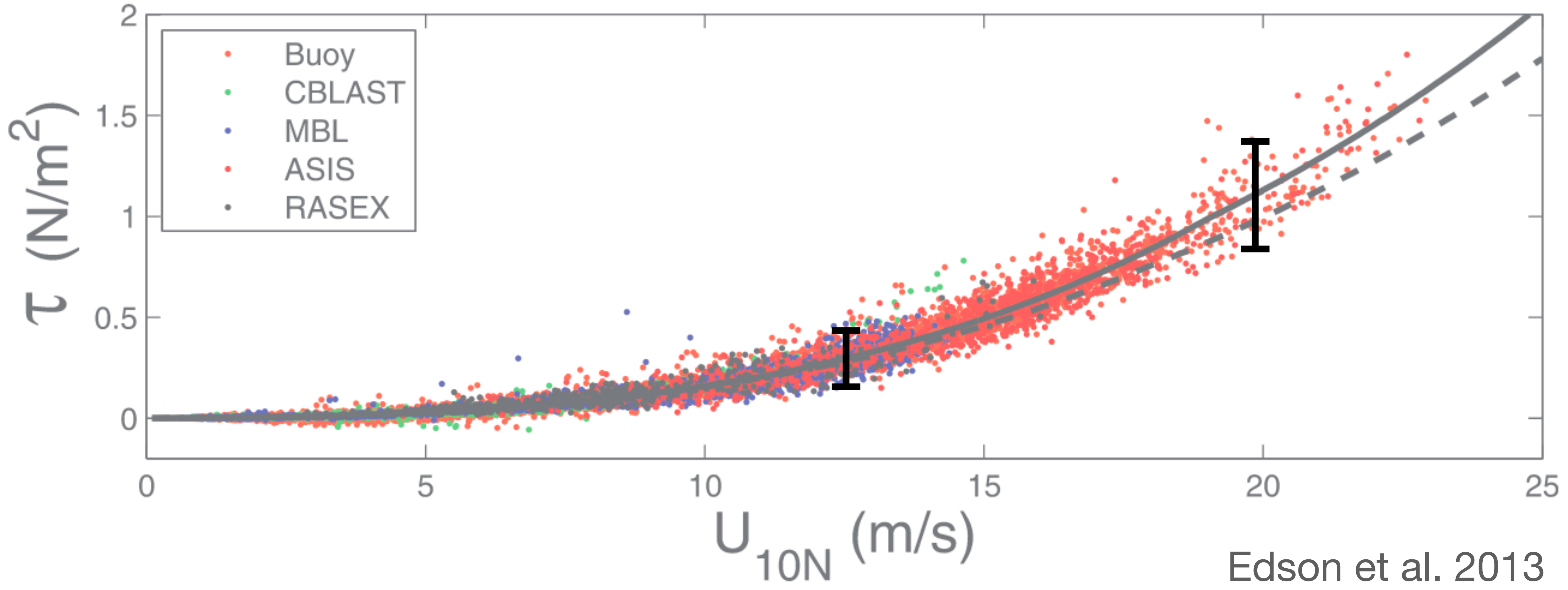


Q_L	RMSE	ANN	30.3
		Bulk	34.0
	R2	ANN	0.682
		Bulk	0.601
	Bias	ANN	0.225
		Bulk	-5.496

Statistical improvements (especially for heat fluxes)

Data-driven probabilistic air-sea flux algorithm

Momentum flux as a function of wind speed

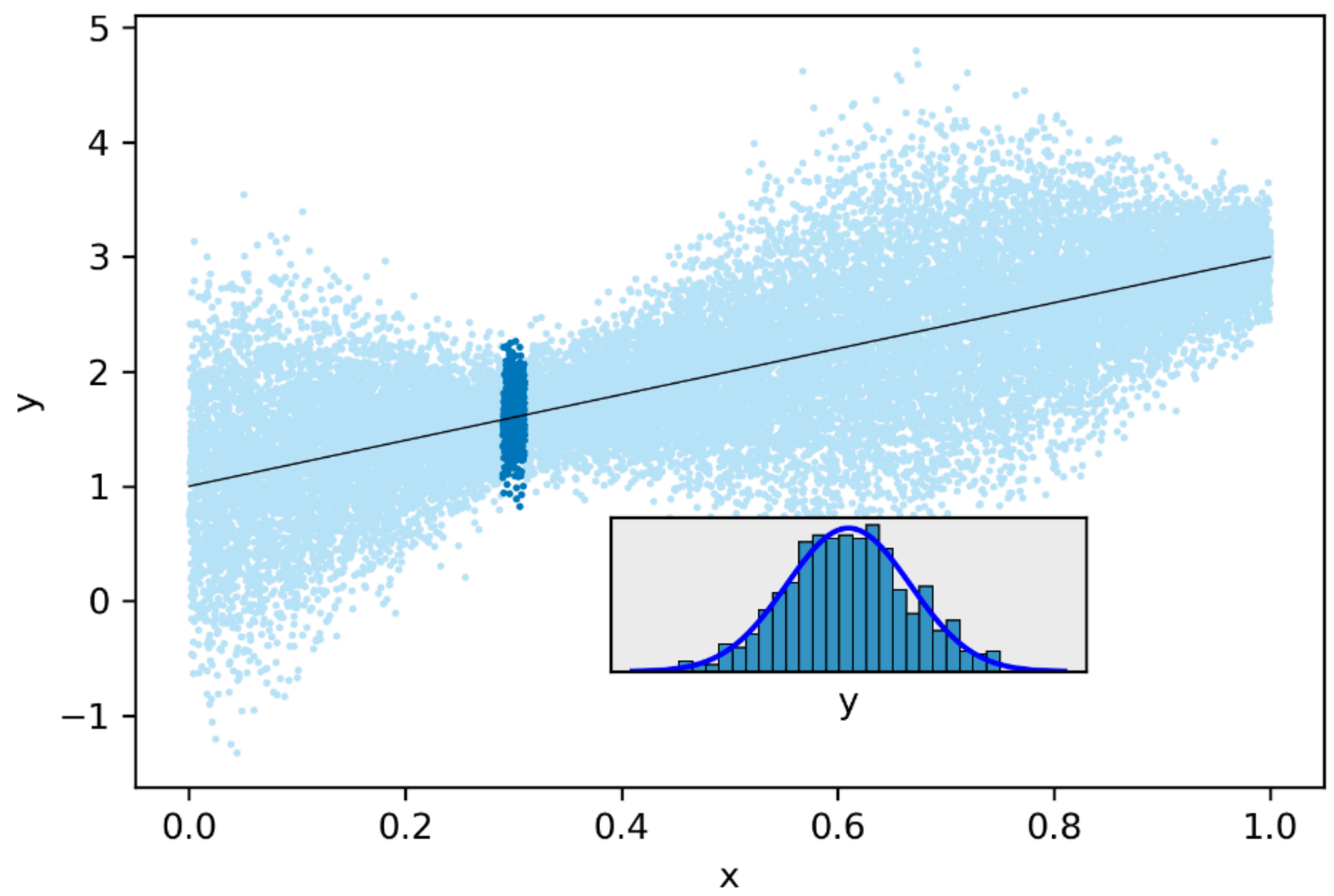


Existing air-sea flux algorithms are designed to represent the mean given the inputs.

