



1 **Environmental controls on methanotrophic oxidation capacity in** 2 **the southeastern North Sea**

3 Yanan Zhao¹, Vera Sidorenko¹, Carsten Lemmen² and Ingeborg Bussmann³

4 ¹Alfred Wegener Institute, Helmholtz Centre for Polar and Marine Research, 27570 Bremerhaven, Germany

5 ²Institute of Systems Analysis and Modeling, Helmholtz-Zentrum Hereon, 21502 Geesthacht, Germany

6 ³Alfred Wegener Institute, Helmholtz Centre for Polar and Marine Research, 27498 Helgoland, Germany

7 *Correspondence to: Yanan Zhao (yanan.zhao@awi.de)*

8 **Abstract.** Shallow coastal seas contribute disproportionately to marine methane (CH₄) emissions,
9 yet the efficiency of the microbial sink that attenuates them remains poorly constrained. Under
10 first-order kinetics, aerobic methane oxidation (MOx) is the product of ambient CH₄ concentration
11 and the fractional turnover rate k' , the latter representing the oxidation capacity of the
12 methanotrophic community. Here we test whether k' can be predicted from routinely measured
13 environmental variables, drawing on water samples collected during repeated campaigns between
14 2010 and 2014 across riverine, estuarine, and marine waters of the Elbe and the adjacent
15 southeastern North Sea. In the estuary and adjacent marine waters, a second-order polynomial
16 model based on temperature, salinity, and nitrate reproduced 80 % of the observed spatiotemporal
17 variability in k' under five-fold cross-validation, indicating that these predictors captured the main
18 environmental controls on k' and that nonlinear interaction terms cannot be omitted. Neither
19 ambient CH₄ concentration nor phosphate improved model performance, indicating that k' is not
20 directly controlled by substrate availability or phosphorus limitation. In riverine waters, by contrast,
21 the same approach systematically underpredicted k' with large uncertainty, suggesting a distinct
22 regional response regime that is likely linked to river-specific environmental controls. Overall, our
23 results highlight that k' can be parameterized as a dynamic, environmentally dependent term,
24 opening a route to estimating MOx in coastal systems.



25 **1 Introduction**

26 Methane (CH₄) is a potent greenhouse gas whose atmospheric concentration has increased
27 continuously since the industrial era, contributing about 16 % of post-industrial radiative forcing
28 (Forster, P. et al., 2021). Although the ocean is a comparatively modest net source of atmospheric
29 CH₄, with global emissions estimated at 6 to 12 Tg yr⁻¹, this flux is highly uneven in space, with
30 shallow coastal and shelf environments contributing disproportionately despite occupying only a
31 minor fraction of total ocean area (Weber et al., 2019). In these shallow coastal environments,
32 methanogenic archaea in anoxic sediments produce substantial amounts of CH₄, which can be
33 transferred to the overlying water column by molecular diffusion, porewater advection, and
34 ebullition (Egger et al., 2018; Hermans et al., 2024). Before this dissolved CH₄ can escape to the
35 atmosphere, however, it encounters a final biological sink in the water column: aerobic methane
36 oxidation (MOx) primarily mediated by methanotrophic bacteria. The amount of CH₄ removed by
37 MOx before atmospheric release remains poorly constrained in coastal carbon budgets, with a
38 global estimate of 1.8 ± 2.7 Tg yr⁻¹ (Mao et al., 2022).

39 A useful way to quantify microbial CH₄ removal is the fractional turnover rate, k' (d⁻¹; Table
40 1). Assuming first-order kinetics, the MOx rate (nmol L⁻¹ d⁻¹) can be calculated by multiplying the
41 dissolved CH₄ concentration by k' . Here, k' describes the fraction of the dissolved CH₄ pool
42 oxidized per unit time. It therefore represents an integrated outcome of active methanotroph
43 abundance, community composition, and cell specific metabolic activity. Field studies have shown
44 that k' can vary by orders of magnitude across aquatic environments (Bussmann et al., 2017).
45 However, the environmental and biological controls underlying this variability remain poorly
46 constrained, particularly in coastal systems where biotic and abiotic conditions are highly dynamic.



47 The southeastern North Sea provides a natural laboratory in which to examine these controls.
 48 The Elbe and Weser rivers deliver methane-enriched freshwater with concentrations one to two
 49 orders of magnitude above atmospheric equilibrium, while the adjacent Wadden Sea tidal flats
 50 export biogenic methane through tidal pumping, together sustaining pronounced CH₄ gradients
 51 across the estuarine-coastal interface (Grunwald et al., 2009; Osudar et al., 2015). Although
 52 methane oxidation has been relatively well constrained in this system, its contribution to the total
 53 CH₄ loss budget varies strongly seasonally, accounting for about 5 % in winter/spring and about
 54

55 **Table 1.** Overview of methane-related terms used in this study.

Term	Symbol	Unit	Definition in this study
Fractional turnover rate	k'	d ⁻¹	First-order rate constant describing the fraction of the dissolved CH ₄ pool oxidized per unit time.
Dissolved methane concentration	[CH ₄]	nmol L ⁻¹	Dissolved CH ₄ concentration in the water column.
Aerobic methane oxidation	MOx	-	Microbial process of aerobic CH ₄ oxidation under oxic conditions.
Methane oxidation rate	MOx rate	nmol L ⁻¹ d ⁻¹	Rate of the MOx process; calculated as $k' \times [\text{CH}_4]$.

56



41 % in summer/fall (Matoušů et al., 2017). This pronounced seasonal contrast suggests that water-column CH_4 oxidation is highly dynamic and likely controlled by multiple interacting environmental factors. For instance, temperature can affect microbial metabolic rates and community composition (Mohanty et al., 2007; Sundh et al., 2005), while salinity gradients may constrain methane oxidation across river–sea transitions (Osudar et al., 2017a). Suspended particulate matter, oxygen availability, and nutrient supply may further influence methanotrophic activity by altering particle associated habitats, redox conditions, and growth constraints (Abril et al., 2007; Bodelier et al., 2000; Steinle et al., 2017). In addition, hydrodynamic processes can redistribute water masses and microbial communities, generating spatial heterogeneity in k' (Steinle et al., 2015; Wilkins et al., 2013). Together, these studies suggest that k' variability is shaped by the combined influence of physicochemical parameters, motivating a multivariate modelling approach to reconstruct k' from multiple environmental variables.

Despite its central role in methane oxidation, direct determination of k' remains methodologically demanding, typically relying on labor-intensive radiotracer-based incubations that yield sparse and temporally discontinuous observations (Bussmann et al., 2015). This practical limitation has constrained efforts to resolve the environmental controls on k' and to incorporate methanotrophic capacity explicitly into water-column methane budgets. To our knowledge, no previous study has directly modelled the spatiotemporal variability of k' . Here, we address this gap using observations from repeated field campaigns conducted in the southeastern North Sea between 2010 and 2014. The aims of this study are: i), to quantify the spatiotemporal variability of k' across a river-estuary-marine gradient; ii), to identify the major environmental factors associated with k' ; and iii), to evaluate whether k' can be reconstructed from environmental



79 variables. These analyses are intended to support a more process-based representation of
80 methanotrophic capacity in coastal methane budgets.

81 **2 Methods**

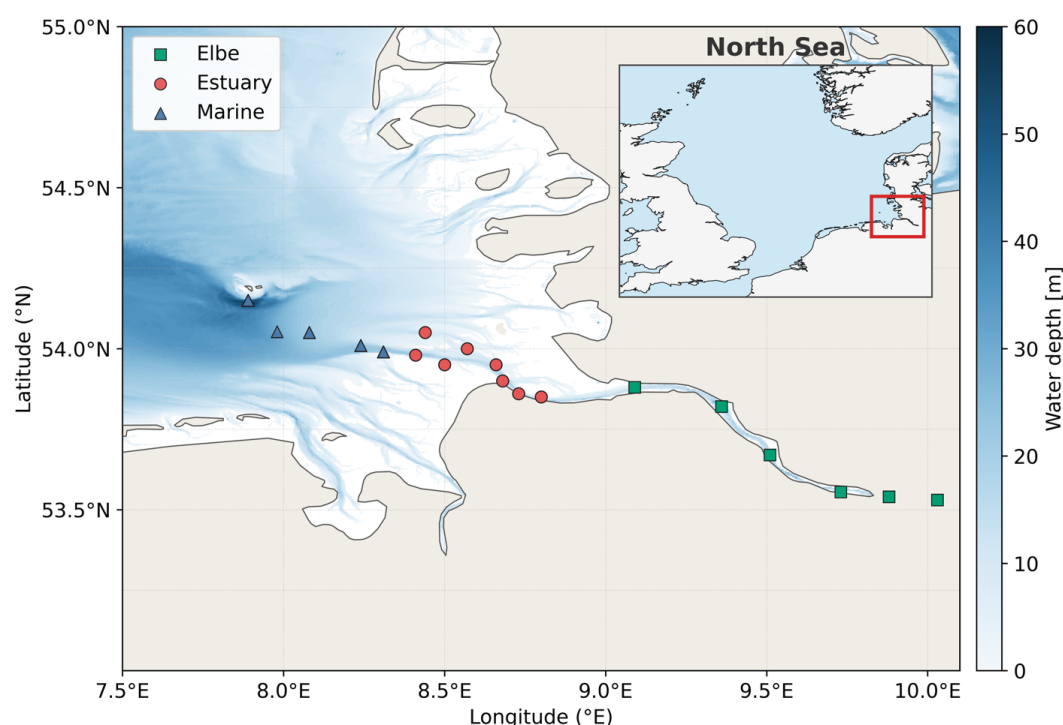
82 **2.1 Study area and available observations**

