

1 **Biochemical oxygen demand as a proxy for dissolved organic carbon in Japanese**
2 **rivers: Conservative estimates for ecological risk assessment**

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15 **Abstract**

16 Dissolved organic carbon (DOC) is a critical parameter for assessing metal bioavailability
17 and toxicity in aquatic systems, but data from routine measurements in Japan are limited
18 to specific sites. The goal of this study was to develop a statistical model to estimate DOC
19 concentrations in Japanese rivers using biochemical oxygen demand (BOD) as a proxy.
20 Because the relationship between BOD and DOC was expected to be highly variable, we
21 focused on obtaining conservative (i.e., lower bound) rather than central tendency
22 estimates of DOC concentrations to support “safe-side” screening-level ecological risk
23 assessments. Based on BOD and DOC measurements from 30 river sites across Japan,
24 we developed a quantile regression model at the 0.1 quantile to provide conservative
25 estimates of DOC. Validation with additional monitoring datasets, including original field
26 surveys in Kanagawa and Osaka Prefectures, demonstrated that the developed model
27 provided reasonably conservative estimates of DOC and hence supported its use for “safe-
28 side” screening-level ecological risk assessment. Because of the variability of the BOD-
29 DOC relationship across sites, direct DOC measurements may be appropriate where
30 screening-level assessments indicate potential ecological risks.

31 **Keywords:** bioavailability, dissolved organic matter, freshwater, biotic ligand model,
32 quantile regression

33 INTRODUCTION

34 Knowledge of chemical speciation is essential for understanding and accurately
35 predicting the bioavailability and toxicity of trace metals and cationic polymers in aquatic
36 systems (Adams et al. 2020; Connors et al. 2023; Paquin et al. 2002). Dissolved organic
37 matter (DOM) plays an important role in this speciation process because binding of trace
38 metals and cationic polymers to DOM can reduce their toxicity. Dissolved organic carbon
39 (DOC) is often used as a metric of DOM to predict metal bioavailability and toxicity
40 (Farley et al. 2015; Tipping et al. 2008). In the case of Cu, for example, DOC has been
41 the most influential parameter among several input parameters, including Ca, Mg, and
42 alkalinity, in the derivation of predicted no-effect concentrations using a biotic ligand
43 model (Peters et al. 2011). Despite its importance, routine monitoring of DOC is not done
44 in many countries, including Japan (Iwasaki & Naito 2024; Peters et al. 2013). This lack
45 of monitoring data has complicated efforts to assess the bioavailability and ecological
46 risks of trace metals or cationic polymers in aquatic environments on a broader scale (e.g.,
47 at a country level). For example, Peters et al. (2013) have developed a statistical model
48 to predict DOC from concentrations of dissolved iron to assess the ecological risks of
49 nickel in the UK.

50 In Japan, 5-day biochemical oxygen demand (hereafter referred to as BOD) has

51 been measured as an indicator of organic pollution in nationwide water quality monitoring
52 programs, but there are no comprehensive data on DOC concentrations in rivers across
53 the country, nor is there a model available to predict DOC concentrations. Our goal was
54 thus to develop a statistical model based on 5-day BOD values to predict concentrations
55 of DOC in Japanese rivers. Because the relationship between BOD and DOC was
56 expected to be highly variable (see below), we focused on obtaining conservative
57 estimates (i.e., very unlikely to be overestimates) of DOC concentrations to support a
58 “safe-side” screening-level ecological risk assessment rather than central tendency
59 estimates such as the arithmetic mean.

60

61 **MATERIALS AND METHODS**

62 **Model development**

63 To develop a statistical model for DOC prediction, we used two different types of DOC
64 and BOD monitoring data: a nationwide water quality dataset for model development and
65 three monitoring datasets for model validation. For the model development, we collected
66 the relevant monitoring data from the Water Information System managed by the Ministry
67 of Land, Infrastructure, Transport and Tourism (<http://www1.river.go.jp/>). By extracting
68 measurement records where DOC and BOD were measured simultaneously at the same

69 sites between 2011 and 2020, we obtained a total of 1583 records from 30 river sites
70 across Japan (Fig. S1; Table S1 for the raw data). When selecting these sites, we excluded
71 three sites that were likely located in brackish water based on their locations on a map
72 and the fact that their measured electrical conductivities exceeded 100 mS/m. For a
73 measurement below the reporting limit of quantification (BOD: 0.5 mg/L; DOC: 1 mg/L),
74 we used half the limit of quantification in the later analysis.

75 Using the extracted data, we developed a quantile regression model at the 0.1
76 quantile to obtain conservative estimates of DOC from BOD. We modeled the BOD-DOC
77 relationship using the following simple linear function:

$$78 \quad \log(DOC) = a \times \log(BOD) + b \quad (1)$$

79 As a supplementary analysis, we also developed a quantile regression model at the 0.5
80 quantile to capture the median relationship. All the statistical analyses were performed
81 using R version 4.4.0 (R Core Team 2024). The quantile regression models (Cade & Noon
82 2003; Koenker & Hallock 2001) were fitted using the function “rq” in the R package
83 “quantreg” (version 5.97).

84

85 **Model validation**

86 To assess whether the developed quantile regression model (i.e., 0.1 quantile) could

87 provide conservative estimates of DOC, we used a monitoring dataset obtained from
88 Takeshita et al. (2019) and two additional datasets from original field surveys that we
89 conducted in Kanagawa and Osaka Prefectures (Fig. S2). Takeshita et al. (2019) selected
90 50 sampling sites in Japanese rivers receiving nickel discharge, including reference sites
91 (see Fig. S2 and Takeshita et al. (2019) for more details).