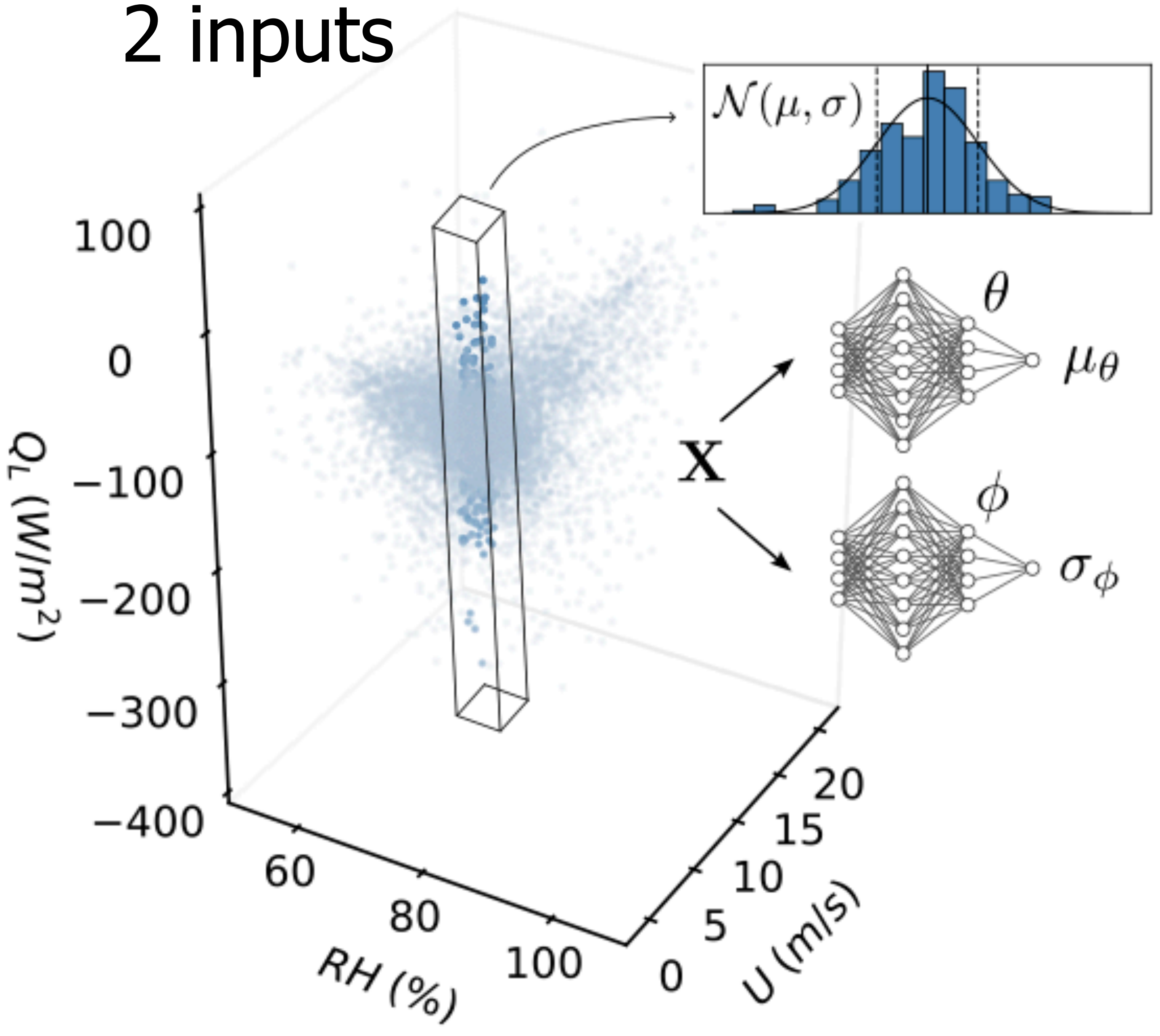
Can we have an algorithm that reflects the uncertainty/variability in air-sea fluxes?