83 The study area encompasses the Elbe Estuary and the adjacent German Bight, a shallow
84 coastal system with typical water depths generally below 50 m (Jacob and Stanev, 2021). The
85 region is hydrographically dynamic, characterized by a large tidal range from 1.5 to 3.6 m
86 (Fofonova et al., 2019; Gräwe et al., 2016; Plüß, Andreas, 2003). The German Bight is directly
87 influenced by the discharge of three relatively large rivers, the Elbe, Weser, and Ems (Becker et
88 al., 1992). The freshwater input leads to intermittent stratification, mediated by tidal and wind
89 forcing in the estuaries and central German Bight. The relatively fresh coastal waters form a
90 buoyancy-driven current along the coast, mediated by Earth's rotation. The transect from the inner
91 estuary to the open German Bight therefore spans a natural gradient of riverine, estuarine, and
92 marine conditions. Sampling stations were classified into three categories based on the median
93 salinity of all samples collected at each station (Fig. 1): riverine water (salinity < 5, in PSU),
94 estuarine water ($5 \leq \text{salinity} \leq 30$), and marine water (salinity > 30). These categories correspond
95 to sampling stations located at 9.09° E–10.03° E, 8.41° E–8.80° E, and 7.89° E–8.31° E,
96 respectively.

97 This study draws on a harmonized dataset compiled from repeated campaigns conducted
98 between October 2010 and November 2014 (Hackbusch et al., 2019; Matoušů et al., 2017; Osudar
99 et al., 2015), with a specific focus on the fractional turnover rate k' . At each station, discrete water
100 samples were collected using Niskin bottles from two depth layers: the surface layer
101 (approximately 1 m below the surface) and near bottom waters (approximately 1 m above the



102 sediment). Measured parameters included CH_4 concentration and k' , together with temperature,
103 salinity, dissolved oxygen, inorganic nutrients (NO_2^- , NO_3^- , NH_4^+ , PO_4^{3-} and silicate), SPM and
104 water depth (Table 2). Analytical procedures are summarized in Supplementary Text S1. The
105 observational datasets used in this study are archived in PANGAEA (Bussmann et al., 2014b, a,
106 2019; Matousu et al., 2015).



107

108 **Figure 1.** Map of the southeastern North Sea showing the locations of sampling stations, classified
109 into three categories according to the median salinity of all samples collected at each station: the
110 Elbe (median salinity < 5 , green squares), the estuary ($5 \leq \text{median salinity} \leq 30$, red circles), and
111 the marine region (median salinity > 30 , blue triangles). Background shading indicates water depth
112 (m).

113



114 2.2 Statistical analysis

115 Spearman's rank correlation coefficient (r_s) was used to assess pairwise relationships between
116 variables, with statistical significance set at $p < 0.01$. Differences between paired surface and
117 bottom samples were tested using the Wilcoxon signed-rank test, as the paired differences did not
118 meet the Shapiro-Wilk normality assumption required for a paired t-test.

119 2.3 Polynomial regression

120 Polynomial regression models were used to evaluate whether k' could be estimated from
121 routinely measured environmental variables. A simple linear model may be too restrictive because
122 it assumes additive effects with constant slopes across the full environmental range and does not
123 account for interactions among predictors. As a subset of GAMs, polynomial regression therefore
124 provides a simple parametric framework for testing whether curvature and pairwise interactions
125 improve the reconstruction of k' while retaining interpretability (James et al., 2021).

126 Models were fitted to k' using 11 candidate predictors: CH_4 concentration, temperature,
127 salinity, dissolved oxygen, SPM, water depth, and dissolved nutrients (NO_2^- , NO_3^- , NH_4^+ , PO_4^{3-} ,
128 and silicate). Polynomial degrees of 1–3 were evaluated across all predictor combinations
129 containing up to five base predictors, thereby limiting model complexity and reducing overfitting
130 (e.g., Fig. 4). Model performance was assessed using repeated five-fold cross-validation with 100
131 repeats. Within each split, predictors were standardized using parameters estimated from the
132 training folds and then applied to the validation fold. Out-of-fold predictions were used to calculate
133 the coefficient of determination (R^2), root mean squared error (RMSE), and mean absolute error
134 (MAE), and metrics were summarized across repeats. Variance inflation factors (VIFs) were
135 calculated for the base predictors to assess multicollinearity (Table S1). Exploratory analyses were
136 initially performed using all samples. Because the Elbe samples showed response patterns distinct



137 from those of the marine-estuary samples (Fig. S1), models were subsequently built separately for
138 the marine-estuary and river regions.

139 **3 Results**

140 **3.1 Environmental setting**

141 Environmental variability in the southeastern North Sea was characterized by a strong
142 seasonal temperature cycle, a pronounced river-to-marine salinity gradient, and nutrient
143 enrichment associated with the Elbe River (Table 2). Based on the station-median salinity
144 classification described above, the dataset covered three hydrographic regions: the Elbe, estuarine,
145 and marine regions. Water temperature ranged from 1.4 to 22.2 °C and was driven primarily by
146 season, whereas longitudinal variation in temperature was comparatively weak. In contrast,
147 salinity increased strongly from the freshwater Elbe region toward the marine stations, spanning
148 0–33.6 PSU across the full dataset, with the largest variability occurring in the estuarine mixing
149 zone.

150 Nitrate spanned nearly four orders of magnitude, from 0.3 to 1659 $\mu\text{mol L}^{-1}$, and generally
151 decreased from the Elbe region through the estuary to the marine region. Phosphate, nitrite,
152 ammonium and silicate broadly followed the same decreasing gradient, consistent with a dominant
153 riverine source. Dissolved oxygen concentrations were above the hypoxic threshold of 2 mg L^{-1}
154 throughout the study period, with a minimum concentration of 3.6 mg L^{-1} . Suspended particulate
155 matter (SPM) ranged from 6 to 832 mg L^{-1} , with a pronounced peak at 9.36° E (station median
156 160 mg L^{-1}), coinciding with the Elbe estuarine turbidity maximum reported by (Kappenberg and
157 Grabemann, 2001). Vertical gradients were generally weak during all campaigns. Temperature and
158 most nutrients showed no consistent surface to bottom differences, whereas SPM was elevated
159 near the bottom, due to bottom shear stress.



Table 2. Overview of physicochemical parameters in the water column during all sampling campaigns from October 2010 to November 2014. Median $\pm$ standard deviation and the range of the data (in brackets) are given. Sampling stations were grouped into three hydrographic regions: marine stations with median salinity > 30 PSU (7.89–8.31° E), estuarine stations with median salinity 5–30 PSU (8.41–8.80° E), and Elbe stations with median salinity < 5 PSU (9.09–10.03° E).

