

1 **Performance of a one-dimensional model of wave-driven**  
2 **nearshore alongshore tracer transport and decay**

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6 **Key Points:**

- 7 • Dye (representing wastewater) in a 3D hydrodynamic model was reproduced using a fast and simple 1D wave-driven advection and loss model with significant  
8 skill
- 9 • Using a human illness probability threshold as a cutoff, the 1D model accurately  
10 predicted 3D model tracer concentration threshold exceedences in 89% of time steps
- 11 • 1D model forecast-informed daily beach advisories agreed with the 3D model on  
12 9% more days than simulated weekly sampling
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**Abstract**

In the San Diego-Tijuana region, current beach advisory metrics do not account for untreated wastewater flow into the ocean. Existing plume transport models are impractical for operational water quality forecasts because the relevant nearshore processes are poorly resolved. A 1D wave-driven advection and uniform loss model was developed for a 30 km nearshore domain spanning the border region. An along-shore uniform bathymetry is used, thus neglecting non-uniformities such as the inlet and shoal near the Tijuana River estuary (TJRE) mouth. Nearshore alongshore velocities were estimated using wave properties at an offshore location with the small angle, weak current approximation and a Rayleigh friction approximation. The 1D model was evaluated using the year-long hourly output of a 3D regional hydrodynamic model. Both velocity formulas had similar skill reproducing the alongshore-averaged nearshore alongshore velocities from the 3D model, but the 1D model run with the Rayleigh friction approximation had much lower skill in reproducing tracer. The 1D and 3D models agreed on tracer exceedance above a human illness probability threshold for 89% of time steps. Simulated daily beach advisories in the 3D model were compared with the 1D model and simulated weekly water quality sampling. 1D model-informed daily beach advisories agreed with the 3D model on 9% more days than simulated weekly sampling, and agreement did not decrease downstream of the TJRE inlet and shoal. This demonstrates that a 1D nearshore wave-advection model can reproduce nearshore tracer evolution from a 3D model over a range of wave conditions ignoring bathymetric non-uniformities.

**Plain Language Summary**

In the San Diego-Tijuana region, water quality problems originating from inadequate wastewater treatment are not well predicted by rainfall or weekly water sampling. A 1D model of the nearshore ocean was developed to predict how dye (standing in for wastewater) is moved along the coastline by wave-driven currents. The 1D model uses a straight 30 km shoreline, neglecting complex bathymetry such as that near the mouth of the Tijuana River estuary (TJRE). The 1D model was compared to a complex 3D regional ocean model. First, it was shown that nearshore currents could be accurately calculated using an offshore wave buoy. Using only wave-driven currents, the 1D model could accurately reproduce the dye patterns seen in the 3D model in a fraction of the time. The 1D model predicted daily beach advisory conditions on 87% of the same days as the 3D model, which was a 9% improvement over simulated weekly water sampling. Depending on the analysis, the 1D model performance decreased only slightly or not at all downstream of the TJRE. Therefore, a simple, fast, 1D model with a uniform coastline can

49 be used in place of or in concert with complex 3D models in applications where 3D mod-  
50 els are impractical, such as public health websites.

## 51 1 Introduction

52 When nearshore waters are contaminated with pollution, surfers and swimmers can  
53 ingest waterborne pathogens that cause gastrointestinal illness (Shuval, 2003). Nearshore  
54 pollution reduces tourism, as beaches are issued advisories or closures when waterborne  
55 pathogens are detected. Water pollution can originate from non-point sources, such as  
56 urban and agricultural run-off after rain, or from point sources, such as wastewater in-  
57 frastructure failure (de Brauwere et al., 2014). The San Antonios de los Buenos Wastew-  
58 ater Treatment Plant (SABWTP) is an example of a point source of untreated sewage  
59 in the San Diego-Tijuana region. Of the 50 million gallons per day (mgd) outflow from  
60 SABWTP, treatment capacity is only 15 mgd and the remaining 35 mgd are untreated  
61 (ARCADIS, 2019). The SABWTP outfall flows directly onto the beach near Punta Ban-  
62 dera (PB), 10 km south of the United States-Mexico border. On a straight coastline, pol-  
63 lution point sources along the beach can contaminate nearshore waters tens of kilome-  
64 ters away because tracers are transported along coast effectively and exported offshore  
65 slowly (Grant et al., 2005; Hally-Rosendahl et al., 2015; Feddersen et al., 2016; Grimes  
66 et al., 2021). The coastline of the San Diego bight has over thirty kilometers of mostly  
67 straight, sandy beach with bathymetric irregularities only near the Tijuana River Es-  
68 tuary (TJRE) and coastline curvature at the northern end of the bight near the San Diego  
69 Bay entrance (Fig. 1).

70 In San Diego county, beach advisories are issued when fecal indicator bacteria (FIB)  
71 are found in weekly beach water quality sampling or after rainfall (San Diego County,  
72 n. d.). However, beach advisory postings based on weekly testing have been estimated  
73 to be inaccurate up to 40% of the time because FIB concentrations can change quickly  
74 and are spatially heterogeneous (J. Kim & Grant, 2004). Further, testing for FIB may  
75 not be a sufficient indicator of the likelihood of illness for beach goers (Boehm et al., 2009).  
76 FIB decay faster than other pathogens that live in wastewater and cause illness in swim-  
77 mers, such as human norovirus (Boehm & Soller, 2020). Norovirus is a leading cause of  
78 gastrointestinal disease among wastewater pathogens and is plentiful in raw sewage (Boehm  
79 & Soller, 2020). Rainfall is also an incomplete indicator. Rainfall is commonly used in  
80 the United States to indicate water quality because stormwater runoff from cities and  
81 farms is high in FIB from either human or animal sources, or both (Francy, 2009; Stid-  
82 son et al., 2011; Aguilera et al., 2019). In the San Diego-Tijuana region, rainfall causes  
83 additional water quality problems because the South Bay International Wastewater Treat-

84 ment Plant closes during rain events and diverts flow to the TJRE to preempt infras-  
85 tructure clogging (ARCADIS, 2019). However, rainfall does not account for dry weather  
86 runoff, which is increasingly recognized to have a disproportionate effect on water qual-  
87 ity at urban coastlines (Rippy et al., 2014). Inadequacy of wastewater treatment plant  
88 infrastructure, as is the case for SABWTP, is a large source of dry weather runoff. Mi-  
89 crobial source testing during dry weather has found evidence of the SABWTP wastew-  
90 ater plume on the shoreline 20 km north of PB (Zimmer-Faust et al., 2021). Coupled  
91 hydrodynamic and human illness models suggest SABWTP is responsible for exposing  
92 more beachgoers to wastewater than the rainfall-dependent TJRE (Feddersen et al., 2021).  
93 To capture SABWTP pollution, current beach advisory criteria should be supplemented  
94 with dynamical modeling.

95 Some models of wastewater plume transport in the San Diego-Tijuana region do  
96 currently exist, but have drawbacks. A plume tracker model advects particles released  
97 from the TJRE mouth, PB, and the South Bay ocean outfall using high-frequency radar  
98 (HFR) currents to make daily water quality predictions (S. Y. Kim et al., 2009). The  
99 shoreline exposure to FIB in the plume tracker model captured 70% of beach advisories  
100 from water quality sampling during rain events over four years (S. Y. Kim et al., 2009).  
101 However, the plume tracker has several issues (e.g., Rogowski et al., 2015). First, pol-  
102 lution plumes are often located within 1 km of shore (Wu et al., 2020; Grimes et al., 2021)  
103 where HFR cannot estimate currents. In addition the data coverage on the shelf varies  
104 spatially and temporally and the uncertainties in the estimated currents are up to  $10 \text{ cm s}^{-1}$ .  
105 Lastly, the plume tracker particles are surface trapped and thus dilution due to verti-  
106 cal mixing is neglected. Currents in the nearshore region are predominately driven by  
107 wave breaking (Feddersen, 1998; Lentz et al., 1999), and are uncoupled from inner shelf  
108 currents. A hydrodynamic model of the San Diego-Tijuana coastal ocean that resolves  
109 both the shelf and the nearshore and tracks plumes from both TJRE and PB (referred  
110 to as the “SD Bight model”) was built by coupling an ocean model to a wave model us-  
111 ing the COAWST framework (Wu et al., 2020; Feddersen et al., 2021) (described in Sec-  
112 tion 2.1). However, the SD Bight model is computationally expensive and currently only  
113 exists as a hindcast.

114 An alternative solution is a model of only the nearshore. Transport through the  
115 nearshore is dynamically simple. Alongshore momentum is dominated by wave-breaking  
116 which can be estimated from an offshore wave buoy (Feddersen, 1998; Lentz et al., 1999).  
117 A nearshore model is appropriate to the problem because the input (SABWTP outflow),  
118 dynamics (wave-driven advection), and desired output (shoreline exposure) are all lo-  
119 cated nearshore. Previous nearshore wave-advection models have reduced the problem

120 to a 1D alongshore-uniform grid by cross section-averaging tracer concentrations and along-  
 121 shore transport (Boehm, 2003; Boehm et al., 2005; Grant et al., 2005; Grimes et al., 2021).  
 122 The effects of pathogen mortality and offshore transport can be represented by loss of  
 123 dye from the 1D domain (Boehm, 2003). Operationally, such a model would be orders  
 124 of magnitude faster than a full hydrodynamic regional model, and therefore more prac-  
 125 tical for daily forecasts and ensemble studies. However, validation of 1D nearshore mod-  
 126 els has been limited by the available observational data. Historical water quality records  
 127 may span decades, but the samples are only taken once per week. This sampling rate  
 128 is too infrequent to capture the propagation of individual plumes along the shoreline.  
 129 Models tuned to historic water quality data such as Boehm (2003) have demonstrated  
 130 ensemble agreement, but cannot demonstrate the reproduction of individual events. Field  
 131 experiments can observe the propagation of individual plumes at high spatial and tem-  
 132 poral resolution, but only span short time periods, for example, 5 hr (Rippy et al., 2013),  
 133 24 hr (Grant et al., 2005), or 30 hr (Grimes et al., 2021). Models validated by field stud-  
 134 ies can reproduce individual plume events well (Grimes et al., 2021), but do not demon-  
 135 strate model performance under a range of wave conditions. Here, we will evaluate per-  
 136 formance of a 1D wave-advection model in reproducing individual plume events over dif-  
 137 ferent seasons using the SD Bight model, which has hourly output for a year.