Data-driven **probabilistic** air-sea flux algorithm

1 input

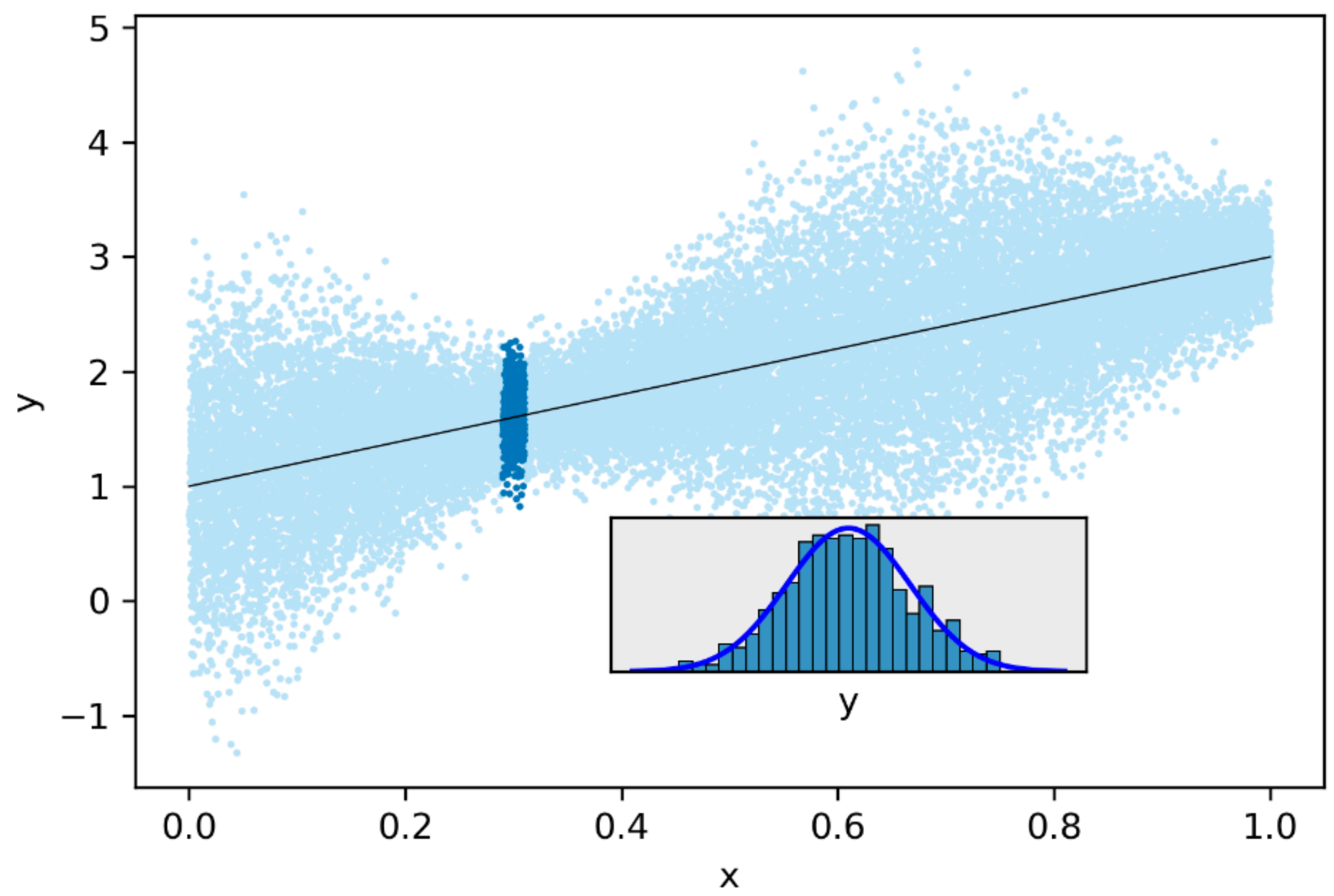


2 inputs

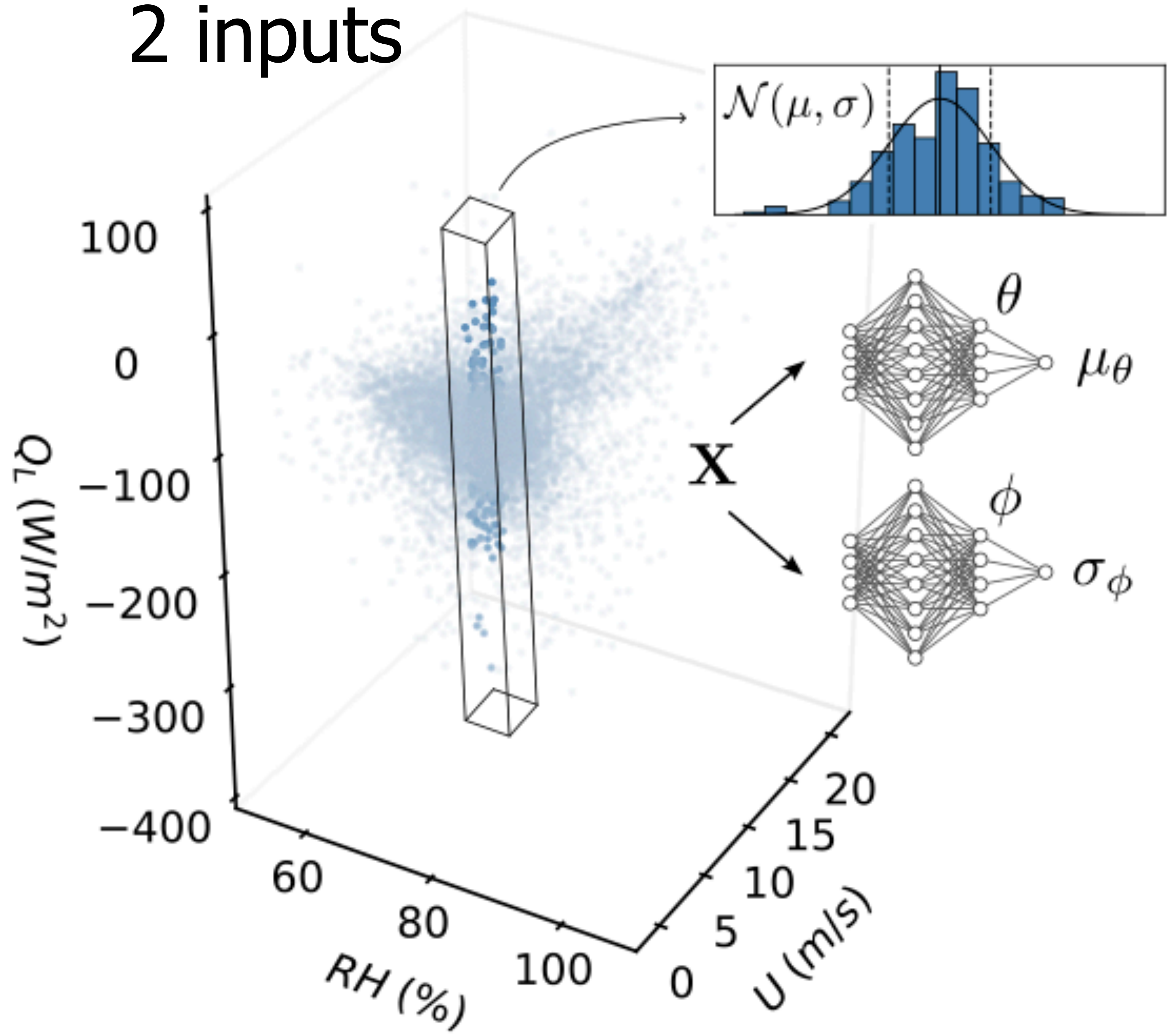


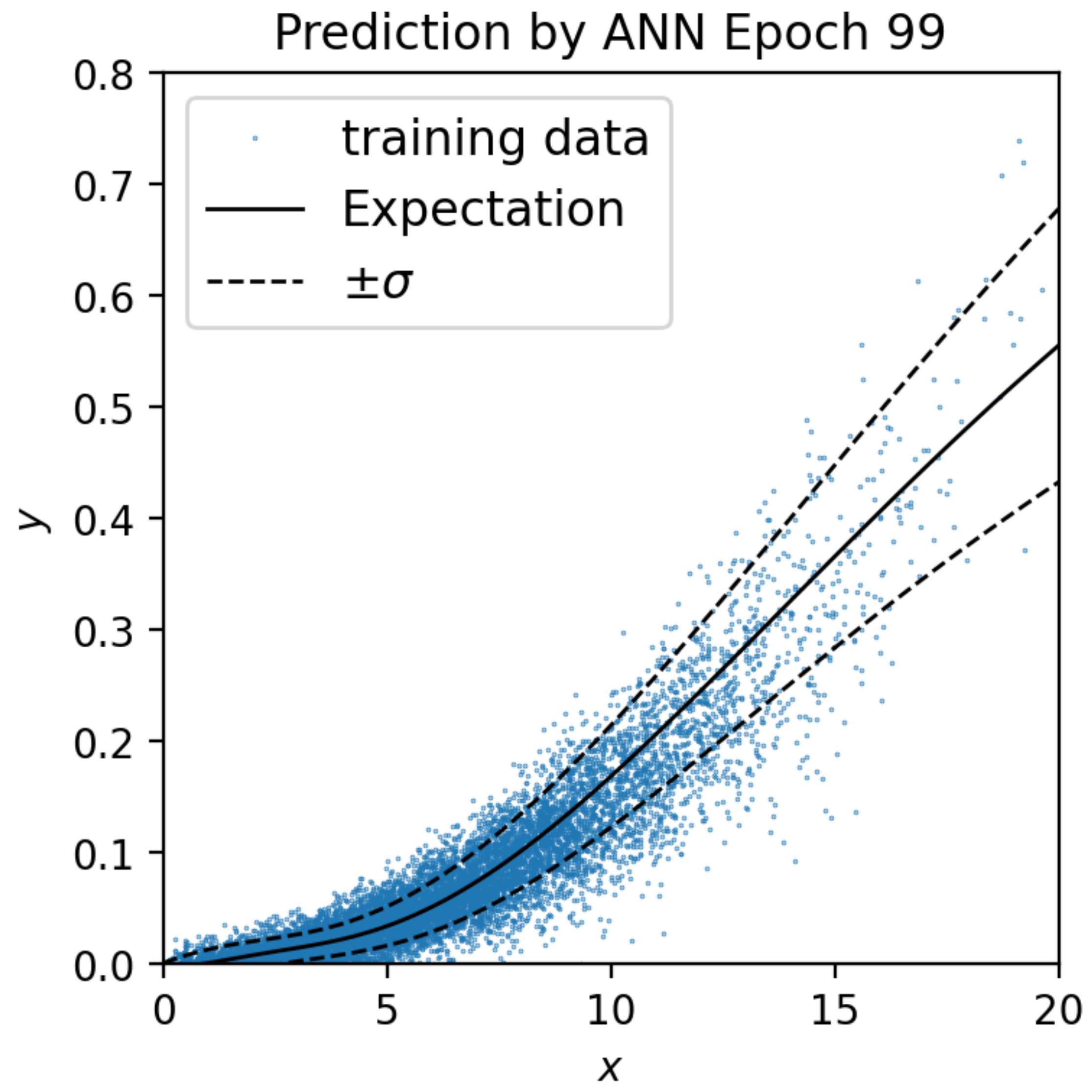
Data-driven probabilistic air-sea flux algorithm