Station [° E]	Salinity [PSU]	Temperature [°C]	Oxygen [mg L ⁻¹]	SiO ₄ [μmol L ⁻¹]	PO ₄ [μmol L ⁻¹]	NO ₂ [μmol L ⁻¹]	NO ₃ [μmol L ⁻¹]	NH ₄ [μmol L ⁻¹]	SPM [mg L ⁻¹]
Marine stations									
7.89	32.5 $\pm$ 0.9 [30.2–33.6]	9.8 $\pm$ 5.2 [4.2–18.5]	8.6 $\pm$ 1.3 [6.1–10.6]	6.0 $\pm$ 5.3 [0.5–18.9]	0.5 $\pm$ 1.3 [0.1–5.4]	0.4 $\pm$ 1.9 [0–6.1]	3.2 $\pm$ 8.2 [0.4–28.2]	1.3 $\pm$ 0.9 [0–3.9]	74 $\pm$ 18 [43–104]
7.99	31.6 $\pm$ 1.3 [28.5–33.5]	9.3 $\pm$ 5.5 [3.8–18.2]	9.4 $\pm$ 1.5 [6.0–11.3]	8.0 $\pm$ 8.2 [2.6–31.5]	0.8 $\pm$ 0.4 [0.1–1.6]	0.4 $\pm$ 0.4 [0–1.1]	5.4 $\pm$ 11.6 [0.3–42.1]	2.1 $\pm$ 0.7 [0.6–3.1]	71 $\pm$ 33 [15–149]
8.08	31.6 $\pm$ 2.0 [27.0–32.6]	6.3 $\pm$ 1.7 [2.8–6.8]	10.1 $\pm$ 0.9 [9.1–11.5]	17.4 $\pm$ 12.2 [6.6–40.9]	0.8 $\pm$ 0.2 [0.7–1.2]	0.8 $\pm$ 0.2 [0.7–1.2]	20.4 $\pm$ 17.4 [6.5–54.9]	3.0 $\pm$ 0.7 [2.5–4.4]	86 $\pm$ 17 [59–111]
8.24	31.4 $\pm$ 0.9 [29.6–33.1]	11.0 $\pm$ 5.4 [2.8–18.9]	8.5 $\pm$ 1.2 [7.3–11.3]	10.1 $\pm$ 9.1 [1.3–28.8]	0.8 $\pm$ 0.4 [0.3–1.7]	0.6 $\pm$ 0.4 [0.2–1.4]	7.5 $\pm$ 12.4 [0.5–37.7]	2.5 $\pm$ 1.5 [0.2–5.2]	87 $\pm$ 29 [8–134]
8.31	30.7 $\pm$ 1.4 [27.1–33.0]	8.4 $\pm$ 5.9 [2.1–19.3]	8.4 $\pm$ 1.4 [6.2–11.6]	14.0 $\pm$ 12.1 [0.8–42.5]	0.8 $\pm$ 0.5 [0.1–2.0]	0.6 $\pm$ 0.4 [0.2–1.4]	13.7 $\pm$ 14.6 [0.6–44.5]	2.2 $\pm$ 1.6 [0.1–5.9]	91 $\pm$ 25 [18–132]
Estuarine stations									
8.41	29.8 $\pm$ 2.1 [23.5–32.8]	11.0 $\pm$ 6.1 [2.1–19.9]	9.5 $\pm$ 1.2 [7.5–11.4]	13.0 $\pm$ 16.5 [0–68.1]	0.9 $\pm$ 0.5 [0.4–2.2]	0.7 $\pm$ 0.5 [0.2–1.7]	19.3 $\pm$ 31.7 [1.2–131]	3.0 $\pm$ 1.5 [0.2–6.0]	91 $\pm$ 31 [15–136]
8.44	28.3 $\pm$ 2.0 [24.1–31.8]	9.0 $\pm$ 5.1 [2.6–18.1]	10.5 $\pm$ 3.1 [5.2–13.3]	22.2 $\pm$ 25.6 [1.6–80.8]	1.3 $\pm$ 0.9 [0.1–3.2]	0.9 $\pm$ 0.8 [0.2–2.6]	47.1 $\pm$ 382 [17.5–1037]	6.6 $\pm$ 4.5 [3.8–16.5]	104 $\pm$ 35 [28–157]
8.50	26.6 $\pm$ 3.0 [19.4–32.1]	7.7 $\pm$ 6.5 [1.7–20.3]	9.7 $\pm$ 1.2 [8.0–11.9]	18.8 $\pm$ 27.0 [0.8–92.1]	1.2 $\pm$ 0.5 [0.4–1.9]	1.0 $\pm$ 0.6 [0.2–1.9]	47.4 $\pm$ 34.8 [6.0–130]	3.6 $\pm$ 1.8 [0.7–8.1]	93 $\pm$ 25 [72–167]



8.57	24.6 ± 46.0 [9.6–28.2]	9.0 ± 5.3 [2.7–17.7]	8.6 ± 2.2 [5.3–11.3]	32.9 ± 19.5 [1.7–65.2]	1.7 ± 0.7 [0.2–2.4]	0.8 ± 0.7 [0.3–2.6]	49.1 ± 224 [18.3–856]	7.4 ± 4.0 [3.4–15.7]	99 ± 30 [30–157]
8.66	22.9 ± 6.4 [6.0–26.3]	10.1 ± 5.5 [1.8–18.0]	8.8 ± 1.7 [7.6–12.5]	30.4 ± 20.4 [3.9–63.6]	1.4 ± 0.6 [0.4–3.0]	1.0 ± 0.7 [0.3–2.6]	81.8 ± 78.0 [35.3–264]	6.4 ± 3.8 [2.9–13.4]	101 ± 28 [31–147]
8.68	19.2 ± 4.6 [9.9–27.7]	6.8 ± 6.8 [1.4–21.1]	9.2 ± 1.7 [7.9–12.9]	45.5 ± 50.6 [0–156]	1.8 ± 0.8 [0.3–3.3]	1.1 ± 0.7 [0.1–2.4]	53.4 ± 49.3 [14.0–219]	5.2 ± 3.6 [0.8–14.6]	89 ± 22 [59–152]
8.73	15.1 ± 5.6 [0.3–23.2]	10.6 ± 5.0 [4.2–20.1]	8.4 ± 1.7 [5.3–11.0]	62.7 ± 30.8 [14.5–109]	1.9 ± 0.6 [1.1–3.2]	1.0 ± 0.7 [0.5–2.6]	129 ± 477 [60.0–1659]	6.9 ± 2.7 [2.7–12.4]	99 ± 51 [45–216]
8.80	12.1 ± 5.1 [0.2–17.8]	11.2 ± 5.1 [4.1–20.5]	8.2 ± 1.7 [5.5–11.1]	75.7 ± 43.8 [17.1–169]	2.2 ± 2.5 [1.4–14.1]	1.0 ± 0.7 [0.2–2.6]	173 ± 441 [40.0–1659]	5.4 ± 2.7 [2.2–11.3]	90 ± 53 [56–332]
Riverine stations									
9.09	3.2 ± 3.0 [0.1–13.7]	12.1 ± 5.3 [3.9–21.5]	8.2 ± 1.8 [5.5–12.0]	99.4 ± 50.6 [20.8–185]	2.5 ± 2.3 [1.2–11.9]	0.5 ± 0.7 [0–2.6]	207 ± 440 [75.7–1619]	4.0 ± 2.6 [0.9–9.5]	96 ± 119 [29–502]
9.36	0.7 ± 0.6 [0–3.0]	13.3 ± 5.7 [3.4–21.0]	8.0 ± 1.9 [5.3–11.7]	129 ± 48.1 [12.0–170]	1.6 ± 1.9 [0.9–8.4]	0.3 ± 0.8 [0–2.7]	226 ± 395 [116–1510]	3.0 ± 3.4 [0.5–15.7]	160 ± 130 [31–525]
9.51	0.5 ± 0.2 [0–0.9]	10.8 ± 5.6 [4.4–20.9]	8.1 ± 2.1 [5.1–11.5]	110 ± 50.2 [1.7–173]	1.4 ± 1.5 [0.6–6.5]	1.0 ± 0.9 [0–2.5]	251 ± 422 [81–1524]	3.0 ± 3.4 [1.5–15.1]	76 ± 72 [14–258]
9.73	0.3 ± 0.2 [0–0.7]	13.6 ± 5.8 [4.4–21.8]	8.9 ± 2.3 [4.9–11.9]	131 ± 52.9 [0–213]	1.4 ± 1.5 [1.0–6.2]	1.7 ± 0.9 [0–4.1]	260 ± 396 [65–1490]	5.0 ± 3.5 [1.9–12.9]	32 ± 159 [12–832]
9.88	0.4 ± 0.2 [0–0.6]	10.5 ± 5.1 [5.1–22.2]	8.5 ± 2.7 [3.6–11.2]	134 ± 49.8 [0–171.7]	1.3 ± 0.9 [0.4–3.7]	1.4 ± 1.0 [0.7–4.3]	236 ± 410 [119–1387]	6.4 ± 3.0 [3.1–12.6]	20 ± 29 [6–120]
10.03	0.4 ± 0.2 [0–0.7]	13.6 ± 5.4 [5.2–21.9]	8.2 ± 1.6 [6.4–10.9]	138 ± 54.8 [0–179]	1.4 ± 1.5 [0.1–4.8]	1.4 ± 0.8 [0.6–3.8]	262 ± 405 [128–1451]	6.4 ± 5.2 [3.6–20.4]	21 ± 12 [8–52]



167 3.2 The fractional turnover rate k' , and correlations analysis with abiotic conditions

168 The fractional turnover rate k' increased from the marine region toward the river, with regional
169 medians of 0.02 d^{-1} in the marine region, 0.04 d^{-1} in the estuary and 0.43 d^{-1} in the Elbe with
170 maxima reaching 2.86 d^{-1} (Fig. 2a). The higher and more variable k' values in the riverine region
171 may be partly explained by the elevated methanotroph abundance previously reported for the Elbe
172 (Hackbusch et al., 2019). Dissolved CH_4 concentrations also showed a pronounced gradient,
173 ranging from 5 to 2306 nmol L^{-1} (Fig. 2b). Concentrations were lowest in the marine region, with
174 a regional median of 15 nmol L^{-1} , increased in the estuary to 43 nmol L^{-1} , and reached the highest
175 concentrations in the river, where the median concentration was 66 nmol L^{-1} and maximum values
176 exceeded 2300 nmol L^{-1} . MOx ranged from 0.01 to $5542.3 \text{ nmol L}^{-1} \text{ d}^{-1}$ and followed the same
177 marine-river gradient. Regional median MOx values increased from $0.20 \text{ nmol L}^{-1} \text{ d}^{-1}$ in the
178 marine region to $1.88 \text{ nmol L}^{-1} \text{ d}^{-1}$ in the estuarine region and $32.25 \text{ nmol L}^{-1} \text{ d}^{-1}$ in the Elbe region
179 (Fig. 2b). Across regions, k' and CH_4 showed similar spatial gradients, but their weak correlation
180 indicates that they were partly decoupled (Fig. 3); also, no logarithmic relationship as expected
181 from Michaelis–Menten kinetic was observed.

182 Correlations between k' and environmental variables were region dependent and generally
183 insufficient to explain variability in k' (Fig. 3). Marine waters are characterized by relatively low
184 variation in k' which shows no clear correlation with environmental factors that vary only slightly
185 (Fig. 3a). In contrast, the estuarine zone showed clearer environmental structure: k' was negatively
186 associated with salinity ($r_s = -0.58$) and positively associated with temperature ($r_s = 0.61$),
187 indicating that both the estuarine mixing gradient and seasonal temperature conditions were linked
188 to methanotrophic oxidation capacity. In the Elbe region, k' was moderately correlated with



189 temperature ($r_s = 0.49$), but no other environmental variable showed a clear relationship with k' ,
190 suggesting a more complex freshwater process regime.