138 The 1D model assumes that wave-driven alongshore advection in the nearshore can  
 139 be calculated from wave properties at an offshore location. On a long, straight coastline,  
 140 the alongshore momentum balance in the nearshore is dominated by bottom stress and  
 141 the cross-shore gradient of the forcing from breaking waves (Longuet-Higgins, 1970; Fed-  
 142 dersen, 1998; Ruessink et al., 2001),

$$\tau_{b,y} = -\frac{\partial S_{xy}}{\partial x}, \quad (1)$$

143 where  $\tau_{b,y}$  is the bottom stress in the alongshore direction,  $S_{xy}$  is the off-diagonal com-  
 144 ponent of the radiation stress,  $y$  is the alongshore coordinate, and  $x$  is the cross-shore  
 145 coordinate. Because wave energy is conserved until breaking, the wave properties rel-  
 146 evant for  $S_{xy}$  can be estimated from properties at an offshore wave buoy (details in Sec-  
 147 tion 2.4). The alongshore current (averaged over several wave periods),  $v$ , can be found  
 148 by relating  $v$  to the bottom stress,  $\tau_{b,y}$ ,

$$\tau_{b,y} = \rho C_D \langle |\vec{u}|v \rangle, \quad (2)$$

149 where  $\rho$  is the density of seawater,  $\vec{u}$  is full velocity vector,  $C_D$  is a dimensionless drag  
 150 coefficient, and  $\langle \cdot \rangle$  is a time average. Two approximations can be made to calculate  $\langle |\vec{u}|v \rangle$   
 151 in the nearshore. The first is the weak current approximation, which holds when the cur-  
 152 rent is weaker than the wave orbital velocities,  $v < \sigma_{\vec{u}}$ , where  $\sigma_{\vec{u}}$  is the total velocity

153 variance,  $\sigma_{\bar{u}}^2 = \sigma_u^2 + \sigma_v^2$ . The second is the small angle approximation, which holds when  
 154 the wave propagation direction is near shorenormal,  $\sigma_v < v$ . Using the small angle and  
 155 weak current approximations, the bottom stress can be represented (Wright & Thomp-  
 156 son, 1983),

$$\tau_{b,y} = 1.5 \sqrt{\frac{\pi}{2}} \rho C_D \sigma_{\bar{u}} v. \quad (3)$$

157 Some studies have further approximated bottom stress by assuming a constant  $\sigma_{\bar{u}}$ , also  
 158 known as a linear or Rayleigh friction approximation (Lentz et al., 1999; Feddersen et  
 159 al., 2000; Grimes et al., 2021),

$$\tau_{b,y} = \rho \mu v, \quad (4)$$

160 where  $\mu$  is a constant with dimensions  $\text{m s}^{-1}$ . Using wave-estimated alongshore currents,  
 161 the nearshore transport of a tracer (such as untreated wastewater) can be modeled. This  
 162 study will compare model skill of 1D models run with alongshore velocities estimated  
 163 using (3) and (4).

164 A potential challenge that has not been addressed in previous nearshore transport  
 165 models is the effect of alongshore-variable bathymetry on alongshore transport. Along  
 166 the San Diego-Tijuana shoreline, the TJRE mouth lies between PB and many of the recre-  
 167 ational beaches known to be affected by wastewater from the SABWTP (Fig. 1). Dur-  
 168 ing times when the Tijuana River is flowing, the impact of the TJRE plume on the along-  
 169 shore transport of the wastewater from PB is unknown. Larger buoyant plumes have been  
 170 demonstrated to form a barrier to alongshore transport (Banas et al., 2009). Even though  
 171 the Tijuana River only flows episodically, the estuary mouth is a permanent topographic  
 172 feature that may affect the alongshore transport of untreated wastewater from PB. Tidal  
 173 currents through the estuary mouth may affect alongshore transport through wave-current  
 174 interaction, offshore ejection or by retaining dye in the estuary, a process known as tidal  
 175 trapping. The effect of tidal trapping on alongshore transport is not known, but in es-  
 176 tuarine channels, tidal trapping has been found to disperse the along-estuary distribu-  
 177 tion of salt (Okubo, 1973; MacVean & Stacey, 2011). It is hypothesized, then, that over  
 178 many tidal cycles, tidal trapping of a tracer in the TJRE would disperse the tracer con-  
 179 centrations along the shoreline. Another hypothesized effect of the TJRE would be the  
 180 local acceleration of wave-driven transport over the shoal built of sediment deposited out-  
 181 side the estuary mouth. While this analysis cannot tease out each of these potential mech-  
 182 anisms (i.e., buoyant plume, wave-current interactions, offshore ejection, tidal trapping,  
 183 non-uniform bathymetry), to examine the net effect of the TJRE in this analysis, model  
 184 skill will be compared upstream (south) and downstream (north) of the TJRE.

185 In summary, the goal of this study is to use the SD Bight model, with hourly nearshore  
 186 current and tracer concentration data from December 12, 2016 to December 20, 2017 to

187 evaluate the skill of a 1D nearshore transport model. The region of interest is a 30 km  
 188 stretch of coastline from the SABWTP outflow at PB to Hotel del Coronado (HdC) (Fig. 1).  
 189 Comparison with a realistic 3D hydrodynamic model will demonstrate how well regional  
 190 nearshore transport can be modeled neglecting inner shelf circulation and using wave prop-  
 191 erties at a single offshore source using (3) and (4). By doing this, we hope to address the  
 192 following questions:

- 193 1. Can nearshore alongshore transport be well-represented using uniform nearshore  
 194 alongshore velocity estimated from an offshore location (such as from a wave buoy),  
 195 and is a linear bottom stress approximation (4) sufficient for estimating alongshore  
 196 velocity?
- 197 2. Can alongshore tracer distributions be adequately reproduced in a nearshore model  
 198 which neglects shelf circulation?
- 199 3. How does alongshore-variable bathymetry (i.e., the presence of an estuary inlet  
 200 and shoal at the TJRE mouth) impact nearshore model skill?

201 The drawbacks of existing dynamic models, including lack of resolution of relevant pro-  
 202 cesses (S. Y. Kim et al., 2009), computational expense (Wu et al., 2020), and lack of cal-  
 203 ibration across different hydrodynamic conditions (Grimes et al., 2021), are well-documented  
 204 obstacles to the implementation of dynamic models for real-time water quality predic-  
 205 tion (Elko et al., 2022). The 1D model developed here offers a solution to these challenges.  
 206 While we are testing this 1D model in a particular region with known water quality prob-  
 207 lems, we expect the results to be applicable broadly to the skill of 1D wave-advection  
 208 models for the transport of other tracers (e.g. sediment, plankton, or microplastics) and  
 209 other coastlines.

## 210 **2 Methods**

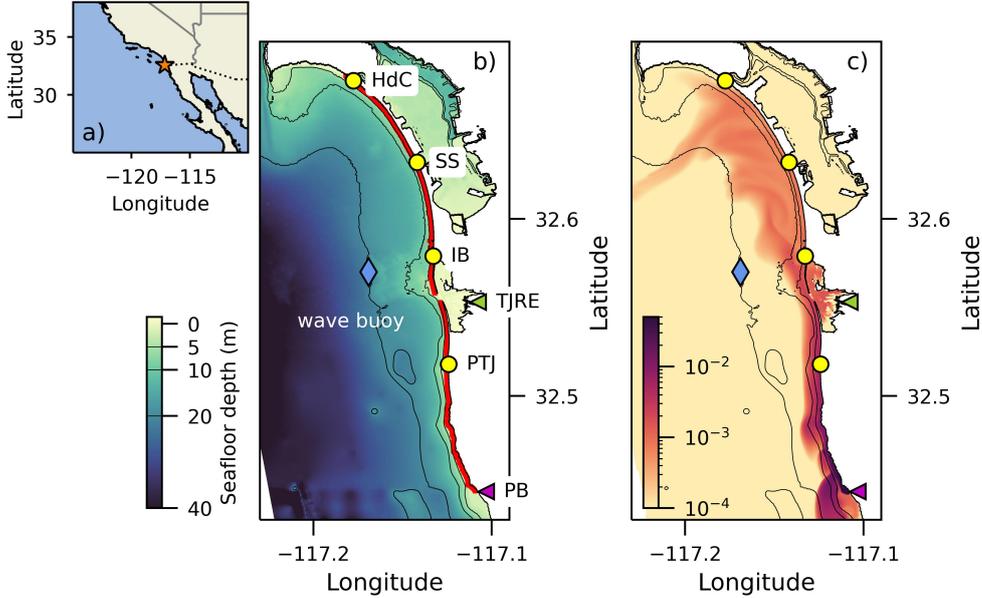
### 211 **2.1 3D realistic SD Bight model**

212 The SD Bight model grid covers a 30 km stretch of coastline from 32.45 N (south  
 213 of PB) to 32.75 (around Point Loma) and extends 10 km offshore (Fig. 1b). This SD Bight  
 214 model has been used in other recent studies investigating the transport of tracers across  
 215 the surf zone and inner shelf in the San Diego-Tijuana region (Wu et al., 2020, 2021a,b,c;  
 216 Feddersen et al., 2021). The model uses the COAWST (Coupled-Ocean-Atmosphere-Wave-  
 217 Sediment-Transport) modeling system (Kumar et al., 2012; Warner et al., 2010). The  
 218 SD Bight model couples Regional Ocean Modeling Systems (ROMS), a 3D hydrostatic  
 219 ocean model with terrain-following vertical coordinates (Shchepetkin & McWilliams, 2005),  
 220 with Simulating WAVes Nearshore (SWAN), a spectral wave model (Booij et al., 1999).

221 The resulting model resolves surf zone, estuarine, and shelf dynamics. The SD Bight model  
 222 uses realistic atmospheric forcing (e.g. wind, heating, atmospheric pressure) from NOAA/NAM,  
 223 tides, and river flow from the Tijuana, Otay, and Sweetwater rivers. The oceanic bound-  
 224 ary conditions (temperature, salinity, sea surface height, and currents) are generated by  
 225 a series of three one-way-nested parent grids (Wu et al., 2020). There are 10 vertical lev-  
 226 els. The horizontal grid is rectangular and telescopic, such that the horizontal resolu-  
 227 tion is highest in the surf zone near the TJRE mouth (8 m) and lower offshore over the  
 228 shelf (110 m). The SD Bight model hindcast simulation used here runs from December  
 229 12, 2016 to December 20, 2017. The baroclinic computational time step varied from one  
 230 to two seconds and the wave field was updated every four minutes. SWAN and ROMS  
 231 exchanged wave field and ocean condition information every 12 minutes. Model output  
 232 was saved hourly to resolve tides. This SD Bight model hindcast included a dye tracer  
 233 to simulate the evolution of an untreated wastewater plume (Fig. 1c). The dye tracer  
 234 was input to the model at PB, the location of the SABWTP outfall, at a concentration  
 235 of 0.7 to match the treatment of 15 mgd of the total 50 mgd outflow (ARCADIS, 2019).  
 236 Complete details of the model implementation are in Wu et al. (2020).

237 Here, we define the nearshore as the region from the 5-m isobath (contoured in Fig. 1)  
 238 to the shoreline, a definition which spans the surf zone and a portion of the inner shelf.  
 239 The 5-m isobath was chosen because it is the furthest offshore extent of the surf zone  
 240 for range of wave heights observed during the simulation period. This is the region typ-  
 241 ically used by surfers and swimmers who could be harmed by exposure to sewage. The  
 242 location of the 5-m isobath is found for every time step to capture tidal variation. Av-  
 243 erage dye concentrations and alongshore transport in the nearshore region were extracted  
 244 from the SD Bight model from PB to the beach at HdC (red line in Fig. 1b). Alongshore  
 245 distance from PB,  $y$ , was calculated following the shoreline, defined such that positive  
 246  $y$  is to the right when facing the sea (roughly north). Dye and velocity were averaged  
 247 vertically and in the cross-shore direction within the nearshore region. Velocity vectors  
 248 were then rotated from grid coordinates into local alongshore and cross-shore coordinates  
 249 using shorenormal angles estimated from the model grid. These shorenormal angles were  
 250 consistent with current principal axes. SD Bight model alongshore velocity was then along-  
 251 shore averaged from PB to HdC to get a representative year-long time series,  $\bar{v}_C(t)$ . Alongshore-  
 252 varying nearshore alongshore velocity and dye extracted from the SD Bight model will  
 253 be referred to as  $v_C(t, y)$  and  $C_C(t, y)$  respectively.

**Figure 1.** a) Regional map with study area indicated (star) along United States-Mexico border (dotted line). b) SD Bight model domain with annotated landmarks. Color indicates bathymetry. The red line highlights the 29 km stretch of coastline represented in the 1D model. Magenta triangle indicates the source of wastewater to the surf zone at Punta Bandera (PB). Yellow circles represent popular recreational beaches: Playas Tijuana (PTJ), Imperial Beach (IB), Silver Strand Beach (SS), and Hotel del Coronado (HdC). Blue diamond is location of CDIP Imperial Beach nearshore wave buoy. The green triangle indicates the head of the Tijuana River estuary (TJRE). c) Snapshot of surface dye concentrations on a logarithmic scale on July 11, 2017 12:00:00 when a plume from PB was transported up the coast during a long-duration south swell. Model bathymetry contoured in b) and c) at 5, 10, and 20m isobaths.