1 input



2 inputs

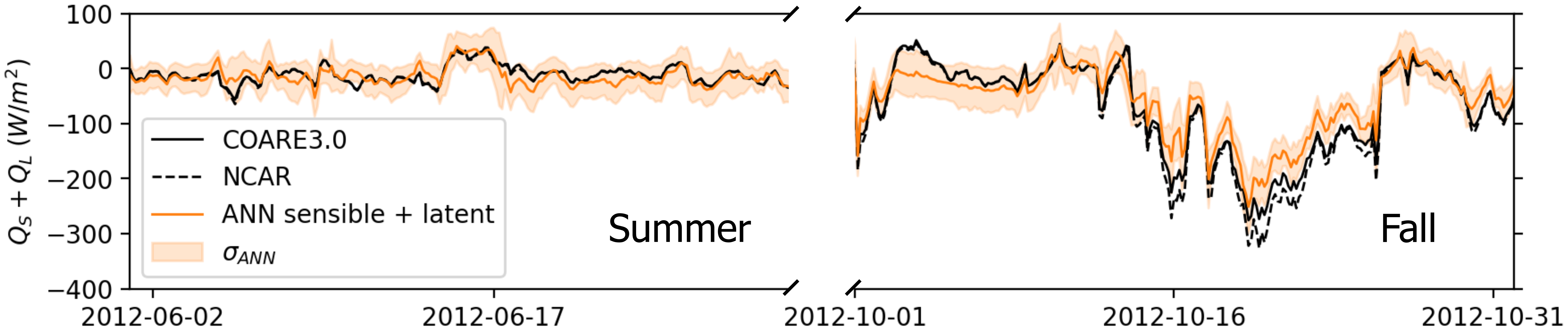




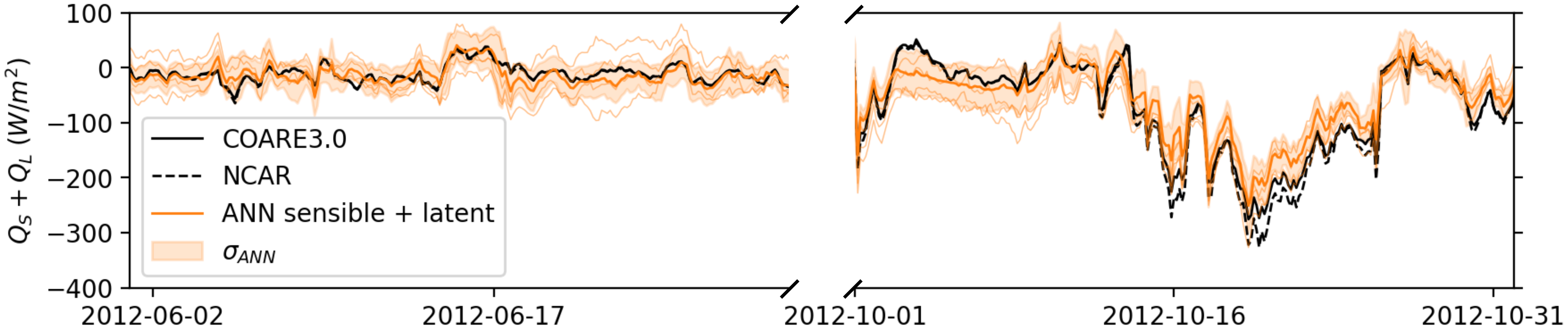
Negative log likelihood loss

$$\mathbf{X} = (U_a, T_a, T_o, RH, p_a) \xrightarrow{\text{NN}} \text{Conditional } \textbf{mean} \text{ and } \textbf{std} \text{ of } Q_S, Q_L, \tau_x, \tau_y$$

Stochastic air-sea flux parameterization



Stochastically perturbed fluxes



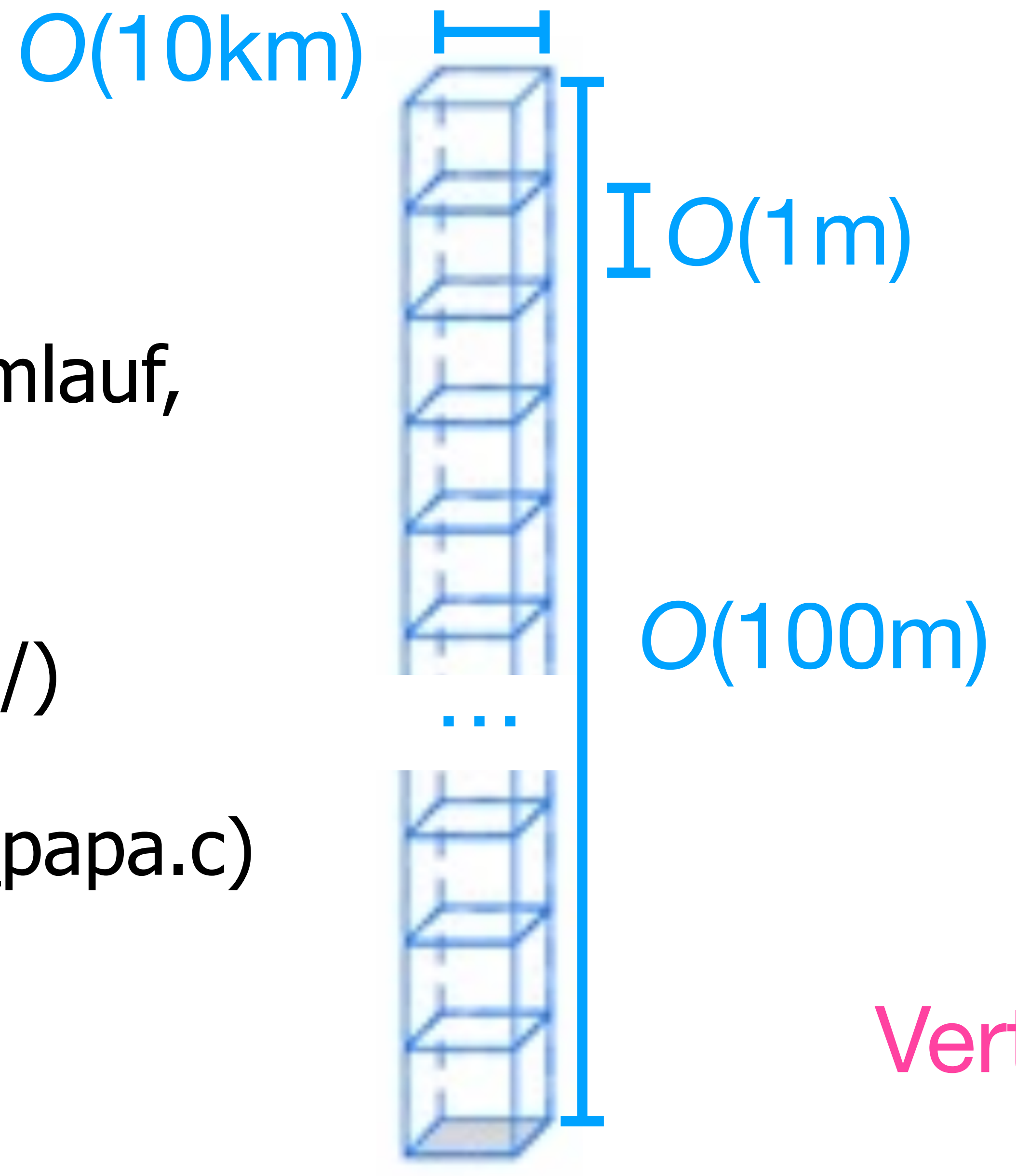
Noise generated by auto-regressive process AR(1):

$$\epsilon_{n+1} = r\epsilon_n + (1 - r^2)^{1/2}\eta_n$$

$$\eta_n \sim \mathcal{N}(0, \sigma_n)$$

Sensitivity test (response of upper ocean to changing fluxes)

- Single column model, ocean only
- General Ocean Turbulence Model (GOTM, Lars Umlauf, Hans Burchard, and Karsten Bolding. 2018.)
- Basilisk's GOTM interface (http://basilisk.fr/src/gotm/)
- Ocean Papa test case (http://basilisk.fr/src/test/ows_papa.c)



Governing equations

$$\partial_t U = \boxed{\partial_z[-\overline{wu}]} + fV$$

$$\partial_t V = \boxed{\partial_z[-\overline{wv}]} - fU$$

$$\partial_t T = \boxed{\partial_z[-\overline{w\theta}]} - \partial_z Q_n - A_T$$

$$\partial_t S = \boxed{\partial_z[-\overline{ws}]} - \partial_z F_n - A_S$$

Vertical mixing: KPP or k-epsilon

KPP: K profile parameterization (mixing length model by Large et al. 1994)
k-epsilon: two-equation closure (deemed expensive by ocean modelers!)