191 No significant surface-bottom differences in k' , CH_4 concentration or MOx rates were
192 detected across regions; therefore, surface and bottom samples were pooled. Overall, the
193 correlation analysis provided a first overview of region-specific monotonic relationships, but it
194 could not account for nonlinear or combined effects among predictors. The next section therefore
195 evaluates whether nonlinear multivariate models can better predict k' across the regions.

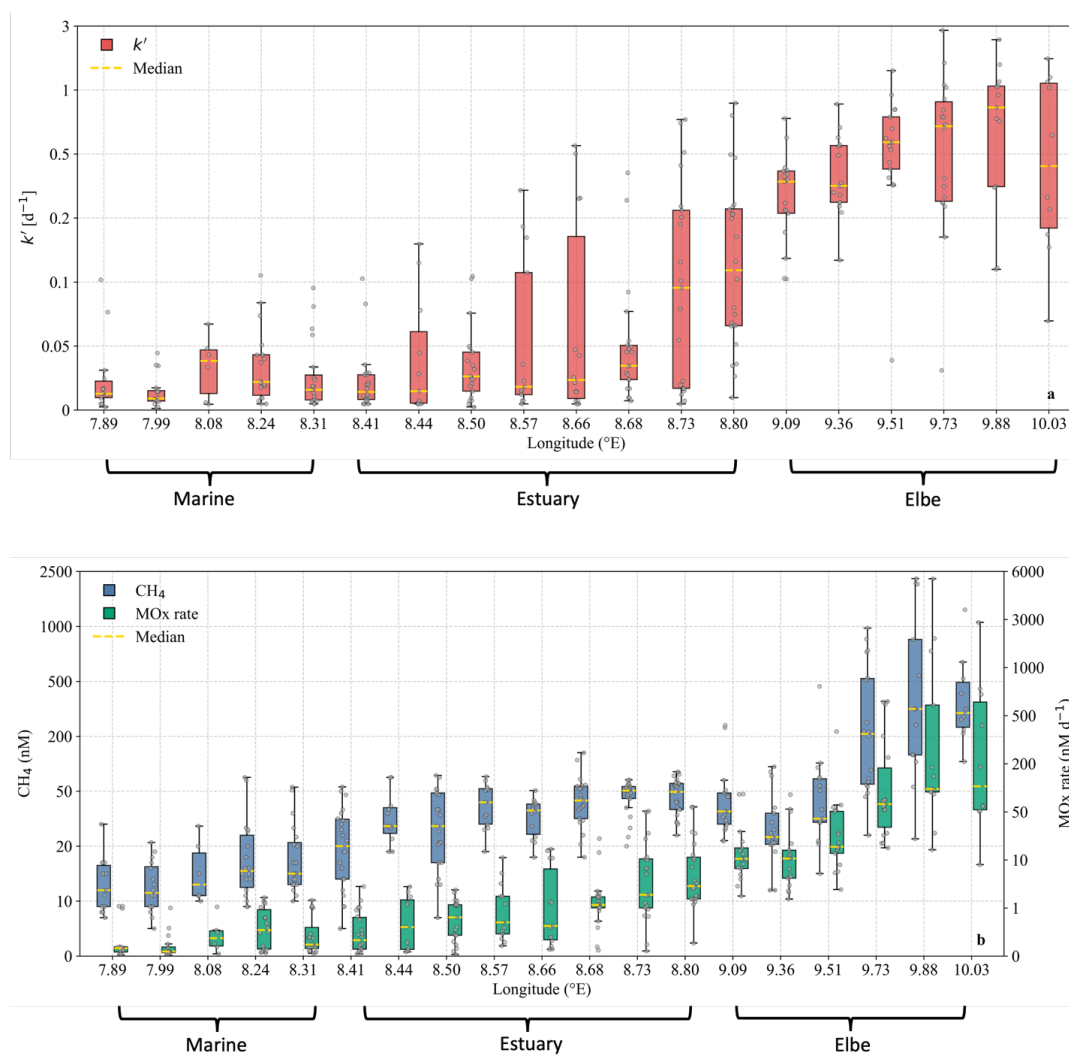
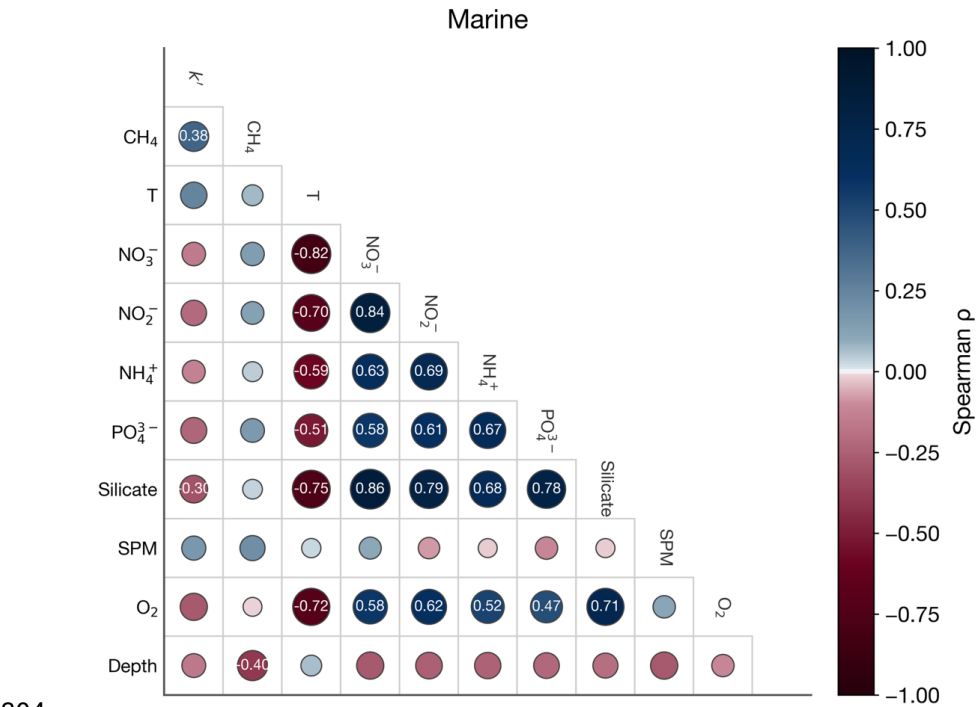
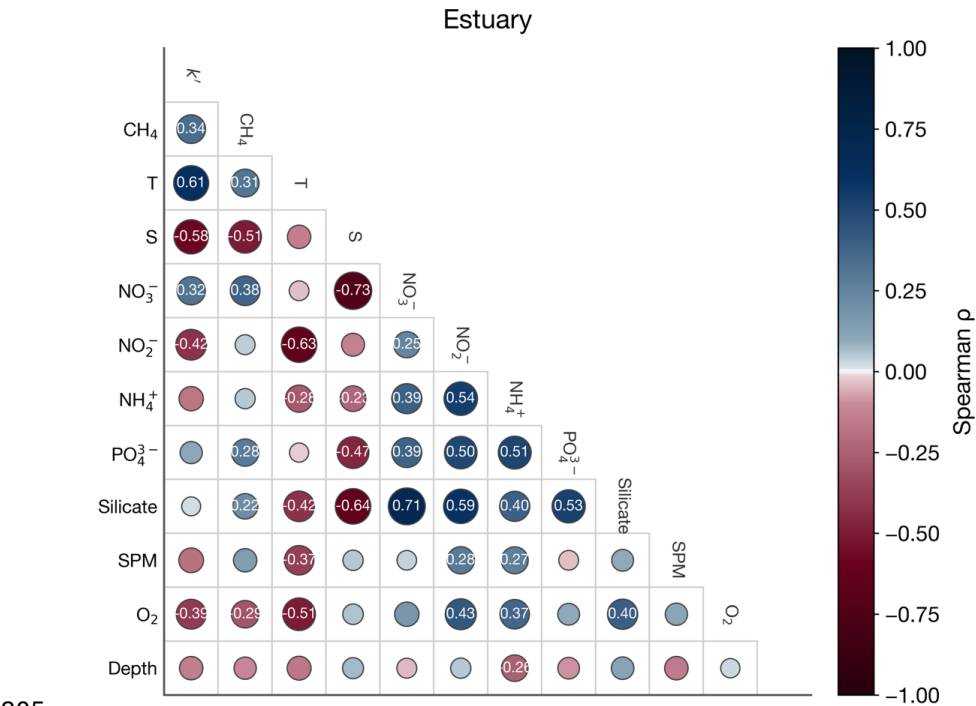


Figure 2. Longitudinal distributions of the fractional turnover rate k' , dissolved CH_4 concentration and MOx rate across the marine, estuarine and Elbe regions. (a) Fractional turnover rate k' . (b) Dissolved CH_4 concentration and MOx rate. Boxplots show the median and interquartile range at each station, and grey dots represent observations. Please note that all y-axes are displayed on non-linear scales for visualization.