## 2.2 Nearshore 1D tracer advection/loss model

Here we describe our 1D tracer advection/loss model for a nearshore dye tracer transported alongshore by wave-driven currents with loss due to physical (i.e., offshore export of dye from the nearshore region) and biological (i.e., pathogen die off) processes. Similar 1D models of dye evolution have been used in studies that consider the transport of waterborne pathogens along beaches (Boehm, 2003; Boehm et al., 2005), in lagoons (Steets & Holden, 2003), and in streams (Jamieson et al., 2005; Cho et al., 2010), although the source of advection differs to fit the appropriate drivers of ambient currents in those environments. This model is hereafter referred to as the 1D model. The 1D model solves,

$$\frac{\partial C_{1D}(t, y)}{\partial t} = -v_{1D}(t) \frac{\partial C_{1D}(t, y)}{\partial y} - (k_B + k_P) C_{1D}(t, y), \quad (5)$$

where  $y$  is the alongshore coordinate,  $t$  is time,  $C_{1D}$  is the dye concentration,  $v_{1D}$  is the wave-driven alongshore current, and  $k_P$  and  $k_B$  are constant loss terms parameterizing physical and biological processes that reduce nearshore dye concentrations, respectively.

266 Both  $v_{1D}$  and loss terms ( $k_P$  and  $k_B$ ) are assumed alongshore-uniform and effects of shore-  
 267 line curvature are neglected.

268 The first loss parameter,  $k_B$ , represents the inverse timescale of pathogen die-off.  
 269 The 1D model used a 10-day e-folding time scale,  $k_B = 1.6 \times 10^{-6} \text{s}^{-1}$ , to match the  
 270 prescribed dye behavior in the SD Bight model (Wu et al., 2020; Feddersen et al., 2021).  
 271 The 10-day timescale used in the SD Bight model corresponds to the mortality of norovirus  
 272 (Boehm et al., 2018). The estimated mean e-folding time scales for other common wastew-  
 273 ater pathogens in seawater range from less than one day (for *Campylobacter*) to one month  
 274 or more (for *Giardia*) (Boehm et al., 2018).

275 The second linear loss parameter  $k_P$  represents the cross-shelf tracer exchange be-  
 276 tween the nearshore region and the inner shelf. The  $k_P$  parameter may be thought of  
 277 as an exchange velocity,  $u_{\text{ex}}$ , divided by the cross shore distance from the shoreline to  
 278 boundary between the nearshore and the shelf,  $L$  (Hally-Rosendahl et al., 2014; Grimes  
 279 et al., 2021). This cross-shelf exchange is often driven by rip currents in observations (Hally-  
 280 Rosendahl et al., 2014, 2015; Moulton et al., 2017, 2021) and models (Hally-Rosendahl  
 281 et al., 2014; Suanda & Feddersen, 2015; Kumar & Feddersen, 2017). Studies in the surf  
 282 zone have found that exchange between the surf zone and inner shelf produces a net non-  
 283 zero offshore dye flux (Hally-Rosendahl et al., 2014; Grimes et al., 2021), which can be  
 284 parameterized as a monotonic decay of nearshore dye concentration.

285 Dye was added to the 1D model using a Dirichlet boundary condition, constant  $C_0$   
 286 at  $y=0$  km. This boundary condition represents the mean dye concentration adjacent  
 287 to the PB outfall considering a persistent flux of 0.7 dye water that dilutes upon enter-  
 288 ing the ocean and is not completely retained in the nearshore. Small plumes partially  
 289 escape being trapped by waves in the nearshore when waves are weak or the tide is high  
 290 (Rodriguez et al., 2018; Kastner et al., 2019). Model output will be compared for  $y >$   
 291 2 km because rapid diffusion occurs near the dye source in the SD Bight model which  
 292 is not represented in the 1D model. The tracer evolution equation (5) was solved numer-  
 293 ically for  $C_{1D}(y, t)$  with a first-order upwind advection scheme, which is simple and un-  
 294 conditionally stable (Roe, 1986). The 1D model used a time step,  $\Delta t = 18$  s and a grid  
 295 cell size  $\Delta y = 32.85$  m. Alongshore diffusivity was neglected (see discussion in Section 4.2).

### 296 **2.3 Determining dye parameters $k_P$ and $C_0$**

297 A value for  $k_P$  was used for all 1D model runs based on dye concentrations from  
 298 the SD Bight model, and  $C_0$  was tuned using an iterative search optimization method  
 299 to maximize model performance for each 1D model run. The physical rate of dye loss

300 was determined from  $k_P = k - k_B$ , where  $k$  is the total rate of dye loss from the nearshore  
 301 region of the SD Bight model. The rate of dye loss was estimated beginning with the ex-  
 302ponential decrease in the time-averaged nearshore dye concentrations,  $\langle C_C \rangle$ , with  $y$ . The  
 303rate of spatial decay is converted into a temporal decay rate using a velocity scale,  $V$  (RMS  
 304of  $v_C$ ),

$$k = V \frac{d \ln \langle C_C \rangle}{dy}. \quad (6)$$

305 The optimal choice for each  $C_0$  varied based on the value of  $k_P$  (and vice versa)  
 306and the velocity model. Alternative parameter selection methods were considered, in-  
 307cluding fixing both parameters to estimates from the SD Bight model or a multivariate  
 308optimization that iteratively tuned both parameters. Fixing one parameter and tuning  
 309the other was opted for as a hybrid approach. With the hybrid approach,  $C_0$  was cho-  
 310sen as the tuning parameter because the mean value of dye near PB in the SD Bight model  
 311was sensitive to the location at which it was estimated, and  $k_P$  had precedence in lit-  
 312erature available for comparison. Resulting  $k_P$  using equation (6) and optimized values  
 313for  $C_0$  are listed in Section 3.2.

#### 314 2.4 Calculating velocity from wave properties

315 The 1D model alongshore-uniform wave-driven nearshore alongshore velocity,  $v_{1D}(t)$ ,  
 316was estimated from wave properties at an offshore location (32.56957 N, -117.1688 E,  
 31720-m isobath, Fig. 1), the position of the Imperial Beach Nearshore Buoy operated by  
 318the Coastal Data Information Program (CDIP). To make use of the established relation-  
 319ship between surf zone alongshore currents and waves, (1) (Longuet-Higgins, 1970; Fed-  
 320dersen, 1998; Ruessink et al., 2001), the alongshore currents in the nearshore region are  
 321presumed to be proportional to surf zone alongshore-mean alongshore currents.

322 To estimate  $v_{1D}$ , first the right hand side of (1) was simplified using a finite dif-  
 323ference approximation. Radiation stress begins decreasing in the surf zone where waves  
 324break, and  $S_{xy}$  decreases to zero at the shoreline. To average this wave forcing across  
 325the nearshore domain, the change in  $S_{xy}$  to zero is divided by the cross-shore distance  
 326to the 5-m isobath  $L$ ,

$$\frac{\partial S_{xy}}{\partial x} \approx \frac{S_{xy}(t)}{L}. \quad (7)$$

327 For simplicity and generalizability to locations without well-known bathymetry, (7) was  
 328evaluated with a constant  $L$ , set to the mean of the tidally-varying distance to the 5-m  
 329isobath. A narrow-banded representation of  $S_{xy}$  is used (Longuet-Higgins, 1970),

$$S_{xy}(t) = E(t) \frac{c_g(t)}{c_p(t)} \cos \theta'(t) \sin \theta'(t), \quad (8)$$

330 where  $E$  is the wave energy,  $c_g$  is the group velocity,  $c_p$  is the phase velocity, and  $\theta'$  is  
 331 the difference between the mean wave direction,  $\theta$ , from shorenormal,  $\theta_{\text{SN}}$ . For these es-  
 332 timates of alongshore-uniform wave-driven alongshore velocity,  $\theta_{\text{SN}}$  was a constant cho-  
 333 sen to optimize model performance. The wave energy term in (8),  $E$ , was determined  
 334 using,

$$E(t) = \frac{1}{16} \rho g H_s(t)^2, \quad (9)$$

335 where  $g$  is gravitational acceleration,  $\rho$  is the mean seawater density, and  $H_s$  is the sig-  
 336 nificant wave height.

337 We evaluated two bottom stress formulas, (3) and (4), resulting in two alongshore  
 338 current estimates. The total velocity variance  $\sigma_{\bar{u}}$  in (3) can be written out as a function  
 339 of  $H_s$  at the 5-m isobath. By definition,  $H_s = 4\sigma_\eta$ , where the  $\sigma_\eta$  is the standard de-  
 340 viation of the sea surface height (Young, 1999). Because velocity and sea surface height  
 341 have the same frequency,  $\sigma_{\bar{u}}$  is proportional to  $\sigma_\eta$ , using a scale factor of  $\sqrt{\frac{g}{h}}$  to change  
 342 the dimension (Mei, 1989). The resulting expression for  $\sigma_{\bar{u}}$  is,

$$\sigma_{\bar{u}}(t) = \sqrt{\frac{g}{h_{5\text{m}}}} \frac{H_{s,5\text{m}}(t)}{4}, \quad (10)$$

343 where  $h$  is the constant depth of the water column.  $H_{s,5\text{m}}$  can be estimated from the sig-  
 344 nificant wave height at the offshore location of the wave buoy,  $H_{s,\text{WB}}$  using Snell's Law  
 345 and the conservation of wave energy flux given the difference in water depths. For this  
 346 data set,  $H_{s,5\text{m}} = 0.88H_{s,\text{WB}}$  on average. Combining (1), (3), (7), and (10) gives the  
 347 following equation for  $v_{1\text{D}}$ ,

$$v_{1\text{D}}(t) = -\frac{8}{3L\rho C_D} \sqrt{\frac{2h_{5\text{m}}}{\pi g}} \frac{S_{xy}(t)}{H_{s,5\text{m}}(t)}, \quad (11)$$

348 where  $C_D$  has flexibility as a fitting parameter. The velocity calculated using the Rayleigh  
 349 friction model will be called  $v_{1\text{DR}}$ . In the Rayleigh friction velocity model, (4),  $\sigma_{\bar{u}}$  is con-  
 350 stant. Constant  $\sigma_{\bar{u}}$  and combining (1), (4), and (7), gives the following formula for  $v_{1\text{DR}}$ ,

$$v_{1\text{DR}}(t) = \frac{S_{xy}(t)}{\rho\mu L}. \quad (12)$$

351 Values for  $C_D$  and  $\mu$ , for  $v_{1\text{D}}$  (11) and  $v_{1\text{DR}}$  (12) respectively, were calculated using a  
 352 simple linear regression (with intercept fixed to zero) between the wave-estimated ve-  
 353 locity and  $\bar{v}_C$ .

354 1D model performance will depend on the accuracy of the velocity formulas as well  
 355 as on model assumptions such as using a uniform grid which neglects shoreline curva-  
 356 ture and a uniform dye loss parameterization which neglects inner shelf circulation. To  
 357 test the assumptions of the 1D model method not related to the advection calculation,  
 358 (5) was also solved with the alongshore-varying nearshore alongshore velocity extracted

359 from the SD Bight model,  $v_C(t, y)$ . “1DC model” will refer to the run using  $v_C(t, y)$  with  
 360 dye output  $C_{1DC}$ . “1D model” will refer to the model run using  $v_{1D}(t)$  (i.e., the small  
 361 angle, weak current approximation, (11)) with dye output  $C_{1D}$ . “1DR model” will re-  
 362 fer to the model run using  $v_{1DR}$  (i.e., the Rayleigh friction model, (12)) with dye out-  
 363 put  $C_{1DR}$ . The 1D grid resolution, time step, and dye loss parameter ( $k_P$  and  $k_B$ ) were  
 364 the same for all three runs, but the 1DC run used a modified numerical implementation  
 365 that allowed for alongshore-varying alongshore advection. Although the numerical im-  
 366 plementation is modified to allow for alongshore velocity variations, the 1DC model can  
 367 be viewed as an upper-bound on 1D model performance with these assumptions (fixed  
 368  $L$ , uniform dye loss parameters  $k_B$  and  $k_P$ , etc.).