Implementation in a single-column model of upper ocean

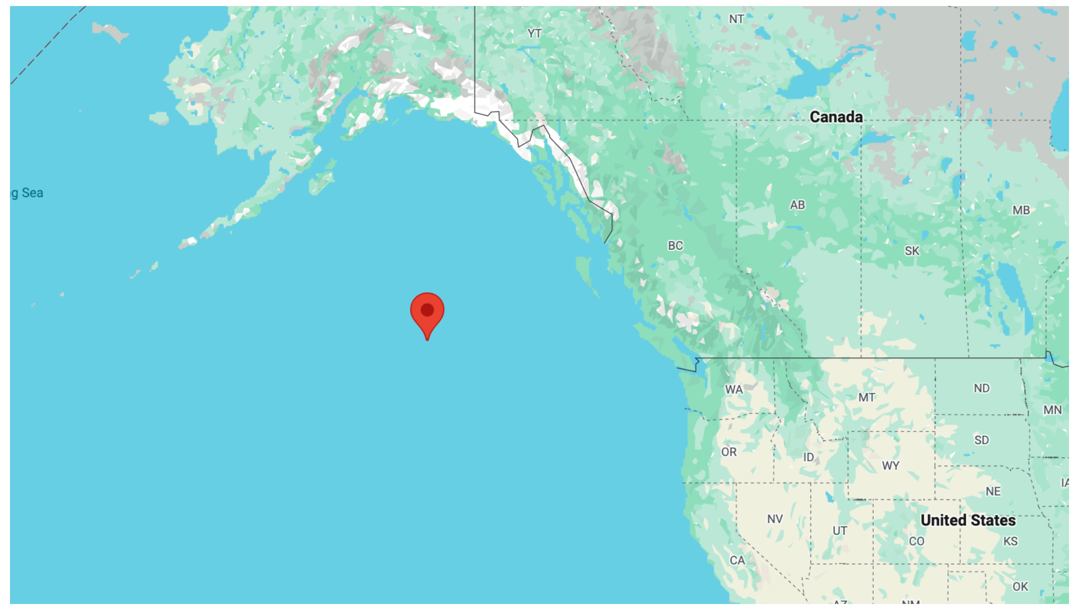
- Mooring records of 2011, 2012, 2015, 2016
- Surface fluxes imposed as boundary condition (also affect vertical mixing parameterization)
- Running the model in ‘forced’ way; fluxes computed offline; only modifying the (more uncertain) heat fluxes.

Governing equations

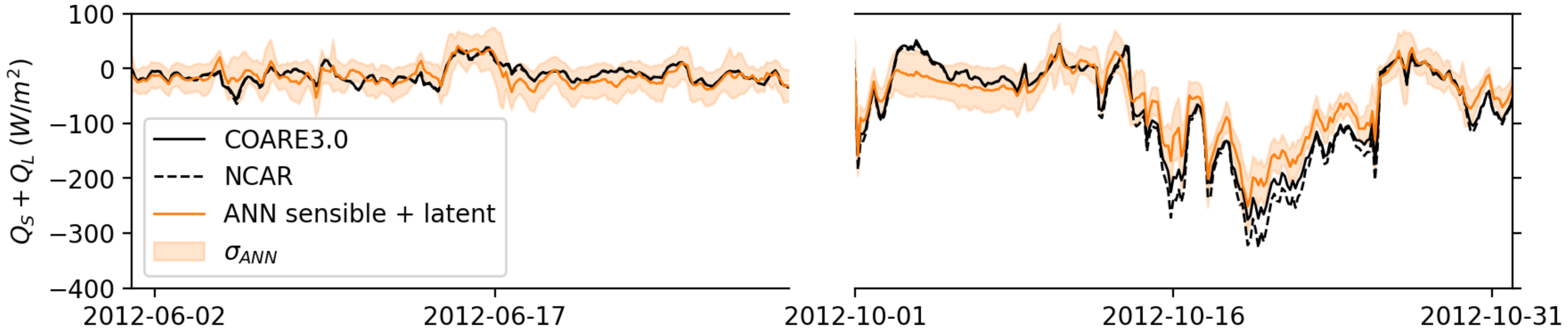
$$\partial_t U = \boxed{\partial_z[-\overline{wu}]} + fV$$
$$\partial_t V = \boxed{\partial_z[-\overline{wv}]} - fU$$
$$\partial_t T = \boxed{\partial_z[-\overline{w\theta}]} - \partial_z Q_n - A_T$$
$$\partial_t S = \boxed{\partial_z[-\overline{ws}]} - \partial_z F_n - A_S$$

Vertical mixing: KPP or k-epsilon

Most time was spent on engineering file I/O



Ocean Weather Station Papa



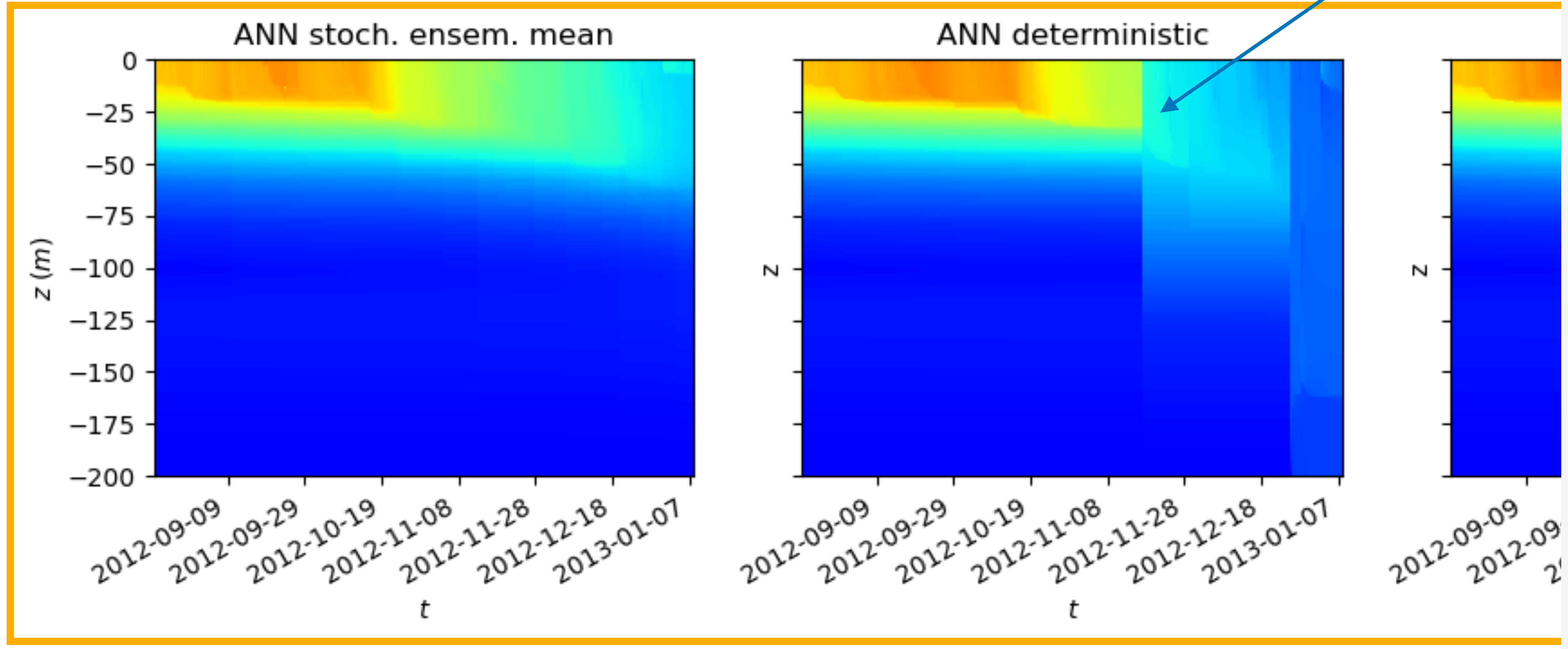
Long-term mooring records of state variables
No direct flux measurements