92 For our original surveys in Kanagawa and Osaka Prefectures, a total of 10 and
93 16 sampling sites, respectively, were selected from nationwide water quality monitoring
94 sites in order to include both sites with relatively low BOD (≤ 1 mg/L) and those with
95 relatively high BOD ($> 2\text{--}3$ mg/L) based on previously reported values (Iwasaki et al.
96 2022). The sampling was conducted in January and June 2024, respectively. For the
97 Kanagawa Prefecture survey, we selected nine sampling sites from the Tsurumi River and
98 one site from the Tama River; 16 sampling sites were set up in various rivers for the Osaka
99 Prefecture survey (see Fig. S2 and Table S2 for more details, including latitudes and
100 longitudes). The analyses of DOC and 5-day BOD were conducted in accordance with
101 Japanese Industrial Standard (JIS) K0102 testing methods for industrial wastewater.
102 Dissolved organic carbon was measured in water samples filtered through a 0.45- μm
103 membrane filter using a total organic carbon analyzer (TOC-L CPH, Shimadzu).

104

105 **RESULTS AND DISCUSSION**

106 Values of BOD at the 30 monitoring sites across Japan ranged from 0.1 to 14 mg/L. The
107 DOC concentrations were highly variable at a given BOD (Fig. 1). The relationships
108 between BOD and DOC were generally unclear, even when examined at individual sites
109 (Fig. S1; Pearson's $r = -0.21$ to 0.71 ; median = 0.37). The magnitudes of ~90% of the
110 correlation coefficients were less than 0.6.

111 Using these monitoring data for model development, the quantile regression
112 model at the 0.1 quantile was estimated as follows (Fig. 1):

113
$$\log(DOC) = 0.5558 \times \log(BOD) - 0.2306 \quad (2)$$

114 Both the intercept (b) and slope (a) of the model were statistically significant ($p < 0.001$).
115 This regression line was estimated so that 10% of the measured DOC values fell below
116 the line. Compared with the model validation data, all but a few of the data points were
117 above the 0.1 quantile regression line (Fig. 2). This result suggests that this quantile
118 regression model provides conservative estimates of DOC from BOD.

119 We also estimated the quantile regression model at the 0.5 quantile:

120
$$\log(DOC) = 0.3155 \times \log(BOD) + 0.1364 \quad (3).$$

121 Both the intercept (0.1364) and slope (0.3155) of the model were statistically significant

122 ($p < 0.001$). This 0.5-quantile model could facilitate obtaining moderate (i.e., median)
123 estimates of DOC concentrations for environmental risk assessment or for examining how
124 the results of a risk assessment depend on DOC values. However, note that given the
125 variations in the BOD-DOC relationship among sites (and likely among seasons; Figs. 2
126 and S1), caution is required when using DOC values predicted from the 0.5 quantile
127 regression model. Indeed, the observed BOD-DOC relationship from the Osaka
128 Prefecture survey clearly differed from the relationships apparent in the other two datasets
129 (Takeshita et al. (2019) and the Kanagawa Prefecture survey; see Fig. 2), although the
130 underlying reasons for these differences are unclear.

131 In this study, largely due to limited data availability, we analyzed the relationship
132 between BOD and DOC by pooling monitoring data from 30 sites in rivers across Japan
133 and developed a quantile regression model that provided conservative estimates of DOC
134 from BOD. However, the BOD-DOC relationships likely depended on site-specific
135 characteristics, such as catchment land use, vegetative cover, and resident
136 microorganisms. Further data accumulation might enable evaluations that take account of
137 these characteristics. However, it is important to note an essential difference: BOD is an
138 indicator of biodegradable organic matter, whereas DOC is the amount of dissolved
139 organic carbon and includes both refractory and biodegradable organic matter. This

140 important difference suggests that there may be inherent limitations to accurately
141 estimating DOC from BOD. Direct measurements of DOC may be appropriate at sites
142 where screening-level assessments based on the conservative estimates of DOC indicate
143 ecological risks of concern.

144

145 **Author contributions**

146 Conceptualization: YI and WN; Data curation: YI; Formal analysis: YI; Funding
147 acquisition: YI and WN; Methodology: YI; Writing—original draft preparation: YI;
148 writing—review and editing: YI and WN.

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153 **Data and code availability**

154 All data are available in the Supplementary Materials.

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161

162 **Conflict of interest**

163 The authors declare no conflicts of interest.

164

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208 [in Japanese with English abstract]

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210 **Figure legends**

211 **Fig. 1.** Relationship between biochemical oxygen demand (BOD) and dissolved organic
212 carbon (DOC) in Japanese rivers. Different colors indicate 30 water-quality-monitoring
213 sites selected from the Water Information System (see Fig. S1 for more details). The solid
214 and dashed lines represent the results of quantile regression models at the 0.1 and 0.5
215 quantiles, respectively.

216

217 **Fig. 2.** Relationship between biochemical oxygen demand (BOD) and dissolved organic
218 carbon (DOC) in three monitoring datasets (Takeshita *et al.*, 2019 and original field
219 surveys in Kanagawa and Osaka Prefectures). The solid and dashed lines represent the
220 results of quantile regression models at the 0.1 and 0.5 quantiles, respectively, fitted to
221 data from the Water Information System.

222