## 369 2.5 Performance metrics

370 Performance for the 1D models was evaluated by comparing  $C_{1D}$ ,  $C_{1DR}$ , and  $C_{1DC}$   
 371 with  $C_C$ , the nearshore dye extracted from the SD Bight model. Three performance met-  
 372 rics were used: Pearson’s correlation coefficient (R), the normalized root-mean-square-  
 373 error (NRMSE), and Willmott’s skill score (WSS). To calculate NRMSE, the root-mean-  
 374 square-error was normalized by the time-averaged value of  $C_C$  for each alongshore lo-  
 375 cation. WSS is a comprehensive model agreement metric that scales the mean square  
 376 error by the potential error for a data set (Willmott, 1981),

$$\text{WSS} = 1 - \frac{\sum_{i=1}^{i=N} (m_i - o_i)^2}{\sum_{i=1}^{i=N} (|m_i - \langle o \rangle| + |o_i - \langle o \rangle|)^2} \quad (13)$$

377 where  $m$  is the 1D model value,  $o$  is the SD Bight model value, and  $N$  is the number of  
 378 data points. The range of WSS is 0 to 1, with 1 being best. The range of R is  $-1$  to 1,  
 379 with 1 being best. The NRMSE is positive definite, with 0 being best. When describ-  
 380 ing trends in the metrics together, “better” means an increase in WSS and R and a de-  
 381 crease in NMRSE.

382 The condition  $C_{\text{BAC}} = 5 \times 10^{-4}$  was chosen as a cut off value to determine whether  
 383 dye plume events were significant, referred to as the beach advisory condition. This  $C_{\text{BAC}}$   
 384 corresponds to a 10% likelihood of swimmer illness (Feddersen et al., 2021). When dye  
 385 concentrations exceed  $C_{\text{BAC}}$ , norovirus concentrations in the wastewater plume would  
 386 be sufficient to require posting a beach advisory by EPA standards (U.S. Environmen-  
 387 tal Protection Agency, 2014).

### 3 Results

#### 3.1 Nearshore current calibration, drag coefficients, and shorenormal

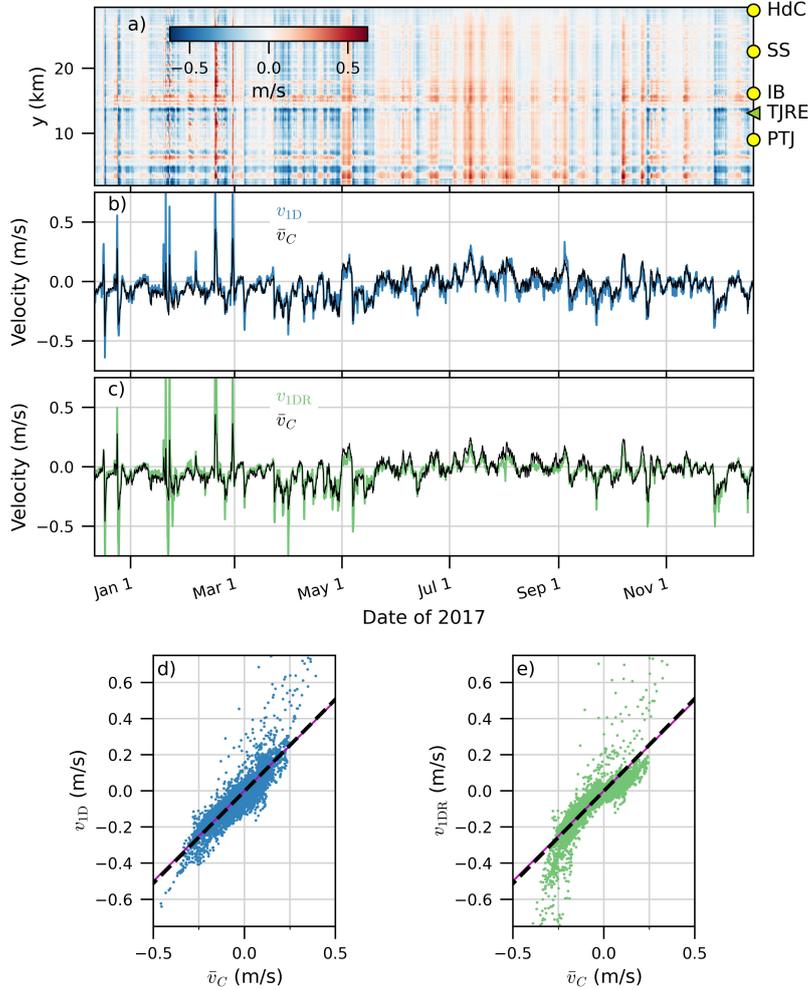
Both  $v_{1D}$  and  $v_{1DR}$  were calibrated by fitting  $C_d$  and  $\mu$  using a linear regression with  $\bar{v}_C$  to a slope of 1 with no intercept (Fig. 2d, e). The resulting  $v_{1D}$  and  $v_{1DR}$  had strong agreement ( $R > 0.8$ ) with  $\bar{v}_C$  (Fig. 2). The small angle, weak current drag coefficient was fit to  $C_D = 0.004$ , consistent with the value of 0.0033 found for the surf zone in Feddersen (1998). The Rayleigh friction coefficient was fit to  $\mu = 3.9 \times 10^{-3} \text{ m s}^{-1}$ , consistent with Rayleigh friction coefficient values of  $5 \times 10^{-3}$  in Lentz et al. (1999) and  $2.5 \times 10^{-3}$  in Grimes et al. (2021). The resulting wave-driven nearshore alongshore velocities captured the variations in the nearshore alongshore velocities from the SD Bight model (Fig. 2b, c). The Rayleigh friction model  $v_{1DR}$  overestimated  $\bar{v}_C$  when  $|\bar{v}_C| > 20 \text{ cm s}^{-1}$  and underestimated small  $\bar{v}_C$  during summertime (Fig. 2c, e). This is consistent with previous evaluations of Rayleigh friction which works poorly across a large range of  $v$  (Feddersen et al., 2000). Both  $v_{1D}$  and  $v_{1DR}$  overestimated  $\bar{v}_C$  during the biggest southerly waves in winter (spikes between Jan 1 and Mar 1 in Fig. 2b, c).

The 1D model was sensitive to the choice of  $\theta_{SN}$  because wave direction is often near shorenormal, and the sign of  $\theta'$  determines the direction of the velocity. Over the stretch of shoreline of interest, the mean shorenormal angle is  $260^\circ$ , varying from  $240^\circ$  to  $270^\circ$ . Shorenormal angles are closest to  $270^\circ$  in center and decrease towards the domain edges. Using uniform shorenormal angle  $\theta_{SN} = 263^\circ$  resulted in best R, NRMSE, and WSS of  $v_{1D}$  out of one hundred  $\theta_{SN}$  values tested in the range  $240^\circ$  to  $270^\circ$ . Overall,  $v_{1D}$  performed better than  $v_{1DR}$  using all skill metrics. The SD Bight model alongshore-varying nearshore alongshore velocities  $v_C(t, y)$  used in the 1DC model and to derive  $\bar{v}_C(t)$  were locally rotated using alongshore-varying shorenormal angles estimated from the land mask in the grid (described in Section 2.1).

#### 3.2 Dye parameter calibration, $k_P$ and $C_0$

Beginning 5 km north of PB,  $\langle C_C \rangle$  decays exponentially with  $y$  at an e-folding length scale of 7.9 km (Fig. 3). A velocity scale  $V = 0.1 \text{ m s}^{-1}$ , the RMS of  $\bar{v}_C$  from the SD Bight model (Fig. 2), was used to estimate  $k$ . The resulting  $k_P = k - k_B$  was  $1.3 \times 10^{-5} \text{ s}^{-1}$ , slightly lower than the estimate of  $5 \times 10^{-5}$  determined for the region between the 4-m isobath and the surf zone edge in Grimes et al. (2021). This  $k_P$  is an order of magnitude greater than  $k_B$ . The optimal Dirichlet boundary conditions for the 1D models were found to be  $C_0 = 0.008$  for the 1D model,  $C_0 = 0.01$  for the 1DR model, and  $C_0 = 0.011$  for the 1DC model (where 0.01 is 1 part dye to 100 parts water).

**Figure 2.** a) SD Bight model alongshore-varying alongshore velocity,  $v_C$ , as a function of time and  $y$ , with alongshore beach locations on right side (compare with Fig. 1). b) Time series of  $\bar{v}_C$  (black) with  $v_{1D}$  (blue), c) Time series of  $\bar{v}_C$  with  $v_{1DR}$  (green), d) scatter plot of hourly  $\bar{v}_C$  vs  $v_{1D}$ , best fit line (black dashed line) has slope = 1.02, intercept =  $-0.0022$ , and  $R = 0.89$ , e) scatter plot of  $\bar{v}_C$  vs  $v_{1DR}$ , best fit line (black dashed) has slope = 1.02, intercept =  $-0.0015$ , and  $R = 0.82$ . One-to-one line (magenta) for comparison with best fit in d) and e). RMS of  $\bar{v}_C$  is  $0.1 \text{ m s}^{-1}$ .



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### 3.3 Reproducing event-scale nearshore dye

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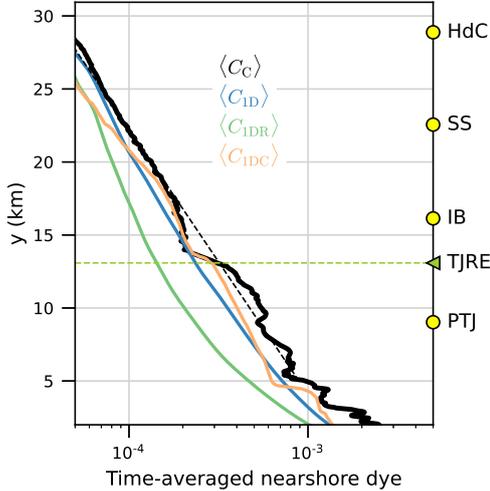
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An example of a south swell event occurred in the SD Bight model in early July, 2017, when dye was present along the entire alongshore span of the nearshore region (snapshot at July 11, 2017 12:00:00 in Fig. 1c). To demonstrate the evolution of this event in the SD Bight model and the 1D model, the nearshore currents and dye concentrations were examined for the four days leading up to that snapshot (Fig. 4). For this demonstration, we do not depict the 1DR or 1DC models because 1D model results are typical. On July 8, before the swell,  $C_C < 10^{-4}$  north of  $y = 2 \text{ km}$  and nearshore cur-

**Figure 3.** Nearshore dye concentrations averaged over the year 2017 as a function of  $y$  for the SD Bight model (solid black line) and the 1D (blue), 1DR (green), and 1DC (orange) models. The 1D, 1DR, and 1DC models used the same  $k_B$  and  $k_P$  but different  $C_0$ . An e-folding decay length scale of 7.9 km was derived using a linear fit to the log of  $\langle C_C \rangle$  from  $y = 5$  to 29 km (dashed black line), implying a decay rate of  $k_P = 1.4 \times 10^{-5} \text{s}^{-1}$ . Dashed green line is location of TJRE mouth and beaches are marked as on other figures.