ANN or Baseline COARE

Issues with weird mixing

Dramatic mixing

KPP (dt=1hr)

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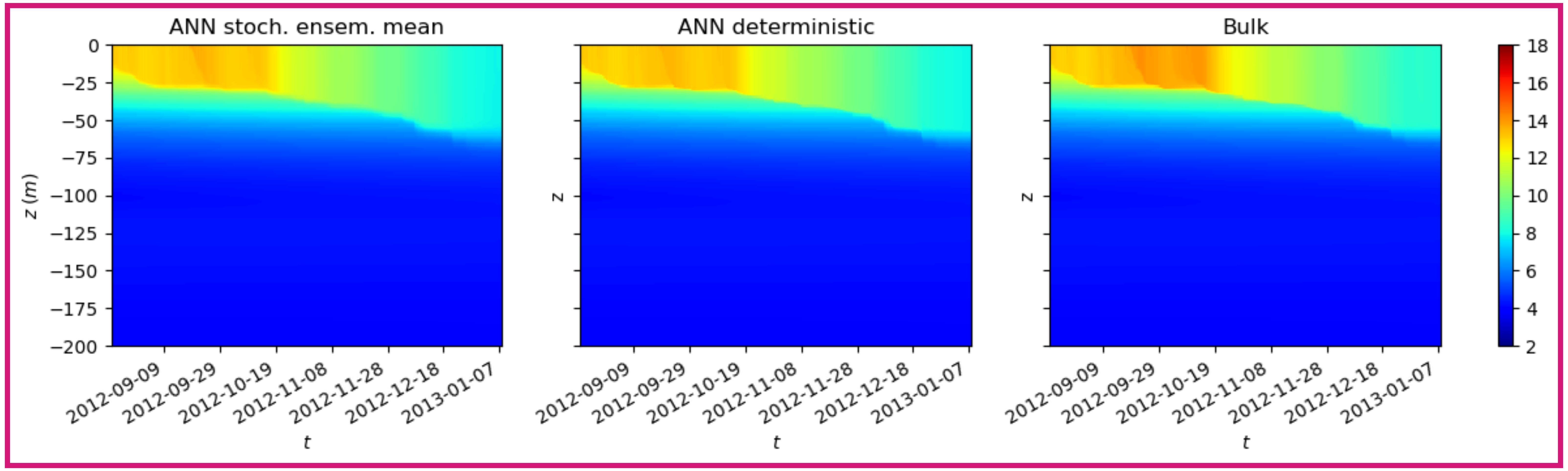
------------------------------------------------------------------------
  You are using the KPP turbulence model
  with the following specifications:

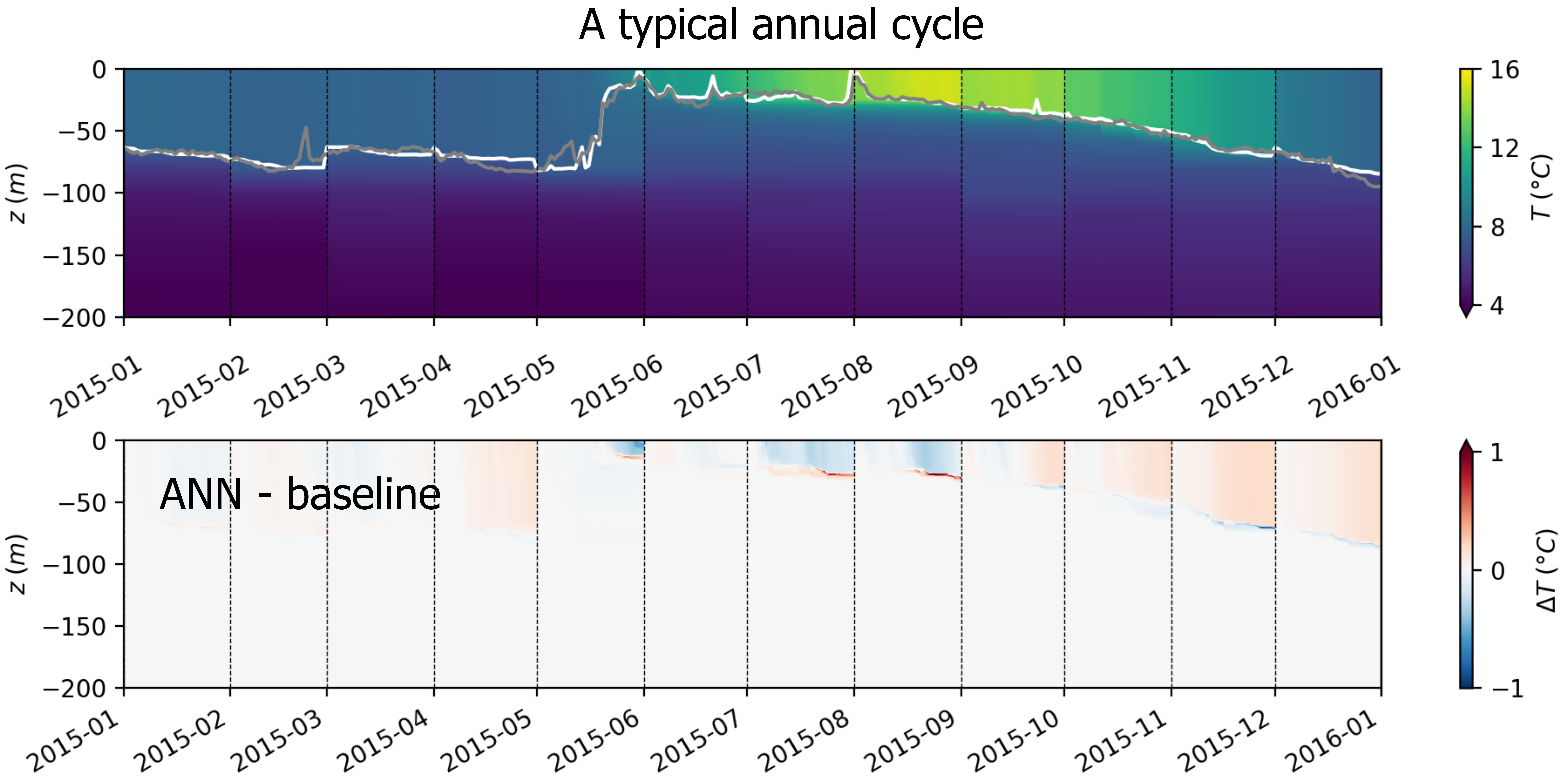
  Interior mixing algorithm                  - not active -
  Surface layer mixing algorithm                 - active -
     Clipping at Ekman/Oboukhov scale        - not active -
     Compute salinity fluxes                     - active -
     Nonlocal fluxes                         - not active -
     Ri_b from 2-point interpolation         - not active -
     F_c =0 criterion for SL-depth               - active -
     Clipping G'(sigma) for matching         - not active -
     Ri_c   =    0.29999999999999999
  Bottom layer mixing algorithm                  - active -
     (Same parameters as surface layer mixing)
------------------------------------------------------------------------
```

✅

k-epsilon (dt=10min)



Comparing state (SST and MLD)



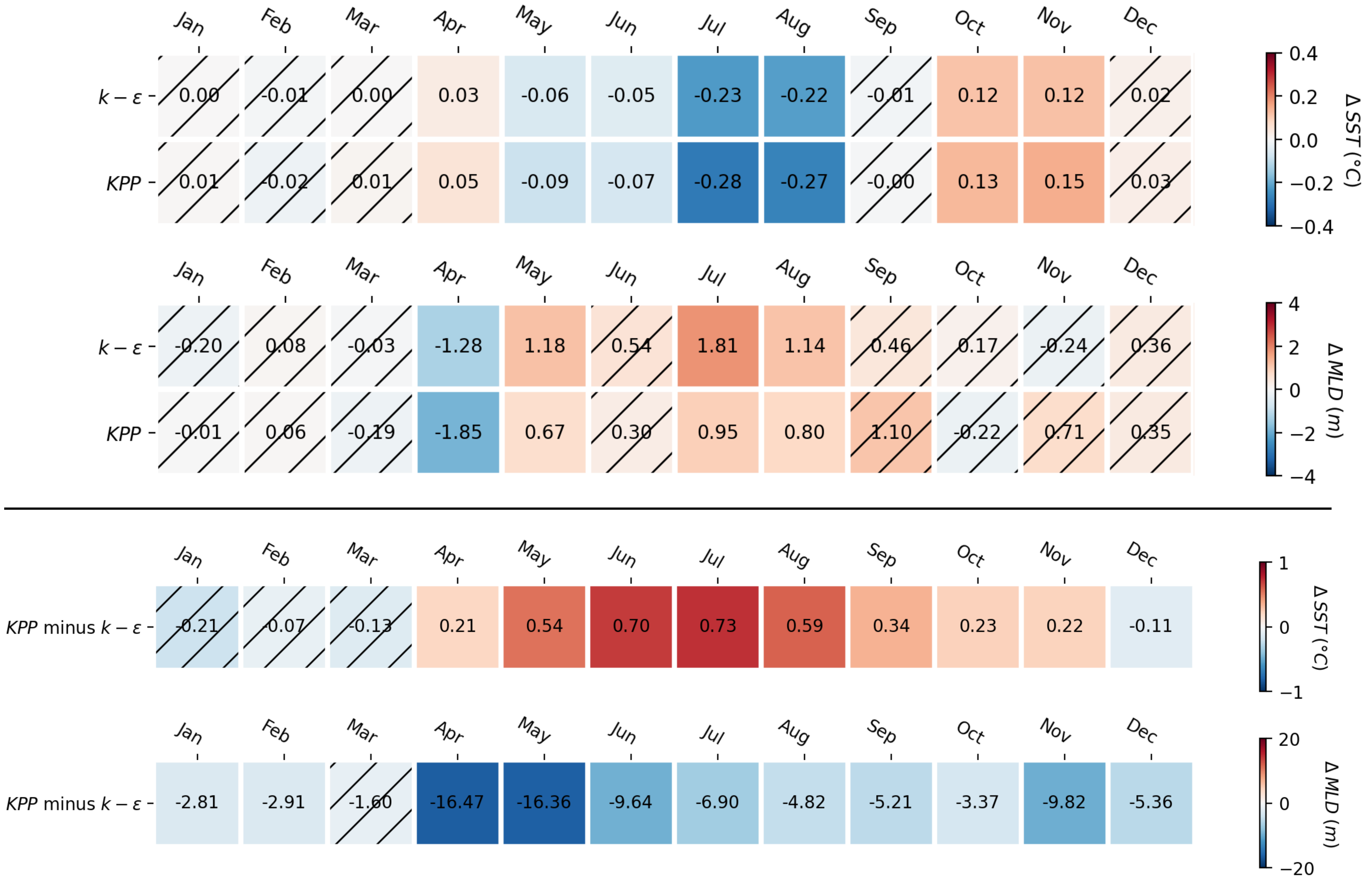
- Limitation of ignoring horizontal advection. Monthly restart to reduce drifting.
- Focus on the response to different flux forcing.

Smaller magnitude but seasonal response

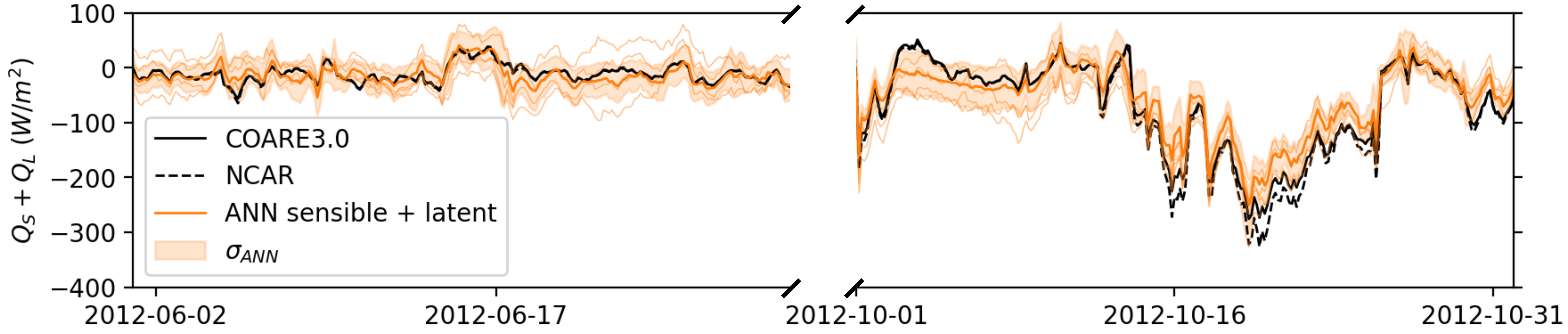
2011, 2012, 2015, 2016

Change flux parameterization

Change vertical mixing parameterization



Effects of stochastic parameterization

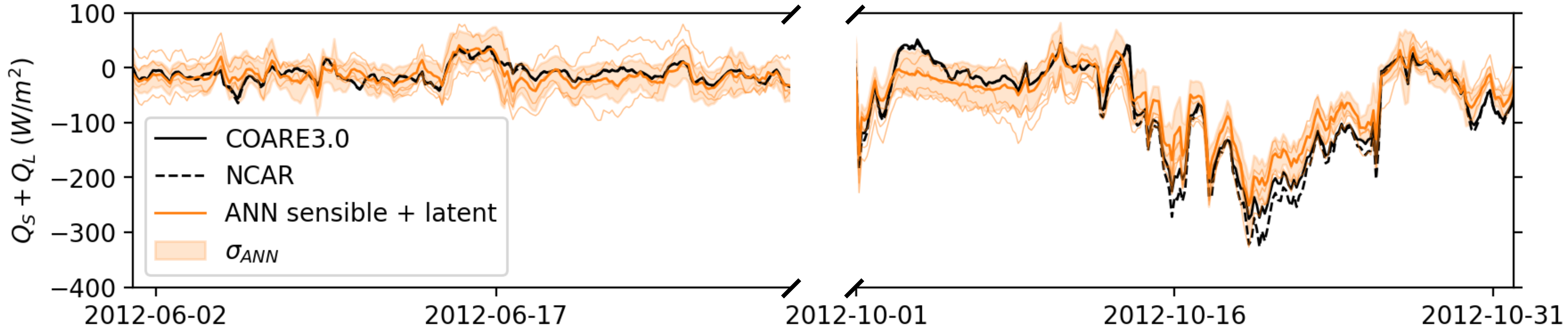


Effects of noise:

- Noise-induced drift
- Enhanced variability, i.e. ensemble spread

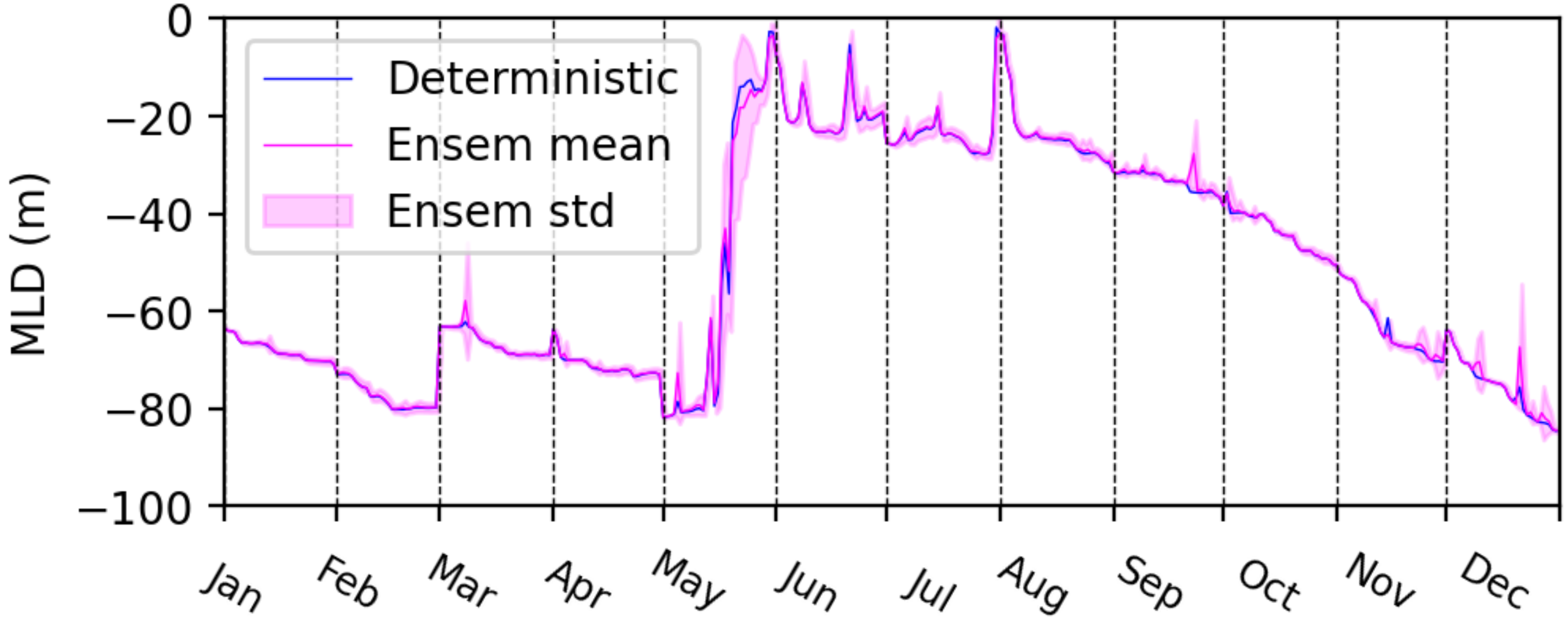