204



205

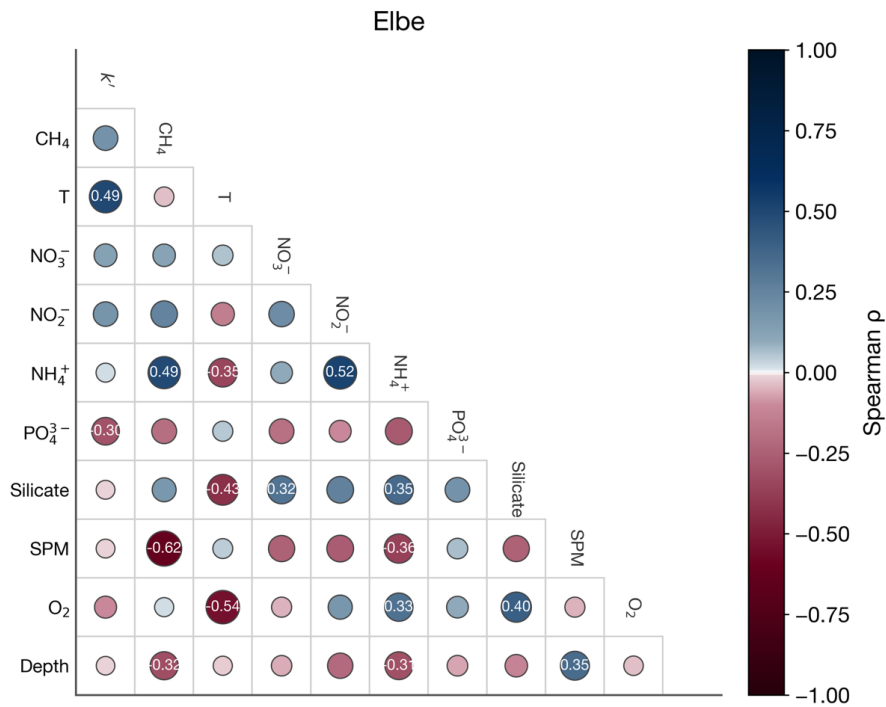


Figure 3. Spearman rank correlation coefficients between the fractional turnover rate (k'), CH_4 concentration and environmental parameters across the three hydrographic regions (marine, estuary, and Elbe). Numbers are shown only for correlations significant at the $p < 0.01$ level (two-tailed). T stands for temperature and S stands for salinity. Salinity was excluded from the coastal marine and Elbe matrices because it showed little variability within these regions.



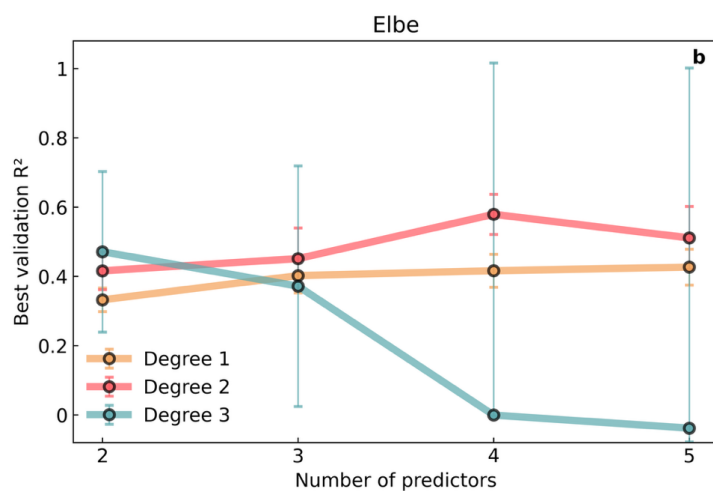
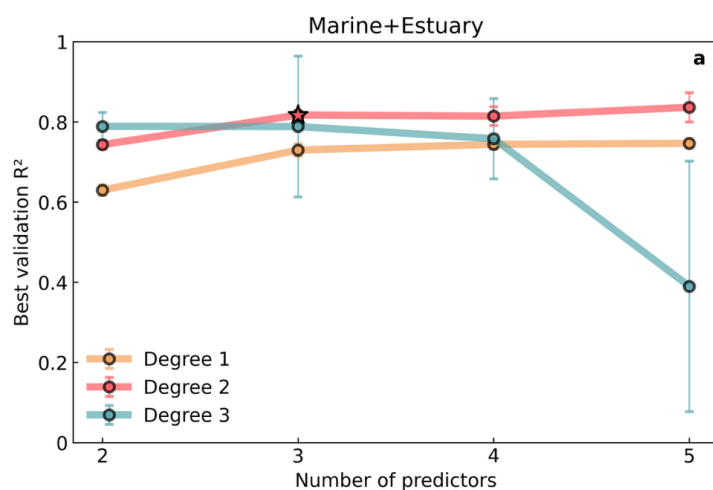
218 3.3 Non-linear approach on the fractional turnover rate (k')

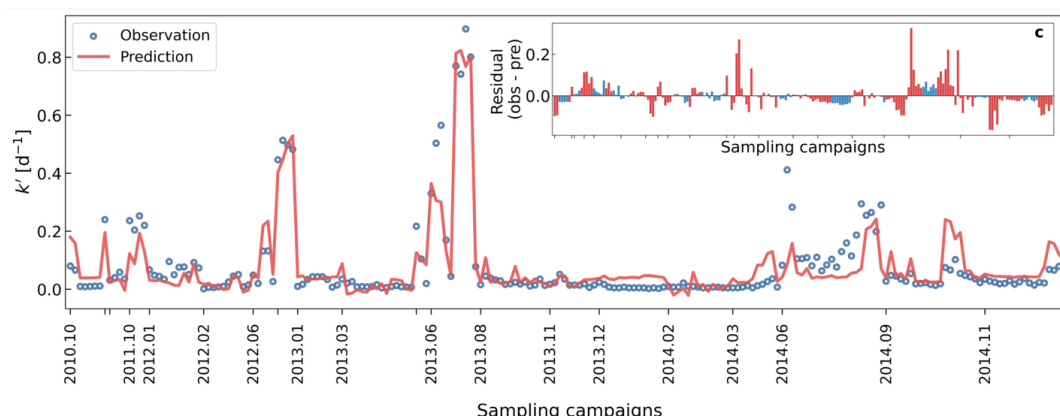
219 In the marine-estuarine regions, the second-degree polynomial model using temperature,
 220 salinity, and NO_3^- as base predictors provided the best predictive performance relative to model
 221 complexity. Lower-degree models underfit the data, whereas higher-degree models showed signs
 222 of overfitting (Fig. 4a). Adding further variables to the selected T + S + NO_3^- framework, including
 223 CH_4 concentration, O_2 , SPM, and water depth, did not improve cross-validated prediction
 224 sufficiently to justify their inclusion in the model. The squared NO_3^- term was removed from the
 225 expansion because its coefficient showed large variability across validation repeats, and its
 226 exclusion did not reduce repeated cross-validation performance (Table S1). VIF values for the base
 227 predictors were all below 2, indicating that multicollinearity among temperature, salinity, and NO_3^-
 228 was low and unlikely to affect model stability. The model (T + S + NO_3^- , polynomial degree = 2)
 229 reproduced the major variability in k' across the estuarine and marine regions (Fig. 4). Model
 230 performance was comparable between training and validation subsets, with $R^2 = 0.85 \pm 0.03$,
 231 $\text{RMSE} = 0.06 \text{ d}^{-1}$, and $\text{MAE} = 0.04 \text{ d}^{-1}$ for training, and $R^2 = 0.82 \pm 0.01$, $\text{RMSE} = 0.06 \text{ d}^{-1}$, and
 232 $\text{MAE} = 0.04 \text{ d}^{-1}$ for validation. The mean residual (observation - prediction) was close to zero,
 233 indicating little overall bias.

234 As noted above, when all samples were included in model training, k' in the Elbe samples
 235 exhibited patterns distinct from those from the marine-estuary regions. Residuals in the Elbe were
 236 predominantly positive, indicating systematic underprediction of riverine k' (Fig. S1). Accordingly,
 237 Elbe-specific models were developed using the same model selection framework as for the marine-
 238 estuarine models. Candidate models were also constructed from the 11 available environmental
 239 variables, with polynomial degrees ranging from 1 to 3 and with up to five predictors included in
 240 each model (Fig. 4b). However, their ability to reconstruct k' remained limited, as indicated by



241 lower R^2 values and higher uncertainty. This result was not confined to particular sampling seasons
242 or stations, fresher-water samples (e.g., salinity < 0.5), or only to the highest k' observations (e.g.,
243 $k' > 1.0 \text{ d}^{-1}$). Together, these findings suggest that riverine k' is governed by a distinct response
244 regime that was not sufficiently captured by the predictors available in this study.





249

250 **Figure 4.** Model selection of k' using polynomial regression. Upper panels (a, b): Best repeated 5-
 251 fold cross-validation R^2 for each combination of polynomial degree (1–3) and number of predictors
 252 (2–5) in the Marine-Estuary ($n = 203$) and Elbe ($n = 80$) regions. Points indicate the highest mean
 253 validation R^2 among tested predictor combinations, and error bars show the standard deviation
 254 across repeated cross-validation estimates. The star marks the model selected for this study ($T + S$
 255 $+ NO_3^-$); the Elbe panel uses a nonlinear y-axis for visualization. Lower panel (c): Reconstruction
 256 of k' in the marine-estuarine region from 2010 to 2014 ($n = 203$). Blue circles show observations,
 257 and the red line shows cross-validated predictions. The inset shows residuals calculated as
 258 observed minus predicted k' . Model performance metrics are reported as the mean $\pm$ standard
 259 deviation across repeated cross-validation runs. For readability, four selected campaign labels were
 260 omitted: 2010.11, 2010.12, 2012.08, and 2013.04.