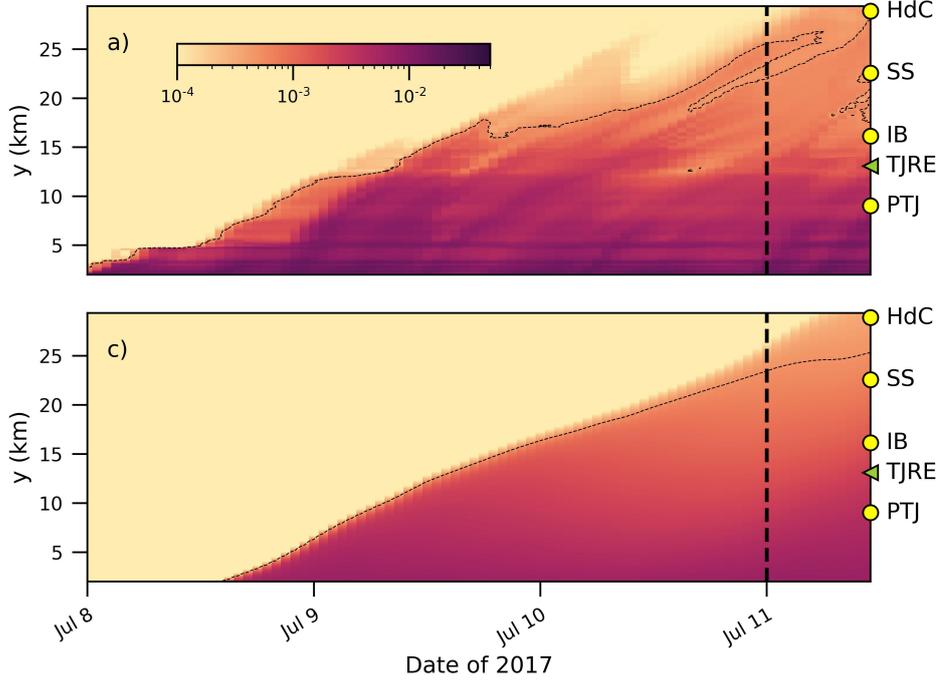
430 rents were near zero. Over three days, a steady wave-driven current over  $10 \text{ cm s}^{-1}$  ad-  
 431 vected the plume 10 km per day until the plume front reached HdC (Fig. 4a, b). Dye  
 432 concentrations were highest near PB ( $C_C \approx 10^{-2}$ ) and became more dilute downstream  
 433 ( $C_C \approx 10^{-4}$  at HdC) (Fig. 4b). The wave-driven nearshore alongshore current,  $v_{1D}$ , was  
 434 very similar in magnitude and timing to  $\bar{v}_C$  (Fig. 4a), consistent with the high skill over  
 435 the course of the year (Fig. 2b). The 1D model, using  $v_{1D}$ , reproduced the plume event.  
 436 The plume front moved up the coast at the same rate, from  $C_{1D} < 10^{-4}$  on July 8, 2017  
 437 to  $C_{1D} > 10^{-4}$  found at  $y > 20$  km on July 11, 2017 (Fig. 4c). The 1D model, com-  
 438 posed of solely wave-driven advection and loss, could largely reproduce the July 11, 2017  
 439 snapshot from the SD Bight model.

### 440 3.4 Comparison of dye performance using different velocity estimates

441 Here we compare the performance of the 1D model with the 1DR model. The two  
 442 models use the same numerical scheme but different formulas for the nearshore along-  
 443 shore velocity (see Section 2.4). The rate of dye loss  $k = k_P + k_B$  was the same, but  
 444 the dye input,  $C_0$ , was optimized for separate runs (see Section 2.2).

445 The dye from the 1D model,  $C_{1D}$ , and the 1DR model,  $C_{1DR}$ , were compared with  
 446  $C_C$  for the alongshore region  $y > 0$  km over the entire year (Fig. 5). Seasonal patterns

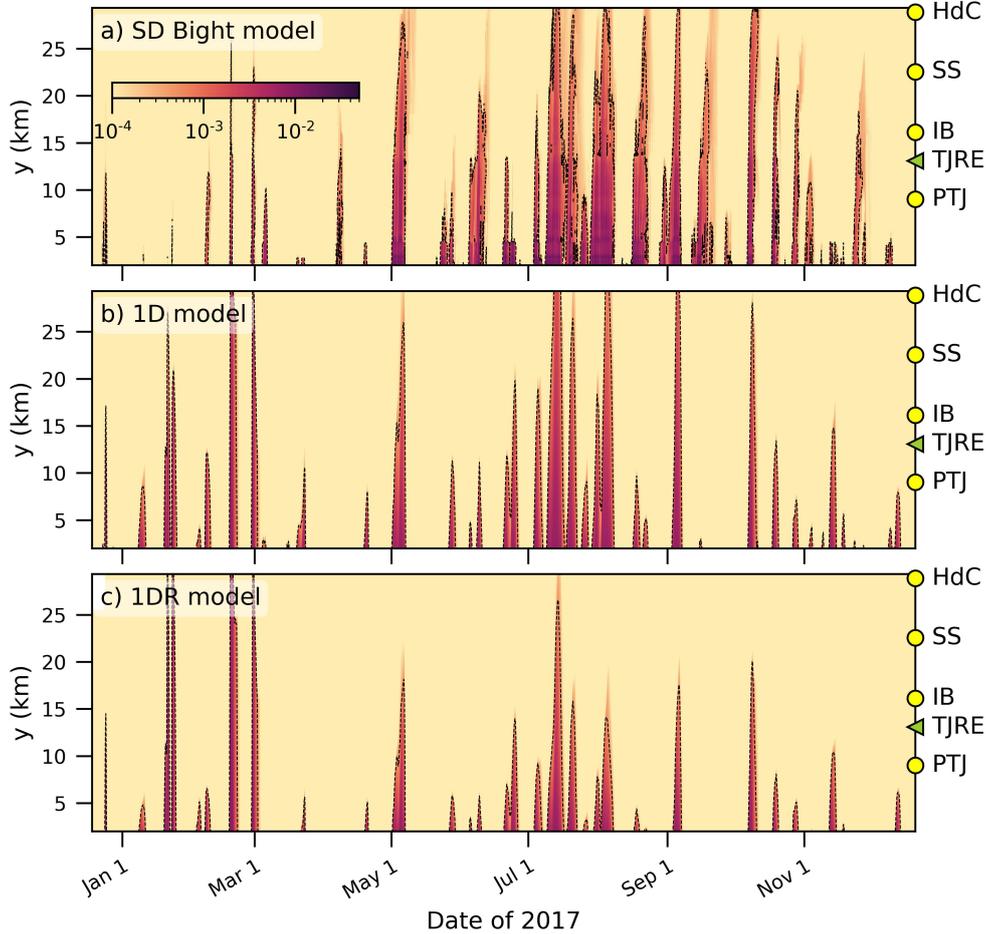
**Figure 4.** a) Time series of  $\bar{v}_C$  (black) and  $v_{1D}$  (blue). Evolution as a function of  $y$  and  $t$  of b)  $C_C$  and c)  $C_{1D}$ . Black dashed line indicates July 11, 2017 12:00:00, time of the snapshot in Fig. 1c. Dashed contour  $C_{BAC} = 5 \times 10^{-4}$  in a) and c).



447 in  $C_C$  were reproduced in both  $C_{1D}$  and  $C_{1DR}$ . More dye was transported northward dur-  
 448 ing summer months (between June 1 and October 1) than non-summer months in all mod-  
 449 els. Both  $C_C$  and  $C_{1D}$  reached  $y > 20$  km most frequently in summer (Fig. 5a,b). Dye  
 450 plumes that reached  $y > 20$  km during summer exceeded  $C_{BAC}$  for many days, often  
 451 up to a week. The example plume from July 11 (Fig. 4) reached  $y > 20$  km in all three  
 452 models and concentrations remained above  $C_{BAC}$  for 3.5 days in the 1DR model, 6 days  
 453 in the 1D model, and 8 days in the SD Bight model. For comparison, during a plume  
 454 that reached  $y > 20$  km in all three models beginning February 28, concentrations ex-  
 455 ceeded  $C_{BAC}$  for just 2 days in all three models, typical for winter conditions. In the SD  
 456 Bight model,  $C_C$  remained longer than  $C_{1D}$  at intermediate concentrations between  $10^{-8}$   
 457 and  $C_{BAC}$  because dye could recirculate back into the nearshore from offshore, which was  
 458 not possible in the 1D or 1DR models (Fig. 5a). More dye was transported northward  
 459 during summertime because alongshore nearshore velocity was persistently northward,  
 460 even though the fastest alongshore velocities occurred in winter (Fig. 2b, c). In winter,  
 461 northwesterly waves drive predominantly southward nearshore alongshore currents re-  
 462 sulting in less dye transport in all models, despite episodic south swells driving nearshore  
 463 alongshore currents greater than  $0.5 \text{ m s}^{-1}$ . The 1DR model transported less dye in sum-  
 464 mertime than the 1D model because  $v_{1DR}$  underestimated summertime northward cur-

465 rents (Fig. 2d). Between June 1 and October 1, the 1D model transported 6.6 times more  
 466 dye north of  $y = 20$  km than the 1DR model.

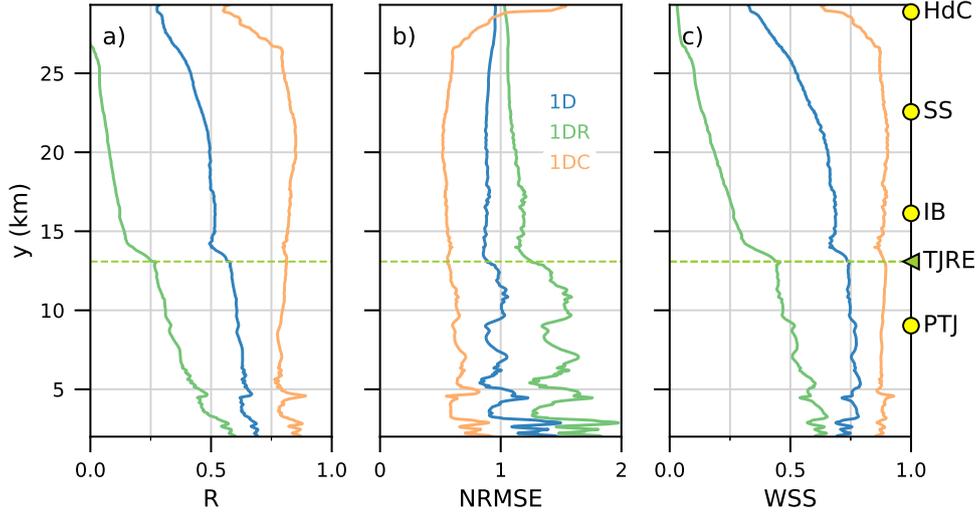
**Figure 5.** Dye concentration,  $C(t, y)$ , for  $y > 0$  km and for the entire year from a) the SD Bight model, b) the 1D model, and c) the 1DR model. Dashed contour is  $C_{BAC}$ .



467 The three performance metrics (R, NRMSE, and WSS) as a function of  $y$  statis-  
 468 tically quantified the ability of the 1D, 1DR, and 1DC model runs to reproduce the nearshore  
 469 dye concentrations from the SD Bight model (Fig. 6). The 1DC model run (orange line  
 470 in Fig. 6) used the exact alongshore velocity from the SD Bight model, demonstrating  
 471 an upper limit on performance for the 1D and 1DR models, which used wave-driven ve-  
 472 locities. The 1DC model performance did not drop at the TJRE, but remained approx-  
 473 imately constant with alongshore distance until  $y = 27$  km. North of  $y = 27$  km, 1DC  
 474 model skill decreased because the shoreline curvature increases (Fig. 6). The 1D model  
 475 performed much better than the 1DR model (compare blue line with green in Fig. 6).  
 476 The 1D model had an approximately constant  $WSS = 0.75$  south of the TJRE (Fig. 6c).