(Low cost of 1D models allows for many ensemble runs.)

Effects of stochastic parameterization



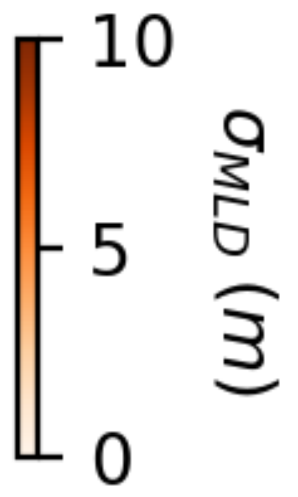
Effects of noise:

- Noise-induced drift (not observed)
- Enhanced variability, i.e. ensemble spread (yes, but of course)

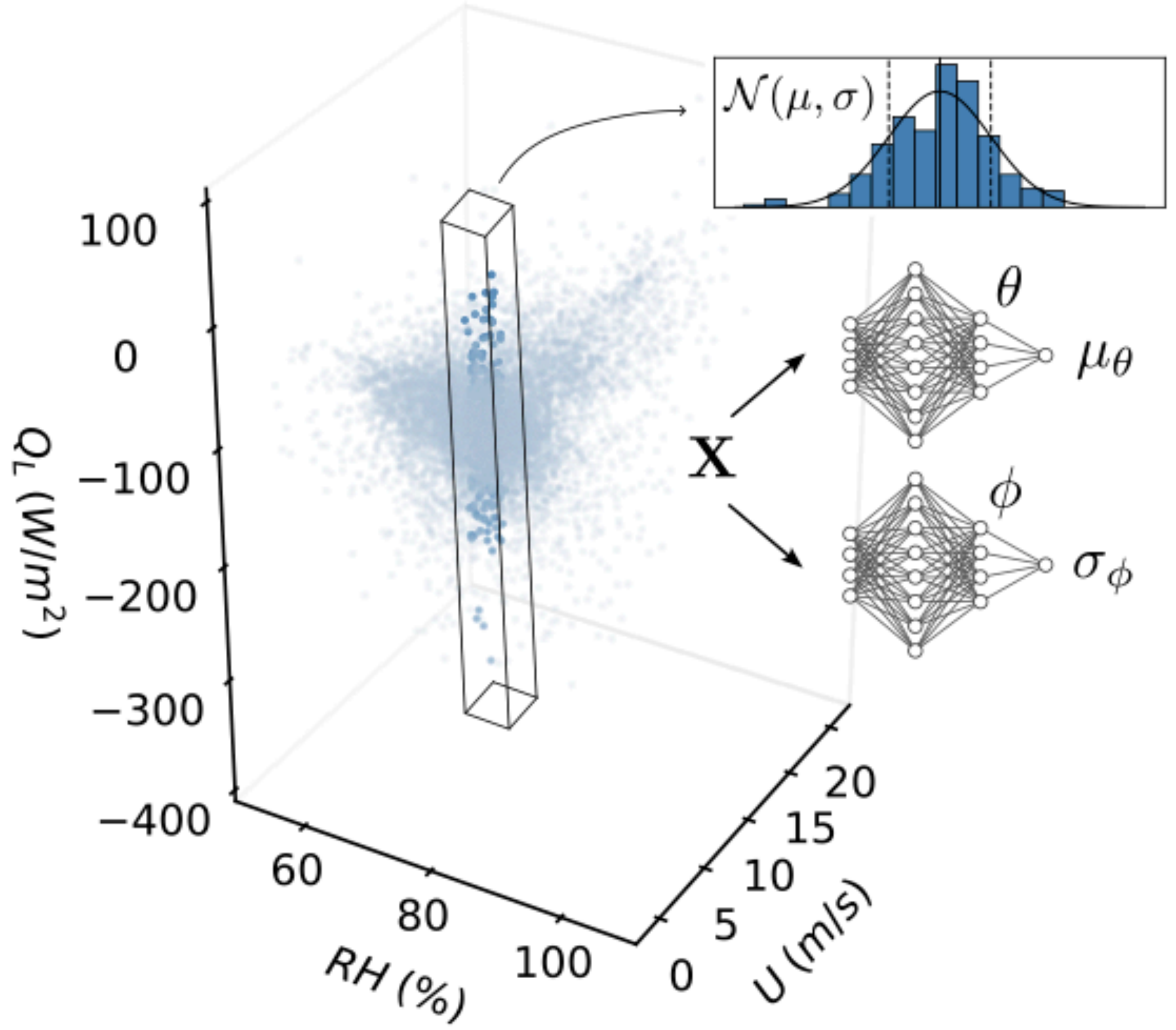


Spread in MLD

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
$k-\varepsilon$	0.93	0.84	0.81	4.33	7.18	3.13	2.47	1.82	1.26	1.95	1.21	0.90
KPP	0.64	1.17	1.38	8.04	7.04	2.57	2.00	1.73	2.76	2.16	1.47	0.81



Summary



- A **probabilistic model** for air-sea fluxes:
  - Compact NNs ($\mathcal{O}(10^3)$ parameters) and bulk inputs
  - **Mean** - similar to bulk algorithm, slightly better statistical correlation to observations
  - **Variance** - UQ and stochastic parameterization

- Implementation in single-column forced upper ocean: strong seasonality in response.
- Limitation of single column model -> coupled general circulation models. Large spread can have implications when coupled to nonlinear processes.

- Some short-term to-dos:
  - Perturbed momentum flux;
  - Online computation of heat fluxes (with evolving SST). Python interface for calling neural networks?

Manuscript:

Wu, J., Perezhogin, P., Gagne., D.J., Reichl, B., Subramanian, A., Thompson, E., and Zanna, L., Data-Driven Probabilistic Air-Sea Flux Parameterization, https://arxiv.org/abs/2503.03990