261

262

263

264

265



266 4 Discussion

267 4.1 Environmental drivers of methanotrophic oxidation capacity

268 In our study, CH₄ concentration provided little explanatory information and showed only
269 weak correlations with k' . From a microbiological point of view, k' should be related to CH₄
270 concentration according to the enzymatic relationship between maximal reaction rate and the
271 substrate concentration (i.e. Michaelis–Menten kinetic). However, this decoupled relationship has
272 been shown in previous studies that an increase in the methanotrophic oxidation capacity can be
273 related to higher methanotroph abundance, higher cell-specific activity, or a shift toward different
274 methanotroph groups, rather than through elevated CH₄ concentration alone (Baily et al., 2026;
275 Mayr et al., 2020). In contrast to substrate availability, our study demonstrates k' variability was
276 shaped by environmental variables, namely temperature, salinity, and NO₃[−], roles of these variables
277 are discussed below.

278 At a broader scale, temperature and salinity can be interpreted as proxies for seasonality and
279 water-mass mixing, respectively. Changes in these gradients may drive shifts and succession in
280 methanotrophic community composition, thereby influencing k' (Deng et al., 2017; Harpenslager
281 et al., 2026; Tobias-Hünefeldt et al., 2026). Beyond these indirect ecological effects, temperature
282 and salinity may also directly affect the physiological state and activity of methanotrophs through
283 changes in growth, cell-specific activity, thermal acclimation, and osmotic stress, although these
284 effects are not independent (Lofton et al., 2014; Osudar et al., 2017b; Tveit et al., 2023). Consistent
285 with these mechanisms, the polynomial model indicated a generally positive but nonlinear and
286 interaction-dependent role of temperature, with positive T and $T \times \text{NO}_3^-$ terms but negative T^2 and
287 $T \times S$ terms. In contrast, salinity-related terms were predominantly negative, including S , $T \times S$,



288 and $S \times \text{NO}_3^-$, while the positive S^2 term indicates that this association was not strictly linear (Table
289 S1).

290 Adding NO_3^- to the T + S model improved model performance (e.g., Fig. 4a), suggesting that
291 nitrate carried additional information. Biological uptake, organic matter remineralization,
292 nitrification, and riverine nitrogen inputs can modify nitrate concentrations independently of
293 salinity-driven mixing, particularly in the Elbe estuary, where internal nitrogen transformations
294 strongly affect dissolved inorganic nitrogen dynamics (Dähnke et al., 2022; Sanders et al., 2018).
295 In the polynomial model, the nitrate signal was expressed mainly through the $T \times \text{NO}_3^-$ interaction,
296 suggesting that nitrate effects were linked to the temperature context. This interaction may reflect
297 warm and nitrate-rich conditions that support higher active methanotroph biomass or activity. The
298 biological interpretation is mechanistically plausible, as mineral nitrogen availability can support
299 methanotroph growth and methane oxidation when nitrogen is limiting, although responses vary
300 among systems and nitrogen forms (Bodelier et al., 2000; Bodelier and Laanbroek, 2004).

301 Other nutrient variables showed limited predictive performance. Although PO_4^{3-} is essential
302 for microbial growth and can affect methanotroph physiology under phosphorus limitation
303 (Nijman et al., 2022; Scanlan et al., 2022), PO_4^{3-} did not sufficiently improve validation in this
304 dataset, suggesting that PO_4^{3-} availability was unlikely to be the dominant limiting factor for k' .
305 Similarly, NO_2^- was not retained as a robust predictor, likely because it is a short-lived intermediate
306 in nitrogen cycling and may inhibit methane oxidation at elevated concentrations, rather than
307 serving as a stable indicator of methanotroph nutrient demand (Nyerges et al., 2010).

308 **4.2 Unaccounted controls on k' in the Elbe**

309 Methanotrophs show habitat specificity, and their occurrence and activity are shaped by
310 multiple abiotic factors, including variables (e.g., pH and trace metals) not fully represented in our



dataset (Knief, 2015). In the Elbe and its downstream waters, these environmental gradients may create distinct microbial habitats, supporting spatial variability in methanotroph assemblages (Rusnak et al., 2026), even among nearby sampling stations (Kaupper et al., 2022). Sediment-associated methanotrophs may add another source of variability, as differences in sedimentary conditions between upstream and downstream reaches may select for distinct assemblages that can enter the water column through resuspension or sediment-water exchange (Sherry et al., 2016; Tobias-Hünefeldt et al., 2026). Finally, hydrological and microbial legacy effects may weaken the relationship between k' and instantaneous predictors, because water-mass history, including travel time, downstream dispersal, and the time required for growth and succession, can shape microbial community structure and activity rather than abiotic conditions at the time of sampling alone (Bambakidis et al., 2024; Demeter et al., 2025).

The possibility that the range of predictors in the Elbe contributed to reduced model performance cannot be excluded. For example, salinity generally spanned a narrow freshwater range, reducing its ability as a proxy for water mass mixing. NO_3^- concentrations in the Elbe were generally higher compared to downstream waters, which likely reduced their sensitivity as a proxy for nutrient limitation or biogeochemical state. Oxygen is mechanistically central to aerobic methane oxidation. however, dissolved oxygen in our study remained within a narrow oxic range, so it was unlikely to be a limiting factor and consequently contributed little explanatory information to the model. This does not imply that oxygen is unimportant for methane oxidation; rather, it indicates that our measured gradient was probably too small to resolve oxygen-related controls on k' (Oswald et al., 2016).

4.3 Advantages and limitations of polynomial approach



333 The main advantage of the polynomial approach is its transparency and simple
334 implementation. It provides an explicit approximation of k' as a function of environmental
335 predictors, making the model feasible to interpret and to incorporate into numerical ocean models
336 with an integrated methane module. Our study shows that the second-order polynomials provide a
337 suitable approximation, and the inclusion of nonlinear terms improved model performance,
338 whereas higher-degree polynomials showed signs of overfitting and would likely require larger
339 datasets.

340 A key limitation is that the resulting approximation is likely region-specific. Temperature and
341 salinity may be more broadly transferable predictors, as they reflect seasonal variability, mixing
342 gradient, and potential shifts in microbial communities. In contrast, the roles of nutrients (e.g.,
343 nitrogen and phosphorus), dissolved oxygen, and other variables likely depend on the local
344 hydrology, biogeochemical status, and methanotroph ecology. Therefore, the present model should
345 be regarded as a transferable framework for developing region-specific polynomial
346 parameterizations.

347 **5 Conclusions**

348 In this study, we examined whether the fractional turnover rate k' can be reconstructed from
349 abiotic observations. In the estuarine and marine waters of the southeastern North Sea, a second-
350 order polynomial in temperature, salinity, and nitrate reproduced most of the observed variability
351 in k' . Ambient CH_4 concentration contributed no predictive information, suggesting that oxidation
352 capacity is determined by the environmental conditions experienced by the methanotrophic
353 community rather than by substrate supply. In the riverine Elbe, where k' was highest and most
354 variable, none of the available abiotic predictors explained its variation, indicating additional
355 controls beyond the abiotic variables considered here.



356 The model structure and selection procedure presented in this study are expected to apply to
357 other coastal regions, whereas the fitted coefficients are region-specific and require refitting with
358 local observations. Because k' responds to temperature and nutrient conditions, such
359 parameterizations also allow the represented methane sink to adjust to ongoing coastal warming
360 and changing nutrient loads, in contrast to representations based on fixed rate constants. Future
361 work should incorporate microbial information, such as methanotroph abundance, community
362 composition, and functional gene expression, to identify the biological controls underlying k'
363 variability and to improve the representation of methane oxidation as a responsive biological sink
364 in coastal methane cycling models.

365

366 **Data availability**

367 Data associated with this study are archived in the PANGAEA database under
368 <https://doi.org/10.1594/PANGAEA.833923>,
369 <https://doi.org/10.1594/PANGAEA.833798>,
370 <https://doi.org/10.1594/PANGAEA.855825>,
371 <https://doi.org/10.1594/PANGAEA.897351>.

372 **Author contribution**

373 Yanan Zhao: Conceptualization, Data curation, Formal analysis, Methodology, Visualization,
374 Writing – original draft preparation. Vera Sidorenko: Conceptualization, Formal analysis,
375 Methodology, Writing – review and editing. Carsten Lemmen: Formal analysis, Writing – review
376 and editing. Ingeborg Bussmann: Investigation, Project administration, Supervision, Writing –
377 review and editing.

378 **Competing interests**



379 Some authors are members of the editorial board of the journal. The authors have no other
380 competing interests to declare.

381 **Acknowledgements**

382 ChatGPT (OpenAI) was used to improve clarity and readability of the manuscript.

383 **Financial support**

384 This study was funded by the Helmholtz Initiative InnoPool through the AGRIO project. This
385 study is part of the Helmholtz program Changing Earth, subtopic 4.1: Fluxes and transformation
386 of energy and matter in and across compartments.