477 Both the 1D and 1DR models decrease in skill at the TJRE, with a drop in R and WSS  
 478 of about 0.15 (Fig. 6a, c). The 1DR model performed the worst, decaying rapidly with  
 479  $y$ . All further analyses will consider only the 1D model.

**Figure 6.** Model performance metrics comparing  $C_{1D}$  (blue),  $C_{1DR}$  (green) and  $C_{1DC}$  (orange) with  $C_C$  as a function of  $y$ . a) R, b) NRMSE, c) WSS. Green dashed line is location of TJRE. Markers on the right indicate alongshore locations of beaches seen in Fig. 1.

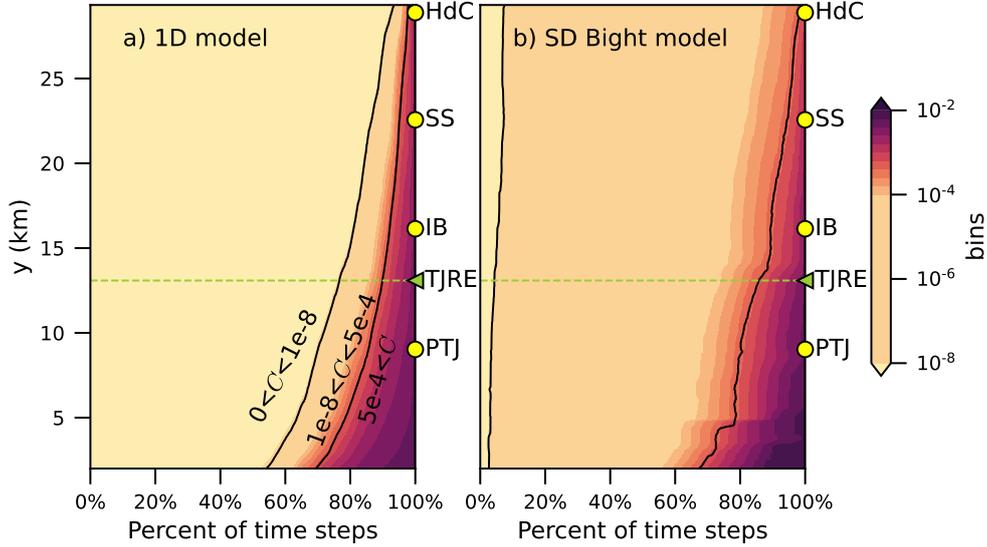


480 The 1D model and SD Bight model had similar counts of time steps when dye ex-  
 481 ceeded  $C_{BAC}$ , but the SD Bight model had more time steps when dye concentrations were  
 482 between  $10^{-8}$  and  $C_{BAC}$  (Fig. 7). Dye in the 1D model was more often near zero than  
 483 between  $10^{-8}$  and  $C_{BAC}$  (Fig. 7). Intermediate dye concentrations between  $10^{-8}$  and  $C_{BAC}$   
 484 in the SD Bight model may be partly due to dye recirculation from the inner shelf, a pro-  
 485 cess not included in the 1D model. Some of the error in 1D model performance is then  
 486 accounted for by these missing intermediate dye concentrations. However, intermediate  
 487 concentrations are below the beach advisory condition threshold by definition, so the ab-  
 488 sence of intermediate dye concentrations in the 1D model is not a significant concern for  
 489 potential public health applications.

### 3.5 Model binary performance using a cutoff value

491 Dye plume events were counted using the  $C_{BAC}$  threshold in a time series of  $C_{1D}$   
 492 and  $C_C$  at IB (Fig. 8). This first analysis focuses only on the summer months, June 1  
 493 to October 1, when beach tourism is elevated and SABWTP plume occurrences are most

**Figure 7.** Horizontally stacked, normalized histogram of occurrences of dye values in a) the 1D model and b) the SD Bight model. Color represents dye concentration bins (colormap similar to dye colormap in previous figures but with added distinction between values greater than or less than  $10^{-8}$ ). Contours delineate three bins (less than  $10^{-8}$ ,  $10^{-8}$  to  $C_{\text{BAC}} = 5 \times 10^{-4}$ , and greater than  $C_{\text{BAC}} = 5 \times 10^{-4}$ ).

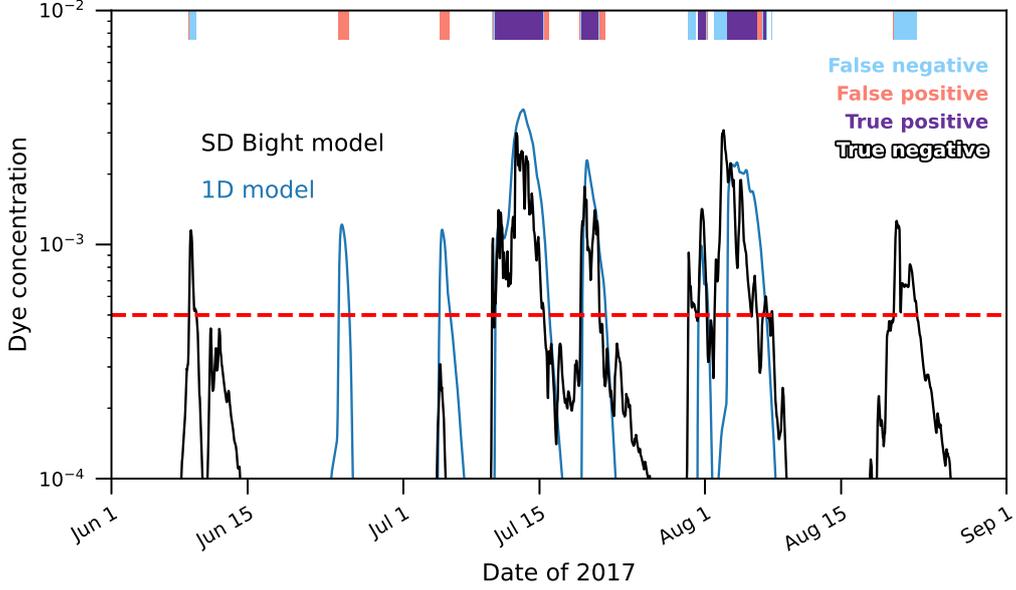


494 frequent (Feddersen et al., 2021). Four conditions are defined using a binary logic cri-  
 495 teria of dye greater than  $C_{\text{BAC}}$ , taking  $C_C$  as the true result,

- 496 1. True Positive: both  $C_{1\text{D}} > C_{\text{BAC}}$  and  $C_C > C_{\text{BAC}}$   
 497 2. False Positive:  $C_{1\text{D}} > C_{\text{BAC}}$  but  $C_C < C_{\text{BAC}}$   
 498 3. False Negative:  $C_{1\text{D}} < C_{\text{BAC}}$  but  $C_C > C_{\text{BAC}}$   
 499 4. True Negative: both  $C_{1\text{D}} < C_{\text{BAC}}$  and  $C_C < C_{\text{BAC}}$

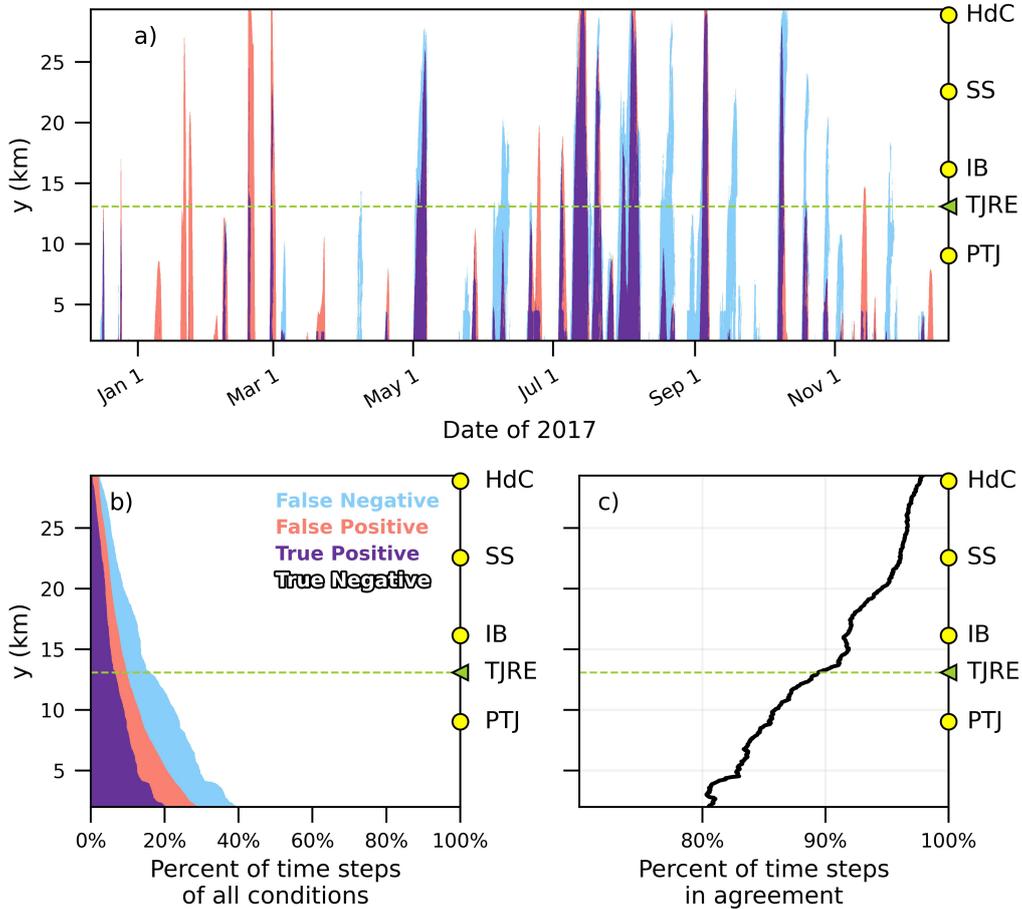
500 If a plume is True Positive at any time during its stay, it was counted as a True Posi-  
 501 tive plume even if it had adjacent periods of False Positive or False Negative. Using this  
 502 binary analysis, eight distinct summertime plumes are counted at IB (Fig. 8). There were  
 503 four True Positive plumes (beginning July 11, July 16, July 31, and August 2), two False  
 504 Positive plumes (beginning June 23 and July 4), and two False Negative plumes (begin-  
 505 ning June 8 and August 18) (Fig. 8). The True Positive plumes were sometimes preceded  
 506 by a brief False Negative period and followed by a brief False Positive period, because  
 507 the plumes in the SD Bight model arrived earlier and retreated earlier.

**Figure 8.** Dye concentrations at Imperial Beach (yellow circle labelled IB in Fig. 1) over three summer months from the SD Bight model (black solid line) and 1D model (blue solid line). The dashed red line indicates  $C_{BAC} = 5 \times 10^{-4}$ . Colored bars at top of figure depict True Positive, (purple), False Positive (orange), False Negative (blue), or True Negative (white). Four conditions defined in text.



508        Next, the binary analysis was extended to all shoreline locations and all time steps  
 509 (Fig. 9). Agreement was defined as the combined number of hourly time steps that had  
 510 True Positive or True Negative conditions, and disagreement was either False Positive  
 511 or False Negative conditions. The 1D model and SD Bight model were in agreement for  
 512 89% of all time steps at all alongshore locations (Fig. 9c). The most common condition  
 513 was True Negative, accounting for 75% of all hourly time steps at all locations. True Pos-  
 514 itives were 14%, False Positives were 7%, and False Negatives were 4%. Disagreement  
 515 was seasonal. During summer, False Negatives were more likely, rising to account for 14%  
 516 of time steps between June 1 and October 1. During all other months, however, False  
 517 Negatives and False Positives were equally likely, occurring in between 4 to 5% of non-  
 518 summer time steps. The percent of time steps in agreement increased with  $y$  (Fig. 9c),  
 519 in contrast to the pattern in model skill (Fig. 6). This increase is due to an increase in  
 520 True Negatives with  $y$  (Fig. 9b). True Negatives accounted for 95% of time steps north  
 521 of  $y > 20$  km because dye concentrations exceeding  $C_{BAC}$  rarely reached  $y > 20$  km  
 522 in either model.

**Figure 9.** a) Time series comparing the binary conditions  $C_C > C_{BAC}$  and  $C_{1D} > C_{BAC}$  as a function of  $y$  for model year 2017, b) horizontal stacked bar plot of percentage of occurrences of the four conditions as a function of  $y$ , c) percent of all time steps that are True Positive or True Negative as a function of  $y$ . Four conditions defined in text.



523 **3.6 Daily beach advisories: comparing 1D model forecast with simulated**  
 524 **weekly sampling**

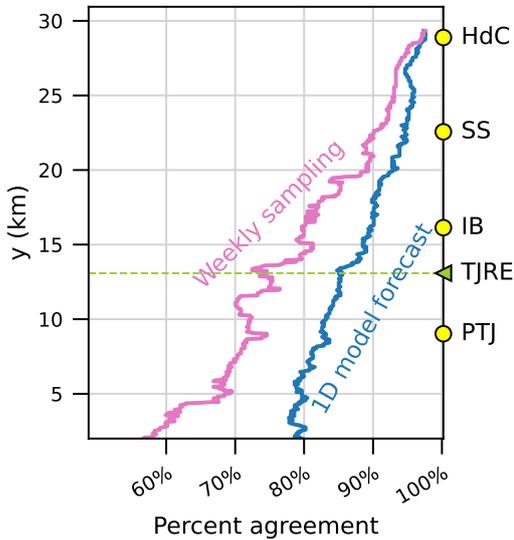
525 The previous analysis considered hourly agreement in the binary analysis, but in  
 526 practice, agreement on a daily time scale would be most relevant for beach managers be-  
 527 cause beach advisories are issued daily. Currently, daily beach advisories in San Diego  
 528 are informed in part by weekly sampling for FIB performed at major beaches (San Diego County,  
 529 n. d.). Samples are sent to labs for analysis and if FIB are found, beach advisories can  
 530 be issued the next day (Francy, 2009). A weekly sampling schedule is currently the min-  
 531 imum frequency recommended for water quality monitoring at heavily used urban beaches  
 532 by the U.S. Environmental Protection Agency (U.S. Environmental Protection Agency,  
 533 2014). However, a study on FIB sampling frequency at beaches in Los Angeles, CA, found

534 that a weekly testing schedule missed up to 75% of FIB exceedances, which frequently  
 535 lasted only one day (Leecaster & Weisberg, 2001). Further, a probabilistic model esti-  
 536 mated that up to 40% of beach advisories at Huntington Beach, CA, are incorrectly posted  
 537 (J. Kim & Grant, 2004). Although here dye was modeled with the 10-day decay rate of  
 538 norovirus, weekly sampling is still likely to misrepresent dye presence because dye con-  
 539 centrations were determined primarily by alongshore advection, which acted on shorter  
 540 time scales. We compared the accuracy of daily beach advisories informed by hourly 1D  
 541 model predictions with a simulation of a weekly sampling schedule using the SD Bight  
 542 model. For this experiment, the ideal daily beach advisory was issued at an alongshore  
 543 location if  $C_C > C_{BAC}$  for at least one hour during that day. A 1D model-informed daily  
 544 beach advisory was issued at an alongshore location if  $C_{1D} > C_{BAC}$  for at least one hour  
 545 during that day. To simulate weekly sampling,  $C_C$  was checked at one time step once  
 546 per week. If that sample exceeded  $C_{BAC}$ , a daily beach advisory was issued the follow-  
 547 ing day (to match the time lag required to process samples) and remained in place for  
 548 the next seven days until the next sample was processed. Accuracy was determined by  
 549 checking if the 1D model-informed and simulated weekly sampling-informed daily beach  
 550 advisories matched the ideal beach advisory. The magnitude and shape of the curve for  
 551 1D model-informed daily beach advisory accuracy (Fig. 10) were consistent with the hourly  
 552 agreement between binary metrics  $C_C > C_{BAC}$  and  $C_{1D} > C_{BAC}$  (Fig. 9b). The range  
 553 of accuracy of simulated weekly sampling-informed daily beach advisories found here (Fig. 10)  
 554 was consistent with the range of 0–40% inaccuracy in daily beach advisories estimated  
 555 for Huntington Beach, CA (J. Kim & Grant, 2004). The 1D model-informed daily beach  
 556 advisories were more accurate than simulated weekly sampling at all locations, averag-  
 557 ing 87% accuracy over all time steps and 10% improvement over simulated weekly sam-  
 558 pling (Fig. 10). Similar to the hourly count, accuracy for both 1D model-informed and  
 559 simulated weekly sampling-informed daily beach advisories increased with  $y$  as distance  
 560 from the point source, and thus true positives decreased.

## 561 4 Discussion

562 There is a growing understanding of the need to supplement *in situ* sampling with  
 563 predictive modeling nowcasts (Francy, 2009). Although predictive modeling of water-  
 564 borne pathogens has been a concern for decades, the majority of operational predictive  
 565 water quality models are regressive rather than mechanistic (Elko et al., 2022). Regres-  
 566 sive models predict FIB concentrations using statistically correlated factors, such as rain-  
 567 fall (de Brauwere et al., 2014). The San Diego-Tijuana region nearshore is frequently con-  
 568 taminated with untreated sewage from SABWTP transported by wave-driven currents  
 569 (ARCADIS, 2019), producing a swimmer illness hazard that must be modeled mecha-

**Figure 10.** Percent agreement with ideal daily beach advisories (days when  $C_C > C_{BAC}$  for any hourly time step) of simulated weekly sampling-informed daily beach advisories (pink) and 1D model-informed daily beach advisories (blue).



570 nistically. Here, we demonstrated that a simple tracer advection model using only wave-  
 571 driven alongshore currents does a good job of reproducing nearshore transport of a tracer  
 572 from a 3D hydrodynamic model of the San Diego-Tijuana coastline. A simple 1D nearshore  
 573 transport model could improve existing shoreline exposure modeling that uses only HFR-  
 574 derived shelf currents (S. Y. Kim et al., 2009; Rogowski et al., 2015) and could be tuned  
 575 and operational as a forecast much more quickly than a 3D hydrodynamic model (Wu  
 576 et al., 2020). Nearshore momentum has been observed to be dominated by wave-forcing  
 577 (Lentz et al., 1999; Feddersen, 1998), and a wave-only model has the advantage of the  
 578 availability of wave forecasts at existing wave buoys. Previous 1D tracer advection mod-  
 579 els of the nearshore environment have been used to estimate the transport of wastew-  
 580 ater (Boehm, 2003) and dye (Grimes et al., 2021), but these have been evaluated over  
 581 limited conditions. With the spatial and temporal resolution of the SD Bight model hind-  
 582 cast for 2017, we could produce a detailed evaluation of the 1D model performance for  
 583 both velocity and dye across a variety of seasonal forcing conditions and realistic shore-  
 584 line features. A binary analysis of presence or absence of tracer concentrations in the 1D  
 585 model above a cut off relevant for human health,  $C_{BAC} = 5 \times 10^{-4}$ , was in agreement  
 586 with the SD Bight model for 89% of all hourly time steps over all  $y$ . Here we summa-  
 587 rize and expand upon our results and discuss applicability to other locations.

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#### 4.1 Comparison of velocity formulas

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Nearshore alongshore velocity was modeled with two different bottom stress formulas using wave properties at an offshore wave buoy location. The first,  $v_{1D}$ , used the small angle, weak current approximation (Wright & Thompson, 1983) and the second,  $v_{1DR}$ , used a further simplified linear Rayleigh friction (Lentz et al., 1999; Feddersen et al., 2000). The scaling difference between the formulas is that  $v_{1D} \propto H_{s,5m}^{-1} S_{xy}$  (11) and  $v_{1DR} \propto S_{xy}$  (12). Once tuned for their respective drag coefficients, both modeled velocities had good agreement ( $R > 0.8$ ) with the alongshore-mean nearshore alongshore velocity,  $\bar{v}_C$ , extracted from the SD Bight model. The velocity estimated using Rayleigh friction,  $v_{1DR}$ , had an  $R$  value 0.07 lower than  $v_{1D}$ . Rayleigh friction models do not capture extremes well, underestimating slow currents and overestimating fast currents (Feddersen et al., 2000), as found here where the 1DR model velocity,  $v_{1DR}$ , underestimated slow summertime alongshore nearshore velocities (Fig. 2c). Due to this underestimate, the 1DR model could not reproduce summer dye plumes when transport was most frequently northward (Fig. 5c). Re-tuning  $v_{1DR}$  to fit only summertime nearshore alongshore velocities would likely improve overall performance of the 1DR model dye transport, but we wanted to demonstrate the results of tuning to available data without *a priori* assumptions about the relative importance of seasonal conditions for model performance. Lentz et al. (1999) found good agreement between Rayleigh friction-estimated wave-driven velocities and observations, but they did not attempt to model tracer transport. Even though the decrease in velocity correlation was small, the decrease in dye transport skill was substantial (compare blue line with green line in Fig. 6). Errors in Lagrangian quantities are magnified from errors in velocity because instantaneous velocity is integrated in space and time. Grimes et al. (2021) had success with a Rayleigh friction model, however they only modeled dye transport over a 30 hour time period during which  $H_s$  was approximately constant. Other bottom stress formulas that include strong current limits were tested (Wright & Thompson, 1983; Feddersen et al., 2000), but did not capture the extreme winter events better than  $v_{1D}$ . Further model improvement to reduce the overestimation of nearshore alongshore velocities during large southerly swells may not improve model transport much overall because northward currents are typically weak.

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Only wave-driven velocities were included here to optimize performance with simplicity. However, model performance would likely be further increased by including wind stress in the velocity formulas. Wind stress has been observed to be the second leading-order term in the nearshore alongshore momentum balance, after wave forcing (Feddersen, 1998; Lentz et al., 1999). The improvement in model performance by including wind here is likely to be small since winds in this region were light, with subtidal wind speeds

624 less than  $2 \text{ ms}^{-1}$  in 2017 (not shown). However, wind stress may be more important for  
 625 nearshore transport in other regions. For example, in Melbourne Beach, FL, where hur-  
 626 ricanes are common, the correlation of wind stress with waves explained net sediment  
 627 transport better than waves alone (Burnette & Dally, 2018).