387



388 References

- 389 Abril, G., Commarieu, M.-V., and Guérin, F.: Enhanced methane oxidation in an estuarine turbidity
390 maximum, *Limnology & Oceanography*, 52, 470–475, <https://doi.org/10.4319/lo.2007.52.1.0470>,
391 2007.
- 392 Baily, J. A., Hudspeth, Z. W., Morningstar, J. L., Mendlovitz, H. P., Martens, C. S., and Lloyd, K.
393 G.: Linking microbes to in situ methane oxidation rates in a eutrophic freshwater lake, *Front.*
394 *Microbiol.*, 17, 1789101, <https://doi.org/10.3389/fmicb.2026.1789101>, 2026.
- 395 Bambakidis, T., Crump, B. C., Yoon, B., Kyzivat, E. D., Aho, K. S., Leal, C. F., Fair, J. H., Stubbins,
396 A., Wagner, S., Raymond, P. A., and Hosen, J. D.: Temperature, water travel time, and dissolved
397 organic matter structure river microbial communities in a large temperate watershed, *Limnology*
398 *& Oceanography*, 69, 1618–1635, <https://doi.org/10.1002/lno.12591>, 2024.
- 399 Becker, G., Dick, S., and Dippner, J.: Hydrography of the German Bight, *Mar. Ecol. Prog. Ser.*, 91,
400 9–18, <https://doi.org/10.3354/meps091009>, 1992.
- 401 Bodelier, P. L. E. and Laanbroek, H. J.: Nitrogen as a regulatory factor of methane oxidation in
402 soils and sediments, *FEMS Microbiology Ecology*, 47, 265–277, [https://doi.org/10.1016/S0168-](https://doi.org/10.1016/S0168-6496(03)00304-0)
403 [6496\(03\)00304-0](https://doi.org/10.1016/S0168-6496(03)00304-0), 2004.
- 404 Bodelier, P. L. E., Roslev, P., Henckel, T., and Frenzel, P.: Stimulation by ammonium-based
405 fertilizers of methane oxidation in soil around rice roots, *Nature*, 403, 421–424,
406 <https://doi.org/10.1038/35000193>, 2000.
- 407 Bussmann, I., Osudar, R., and Matousu, A.: Methane concentrations and methane oxidation rates
408 from Oct 2010 - Jun 2012 on a transect from Cuxhaven to Helgoland, North Sea, Germany,
409 <https://doi.org/10.1594/PANGAEA.833798>, 2014a.
- 410 Bussmann, I., Osudar, R., and Matousu, A.: Methane concentrations and methane oxidation rates
411 from Oct 2010 - March 2012 in the Elbe Estuary, from Hamburg to Cuxhaven, Germany,
412 <https://doi.org/10.1594/PANGAEA.833923>, 2014b.
- 413 Bussmann, I., Matousu, A., Osudar, R., and Mau, S.: Assessment of the radio³ H-CH₄ tracer
414 technique to measure aerobic methane oxidation in the water column, *Limnology & Ocean*
415 *Methods*, 13, 312–327, <https://doi.org/10.1002/lom3.10027>, 2015.
- 416 Bussmann, I., Hackbusch, S., Schaal, P., and Wichels, A.: Methane distribution and oxidation
417 around the Lena Delta in summer 2013, *Biogeosciences*, 14, 4985–5002,
418 <https://doi.org/10.5194/bg-14-4985-2017>, 2017.
- 419 Bussmann, I., Hackbusch, S., and Warnstedt, J.: Methane concentrations and methane oxidation
420 rates from Jan 2013 - Nov 2014 in the Elbe Estuary, from Hamburg to Helgoland, Germany,
421 <https://doi.org/10.1594/PANGAEA.897351>, 2019.



- 422 Dähnke, K., Sanders, T., Voynova, Y., and Wankel, S. D.: Nitrogen isotopes reveal a particulate-
423 matter-driven biogeochemical reactor in a temperate estuary, *Biogeosciences*, 19, 5879–5891,
424 <https://doi.org/10.5194/bg-19-5879-2022>, 2022.
- 425 Demeter, K., Savio, D., Kirschner, A. K. T., Reischer, G. H., Kolarevic, S., Parajka, J., Derx, J.,
426 Jakwerth, S., Wurzbacher, C., Blaschke, A. P., Mach, R. L., Blöschl, G., Farnleitner, A. H., and
427 Eiler, A.: Hydrological regime of a continental river system predicts bacterial macroecological
428 patterns, *The ISME Journal*, 19, wrag013, <https://doi.org/10.1093/ismejo/wrag013>, 2025.
- 429 Deng, Y., Liu, Y., Dumont, M., and Conrad, R.: Salinity Affects the Composition of the Aerobic
430 Methanotroph Community in Alkaline Lake Sediments from the Tibetan Plateau, *Microb Ecol*, 73,
431 101–110, <https://doi.org/10.1007/s00248-016-0879-5>, 2017.
- 432 Egger, M., Riedinger, N., Mogollón, J. M., and Jørgensen, B. B.: Global diffusive fluxes of
433 methane in marine sediments, *Nature Geosci*, 11, 421–425, [https://doi.org/10.1038/s41561-018-](https://doi.org/10.1038/s41561-018-0122-8)
434 0122-8, 2018.
- 435 Fofonova, V., Androsof, A., Sander, L., Kuznetsov, I., Amorim, F., Hass, H. C., and Wiltshire, K.
436 H.: Non-linear aspects of the tidal dynamics in the Sylt-Rømø Bight, south-eastern North Sea,
437 *Ocean Sci.*, 15, 1761–1782, <https://doi.org/10.5194/os-15-1761-2019>, 2019.
- 438 Forster, P., Storelvmo, T., Armour, K., Collins, W., Dufresne, J. L., Frame, D., Lunt, D. J.,
439 Mauritsen, T., Palmer, M. D., Watanabe, M., Wild, M., and Zhang, H.: The Earth’s Energy Budget,
440 Climate Feedbacks, and Climate Sensitivity, in: *Climate Change 2021: The Physical Science Basis*,
441 Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA, 923–1054,
442 <https://doi.org/10.1017/9781009157896.009>, 2021.
- 443 Gräwe, U., Flöser, G., Gerkema, T., Duran-Matute, M., Badewien, T. H., Schulz, E., and Burchard,
444 H.: A numerical model for the entire Wadden Sea: Skill assessment and analysis of hydrodynamics,
445 *JGR Oceans*, 121, 5231–5251, <https://doi.org/10.1002/2016JC011655>, 2016.
- 446 Grunwald, M., Dellwig, O., Beck, M., Dippner, J. W., Freund, J. A., Kohlmeier, C., Schnetger, B.,
447 and Brumsack, H.-J.: Methane in the southern North Sea: Sources, spatial distribution and budgets,
448 *Estuarine, Coastal and Shelf Science*, 81, 445–456, <https://doi.org/10.1016/j.ecss.2008.11.021>,
449 2009.
- 450 Hackbusch, S., Wichels, A., and Bussmann, I.: Abundance, activity and diversity of
451 methanotrophic bacteria in the Elbe Estuary and southern North Sea, *Aquat. Microb. Ecol.*, 83,
452 35–48, <https://doi.org/10.3354/ame01899>, 2019.
- 453 Harpenslager, S. F., Randall, K., Zhu, Y., Jackson, M. C., Sanders, I., Gallo, B., Harris, D., Prentice,
454 H., Bepalaya, Y. V., Aksenova, O. V., Milner, A., Cameron, T. C., McKew, B. A., O’Gorman, E.
455 J., Yvon-Durocher, G., Friberg, N., Purdy, K. J., Woodward, G., Dumbrell, A. J., and Trimmer, M.:
456 A fixed methane filter maximizes freshwater emissions under warming, *Nat. Clim. Chang.*, 16,
457 704–711, <https://doi.org/10.1038/s41558-026-02649-2>, 2026.
- 458 Hermans, M., Stranne, C., Broman, E., Sokolov, A., Roth, F., Nascimento, F. J. A., Mörrh, C.-M.,
459 Ten Hietbrink, S., Sun, X., Gustafsson, E., Gustafsson, B. G., Norkko, A., Jilbert, T., and Humborg,



- 460 C.: Ebullition dominates methane emissions in stratified coastal waters, *Science of The Total*
461 *Environment*, 945, 174183, <https://doi.org/10.1016/j.scitotenv.2024.174183>, 2024.
- 462 Jacob, B. and Stanev, E. V.: Understanding the Impact of Bathymetric Changes in the German
463 Bight on Coastal Hydrodynamics: One Step Toward Realistic Morphodynamic Modeling, *Front.*
464 *Mar. Sci.*, 8, 640214, <https://doi.org/10.3389/fmars.2021.640214>, 2021.
- 465 James, G., Witten, D., Hastie, T., and Tibshirani, R.: *An Introduction to Statistical Learning: with*
466 *Applications in R*, Springer US, New York, NY, <https://doi.org/10.1007/978-1-0716-1418-1>, 2021.
- 467 Kappenberg, J. and Grabemann, I.: Variability of the Mixing Zones and Estuarine Turbidity
468 Maxima in the Elbe and Weser Estuaries, *Estuaries*, 24, 699, <https://doi.org/10.2307/1352878>,
469 2001.
- 470 Kaupper, T., Mendes, L. W., Poehlein, A., Frohloff, D., Rohrbach, S., Horn, M. A., and Ho, A.:
471 The methane-driven interaction network in terrestrial methane hotspots, *Environmental*
472 *Microbiome*, 17, 15, <https://doi.org/10.1186/s40793-022-00409-1>, 2022.
- 473 Knief, C.: Diversity and Habitat Preferences of Cultivated and Uncultivated Aerobic
474 Methanotrophic Bacteria Evaluated Based on *pmoA* as Molecular Marker, *Front. Microbiol.*, 6,
475 <https://doi.org/10.3389/fmicb.2015.01346>, 2015.
- 476 Lofton, D. D., Whalen, S. C., and Hershey, A. E.: Effect of temperature on methane dynamics and
477 evaluation of methane oxidation kinetics in shallow Arctic Alaskan lakes, *Hydrobiologia*, 721,
478 209–222, <https://doi.org/10.1007/s10750-013-1663-x>, 2014.
- 479 Mao, S.-H., Zhang, H.-H., Zhuang, G.-C., Li, X.-J., Liu, Q., Zhou, Z., Wang, W.-L., Li, C.-Y., Lu,
480 K.-Y., Liu, X.-T., Montgomery, A., Joye, S. B., Zhang, Y.-Z., and Yang, G.-P.: Aerobic oxidation
481 of methane significantly reduces global diffusive methane emissions from shallow marine waters,
482 *Nat Commun*, 13, 7309, <https://doi.org/10.1038/s41467-022-35082-y>, 2022.
- 483 Matousu, A., Osudar, R., Simek, K., and Bussmann, I.: Methane concentrations and methane
484 oxidation rates from June 2012 - June 2013 in the Elbe Estuary, from Hamburg to Cuxhaven,
485 Germany, <https://doi.org/10.1594/PANGAEA.855825>, 2015.
- 486 Matoušů, A., Osudar, R., Šimek, K., and Bussmann, I.: Methane distribution and methane
487 oxidation in the water column of the Elbe estuary, Germany, *Aquat Sci*, 79, 443–458,
488 <https://doi.org/10.1007/s00027-016-0509-9>, 2017.
- 489 Mayr, M. J., Zimmermann, M., Dey, J., Wehrli, B., and Bürgmann, H.: Lake mixing regime selects
490 apparent methane oxidation kinetics of the methanotroph assemblage, *Biogeosciences*, 17, 4247–
491 4259, <https://doi.org/10.5194/bg-17-4247-2020>, 2020.
- 492 Mohanty, S. R., Bodelier, P. L. E., and Conrad, R.: Effect of temperature on composition of the
493 methanotrophic community in rice field and forest soil: Effect of temperature on soil
494 methanotrophs, *FEMS Microbiology Ecology*, 62, 24–31, <https://doi.org/10.1111/j.1574-6941.2007.00370.x>, 2007.



- 496 Nijman, T. P. A., Amado, A. M., Bodelier, P. L. E., and Veraart, A. J.: Relief of Phosphate
497 Limitation Stimulates Methane Oxidation, *Front. Environ. Sci.*, 10, 804512,
498 <https://doi.org/10.3389/fenvs.2022.804512>, 2022.
- 499 Nyerges, G., Han, S.-K., and Stein, L. Y.: Effects of Ammonium and Nitrite on Growth and
500 Competitive Fitness of Cultivated Methanotrophic Bacteria, *Appl Environ Microbiol*, 76, 5648–
501 5651, <https://doi.org/10.1128/AEM.00747-10>, 2010.
- 502 Osudar, R., Matoušů, A., Alawi, M., Wagner, D., and Bussmann, I.: Environmental factors
503 affecting methane distribution and bacterial methane oxidation in the German Bight (North Sea),
504 *Estuarine, Coastal and Shelf Science*, 160, 10–21, <https://doi.org/10.1016/j.ecss.2015.03.028>,
505 2015.
- 506 Osudar, R., Klings, K., Wagner, D., and Bussmann, I.: Effect of salinity on microbial methane
507 oxidation in freshwater and marine environments, *Aquat. Microb. Ecol.*, 80, 181–192,
508 <https://doi.org/10.3354/ame01845>, 2017a.
- 509 Osudar, R., Klings, K., Wagner, D., and Bussmann, I.: Effect of salinity on microbial methane
510 oxidation in freshwater and marine environments, *Aquat. Microb. Ecol.*, 80, 181–192,
511 <https://doi.org/10.3354/ame01845>, 2017b.
- 512 Oswald, K., Milucka, J., Brand, A., Hach, P., Littmann, S., Wehrli, B., Kuypers, M. M. M., and
513 Schubert, C. J.: Aerobic gammaproteobacterial methanotrophs mitigate methane emissions from
514 oxic and anoxic lake waters, *Limnology & Oceanography*, 61, <https://doi.org/10.1002/lno.10312>,
515 2016.
- 516 Plüß, Andreas: Das Nordseemodell der BAW zur Simulation der Tide in der Deutschen Bucht, *Die*
517 *Küste*, 67, 84–127, 2003.
- 518 Russnak, V., Koll, R., Keuter, S., Sanders, T., and Dähnke, K.: The Elbe Estuary Microbiome Shifts
519 With Salinity and Discharge and Depends on Fresh Organic Matter and Nutrient Availability,
520 *Environ Microbiol Rep*, 18, e70349, <https://doi.org/10.1111/1758-2229.70349>, 2026.
- 521 Sanders, T., Schöl, A., and Dähnke, K.: Hot Spots of Nitrification in the Elbe Estuary and Their
522 Impact on Nitrate Regeneration, *Estuaries and Coasts*, 41, 128–138,
523 <https://doi.org/10.1007/s12237-017-0264-8>, 2018.
- 524 Scanlan, J., Guillonneau, R., Cunningham, M. R., Najmin, S., Mausz, M. A., Murphy, A., Murray,
525 L. L., Zhang, L., Kumaresan, D., and Chen, Y.: The Proteobacterial Methanotroph *Methylosinus*
526 *trichosporium* OB3b Remodels Membrane Lipids in Response to Phosphate Limitation, *mBio*, 13,
527 e00247-22, <https://doi.org/10.1128/mbio.00247-22>, 2022.
- 528 Sherry, A., Osborne, K. A., Sidgwick, F. R., Gray, N. D., and Talbot, H. M.: A temperate river
529 estuary is a sink for methanotrophs adapted to extremes of pH , temperature and salinity, *Environ*
530 *Microbiol Rep*, 8, 122–131, <https://doi.org/10.1111/1758-2229.12359>, 2016.
- 531 Steinle, L., Graves, C. A., Treude, T., Ferré, B., Biastoch, A., Bussmann, I., Berndt, C., Krastel, S.,
532 James, R. H., Behrens, E., Böning, C. W., Greinert, J., Sapart, C.-J., Scheinert, M., Sommer, S.,



- 533 Lehmann, M. F., and Niemann, H.: Water column methanotrophy controlled by a rapid
534 oceanographic switch, *Nature Geosci*, 8, 378–382, <https://doi.org/10.1038/ngeo2420>, 2015.
- 535 Steinle, L., Maltby, J., Treude, T., Kock, A., Bange, H. W., Engbersen, N., Zopfi, J., Lehmann, M.
536 F., and Niemann, H.: Effects of low oxygen concentrations on aerobic methane oxidation in
537 seasonally hypoxic coastal waters, *Biogeosciences*, 14, 1631–1645, [https://doi.org/10.5194/bg-14-](https://doi.org/10.5194/bg-14-1631-2017)
538 1631-2017, 2017.
- 539 Sundh, I., Bastviken, D., and Tranvik, L. J.: Abundance, Activity, and Community Structure of
540 Pelagic Methane-Oxidizing Bacteria in Temperate Lakes, *Appl Environ Microbiol*, 71, 6746–6752,
541 <https://doi.org/10.1128/AEM.71.11.6746-6752.2005>, 2005.
- 542 Tobias-Hünefeldt, S. P., Woodhouse, J. N., Ruscheweyh, H.-J., Sunagawa, S., Russnak, V., Streit,
543 W. R., and Grossart, H.-P.: Osmotolerance is a driver of microbial carbon processes in the Elbe
544 estuary, *mSystems*, 11, e01790-25, <https://doi.org/10.1128/msystems.01790-25>, 2026.
- 545 Tveit, A. T., Söllinger, A., Rainer, E. M., Didriksen, A., Hestnes, A. G., Motleleng, L., Hellinger,
546 H.-J., Rattei, T., and Svenning, M. M.: Thermal acclimation of methanotrophs from the genus
547 *Methylobacter*, *The ISME Journal*, 17, 502–513, <https://doi.org/10.1038/s41396-023-01363-7>,
548 2023.
- 549 Weber, T., Wiseman, N. A., and Kock, A.: Global ocean methane emissions dominated by shallow
550 coastal waters, *Nat Commun*, 10, 4584, <https://doi.org/10.1038/s41467-019-12541-7>, 2019.
- 551 Wilkins, D., Lauro, F. M., Williams, T. J., Demaree, M. Z., Brown, M. V., Hoffman, J. M.,
552 Andrews-Pfannkoch, C., McQuaid, J. B., Riddle, M. J., Rintoul, S. R., and Cavicchioli, R.:
553 Biogeographic partitioning of Southern Ocean microorganisms revealed by metagenomics,
554 *Environmental Microbiology*, 15, 1318–1333, <https://doi.org/10.1111/1462-2920.12035>, 2013.

555