## 628 4.2 Skill in reproducing tracer distributions

629 For the problem of nearshore alongshore transport of SABWTP wastewater in the  
 630 San Diego-Tijuana region, a 1D grid has been demonstrated to be an effective alterna-  
 631 tive to a realistic 3D hydrodynamic model. Grimes et al. (2021) found that differenti-  
 632 ating and including re-circulation between the surf zone and the inner-shelf (i.e., a 2 box  
 633 model in the cross-shore direction) increased the performance of a 1D wave-advection  
 634 model in reproducing the transport of a single dye plume through the surf zone over 30  
 635 hours. In contrast, here exchange with the inner shelf was parameterized as monotonic  
 636 loss, but the time scale considered was expanded to include dozens of plume events over  
 637 the course of a year. Even with this simplified parameterization of exchange (i.e., loss  
 638 only, no re-circulation) with the shelf, the 1D dye advection-loss model could reproduce  
 639 SD Bight model nearshore dye concentrations with considerable skill (Fig. 6). The 1DC  
 640 model demonstrated that, with perfect knowledge of nearshore currents, a uniform 1D  
 641 grid and simple dye loss parameterization could reproduce nearshore tracer concentra-  
 642 tions from the SD Bight model with a  $WSS = 0.9$ , and with no reduction of  $WSS$  around  
 643 the TJRE (Fig. 6c). The 1DC model performance decreased in all metrics for  $y > 27$   
 644 km (Fig. 6) where shoreline curvature increases (Fig. 1) and nearshore alongshore ve-  
 645 locity slows (Fig. 2). Tracer advection in this region may be underestimated by not in-  
 646 cluding angular acceleration along the curving shoreline. Alternatively, slower nearshore  
 647 alongshore advection of tracer may be compensated for in the SD Bight model by inner  
 648 shelf tracer steered back into the nearshore along the more tightly-curved 10- and 20-  
 649 m isobaths (Fig. 1), a process missing from the 1DC model. Using a wave-driven, alongshore-  
 650 uniform, nearshore alongshore velocity, the 1D model  $WSS$  was only 10% less than the  
 651 1DC model on average (Fig. 6). The 1D and 1DR model performances were lower down-  
 652 stream of the TJRE (Fig. 6). This decreased performance may be attributed to low dye  
 653 concentrations which are less likely to be a public health concern than high dye concen-  
 654 trations. This explanation is supported by analysis of 1D and SD Bight model dye us-  
 655 ing the binary condition of dye exceeding  $C_{BAC}$ . In the binary analysis, agreement be-  
 656 tween the 1D model and the SD Bight model increased with  $y$  (Fig. 9). These low dye  
 657 concentrations missing from the 1D model may arise from tidal trapping diffusion or re-  
 658 circulation of dye into the nearshore from the inner shelf. Recirculation is likely a less  
 659 significant contributor of low dye concentrations than tidal trapping, since recirculation

660 was not included in the 1DC model which did not decrease in performance downstream  
 661 of the TJRE mouth. Future work is needed to explicitly explore the dynamical role of  
 662 inlets and shoals on nearshore alongshore tracer transport.

663 The 1D model equation used here (5) did not include alongshore diffusivity, un-  
 664 like similar 1D models of nearshore alongshore advection (e.g., Grant et al., 2005; Grimes  
 665 et al., 2021). This is because numerical alongshore diffusivity arising from the upwind  
 666 advection scheme provided adequate alongshore diffusivity expected for this environment.  
 667 The numerical alongshore diffusivity,  $K_{yy}^*$ , was estimated using a scale analysis,

$$K_{yy}^* \approx \frac{V\Delta y}{2} \quad (14)$$

668 where  $\Delta y$  was the grid cell length. For this 1D model, the numerical  $K_{yy}^* = 1.5 \text{ m}^2\text{s}^{-1}$ .  
 669 Estimation of expected alongshore diffusivity follows Spydell et al. (2009), who calcu-  
 670 lated nearshore alongshore diffusivity using drifters at Huntington Beach, CA and Tor-  
 671 rey Pines, CA over a nearshore domain which extended beyond the surf zone to an off-  
 672 shore distance of 160 m. Spydell et al. (2009) used two scaling estimates of  $K_{yy}$ . The  
 673 first calculation used mixing length arguments (Tennekes & Lumley, 1972),

$$K_{yy} \approx \gamma VL, \quad (15)$$

674 where  $V = 0.1 \text{ m s}^{-1}$  was used as a typical velocity scale (RMS of  $\bar{v}_C$ , see Fig. 2) and  
 675  $\gamma$  is a fitting parameter, found in Spydell et al. (2009) to be  $\gamma = 0.52 \pm 0.08$ . The sec-  
 676 ond calculation used shear dispersion in a pipe (Taylor, 1953; Spydell et al., 2007),

$$K_{yy} \approx V^2 T_0, \quad (16)$$

677 where  $T_0$  is the timescale of mixing, found in Spydell et al. (2009) to be  $T_0 = 154 \pm$   
 678  $13 \text{ s}$ . Using  $V$  and  $L$  in this study results in  $K_{yy}$  estimates of 10 and  $1.5 \text{ m}^2\text{s}^{-1}$  for the  
 679 mixing length and pipe shear dispersion arguments, respectively. This range is consis-  
 680 tent with the range of  $K_{yy} = 1 - 10 \text{ m}^2\text{s}^{-1}$  estimated in Grimes et al. (2021). Grant  
 681 et al. (2005) found significantly higher estimates of  $K_{yy} = 40-80 \text{ m}^2\text{s}^{-1}$  in their field  
 682 observations at Huntington Beach, CA (same study location as Spydell et al., 2009), but  
 683 Grant et al. (2005) considered only the well-mixed region of the surf zone extending to  
 684 50 m offshore. The numerical diffusivity  $K_{yy}^*$  falls within the range of expected along-  
 685 shore diffusivity found here,  $K_{yy} = 1.5 - 10 \text{ m}^2\text{s}^{-1}$ . Inclusion of additional prescribed  
 686 alongshore diffusivity was tested using  $K_{yy}$  ranging from 1 to  $10 \text{ m}^2\text{s}^{-1}$ , but model per-  
 687 formance metrics varied by at most 3% of their original values. This justified neglect-  
 688 ing additional alongshore diffusivity beyond numerical alongshore diffusivity.

### 689 **4.3 Impact of non-uniform bathymetry on alongshore transport**

690 Model skill was hypothesized to decrease downstream of the TJRE because com-  
 691 plex dynamics near the TJRE mouth could not be represented in a simple 1D advection  
 692 model. The 1DC model did not decrease in skill at the TJRE (Fig. 6), likely because the  
 693 velocities extracted from the SD Bight model already incorporate modulations caused  
 694 by the estuary presence (both bathymetric steering and tidal currents). The 1D and 1DR  
 695 models did have small performance drops of 0.15 in R and WSS at the TJRE (kinks in  
 696 blue and green solid lines at green dashed line Fig. 6). Together, these results suggest  
 697 the TJRE produces an anomaly in the wave-driven alongshore velocity. The TJRE is  
 698 a site of persistent divergence in the alongshore-varying nearshore alongshore velocity  
 699 time series, most pronounced in non-summer months (Fig. 2a). The divergence arises  
 700 between the TJRE and IB, where there is the shoal (visible north of the TJRE mouth  
 701 in 10-m isobath contour in Fig. 1). The shoal affects wave-driven currents but may also  
 702 steer alongshore flow. Divergence may also arise when there is flow out of the TJRE mouth,  
 703 either from the episodically-flowing Tijuana River or ebb tides. Importantly, there was  
 704 no decrease at the TJRE in agreement in the binary analysis comparing time steps with  
 705 dye concentrations exceeding  $C_{BAC}$  in the 1D model with the SD Bight model (Fig. 9b).  
 706 This suggests that discrepancies in small dye concentrations (less than  $C_{BAC}$ ) account  
 707 for the decrease in R and WSS in the 1D model downstream of the TJRE (Fig. 6a, c).

### 708 **4.4 Application for water quality prediction in San Diego-Tijuana re-** 709 **gion**

710 The 1D model was able to reproduce the concentration of a tracer from a point source  
 711 throughout a 30 km nearshore region from the SD Bight model, a much more complex  
 712 COAWST model which includes the alongshore-variable bathymetry and shelf circula-  
 713 tion. These model-model comparisons demonstrate the viability of a 1D wave-advection  
 714 model in predicting individual wastewater plumes over a range of seasonal wave condi-  
 715 tions, not only the recreation of specific events. The methods used here to tune nearshore  
 716 alongshore advection and dye concentrations to SD Bight model values could be applied  
 717 to historical wave, current, and FIB observations in the San Diego-Tijuana region to build  
 718 an operational water quality forecast with minimal adjustments. Velocity could be tuned  
 719 using wave data from the CDIP Imperial Nearshore buoy and observed nearshore cur-  
 720 rents. To calibrate tracer transport, we could use available historic water sampling data.  
 721 Only data from the dry season would be used for calibration to isolate the wastewater  
 722 plume from SABWTP from other pathogen sources, such as the TJRE or storm water  
 723 runoff (as in Zimmer-Faust et al., 2021). Dye decay parameters could be adapted to match

724 the pathogens tested for in water sampling. Here we used norovirus, but historic water  
725 sampling has tested for FIB, *E. Coli*, and *Enterococcus* (San Diego County, n. d.), all  
726 of which decay more rapidly than norovirus. The average measured e-folding time scale  
727 of *E. Coli* is 2–3 days (Boehm et al., 2018). The decay rate of *Enterococcus* is modu-  
728 lated by UV exposure, with populations decreasing by 90% in 81 minutes when exposed  
729 to midday sunlight (Davies-Colley et al., 1994), but in darker, colder environments the  
730 decay timescale can lengthen to a few days (Byappanahalli et al., 2012). To reproduce  
731 the rate of dye loss for *Enterococcus*, the decay rate would require programmed sunlight  
732 dependence.

733 The 1D model could be used in concert with the existing plume tracker model to  
734 improve performance (S. Y. Kim et al., 2009; Rogowski et al., 2015). The offline parti-  
735 cle tracking algorithm which currently uses observed shelf currents to model transport  
736 of FIB could implement a nested 1D wave-driven nearshore transport model when par-  
737 ticles are found within 200 m of the shoreline.

#### 738 **4.5 Applications to other regions and tracers**

739 The 1D wave-advection model tested here was motivated by the problem of wastew-  
740 ater transport in the San Diego-Tijuana nearshore region, but the dynamics of this nearshore  
741 region are not unique. This method could be adapted to model the nearshore transport  
742 of other tracers on other mostly straight, wave-dominated coastlines using wave buoys.  
743 For example, the modeling method could be applied to predict the wave-driven nearshore  
744 transport of microplastics (Kerpen et al., 2020). Although here we used a persistent flux  
745 of polluted waters, a time-dependent source term could represent transient sources of pol-  
746 lution to wave-dominated coastlines. For example, FIB levels are elevated in rivers in  
747 the days following hurricanes in North Carolina (Humphrey et al., 2019; Neville et al.,  
748 2021). Those polluted rivers form buoyant plumes at the coast which are partially trapped  
749 in the nearshore (Rodriguez et al., 2018; Kastner et al., 2019), and the 1D model could  
750 be used to model the wave-driven fate of those plumes along the shoreline. Because the  
751 1D model presented here is simple, it could be coupled to models that currently only use  
752 shelf circulation. Offline particle tracking algorithms used to model transport of harm-  
753 ful algal blooms (Giddings et al., 2014) or larvae (Brasseale et al., 2019) using shelf cur-  
754 rents could implement a nested nearshore 1D wave-driven transport model as described  
755 above for the plume tracker model (S. Y. Kim et al., 2009; Rogowski et al., 2015). With  
756 the inclusion of wind stress, this approach could be used to model sediment transport  
757 during storms on sandy coastlines, such as hurricanes on the Atlantic coast of Florida  
758 (Burnette & Dally, 2018), Nortes on the Yucatan peninsula in Mexico (Medellin et al.,

2021; Torres-Freyermuth et al., 2021), and monsoons on the Nha Trang beach in Vietnam (Tran et al., 2021). Similar to discussed above, some tracers would require additional decay/loss terms such as due to sunlight dependence (e.g., *Enterococcus*) or sinking (e.g., sediment).

## 5 Conclusions

A 1D transport-decay model has been shown to reproduce the mean alongshore currents and nearshore concentrations of a tracer from a 3D hydrodynamic model of the San Diego-Tijuana coastal ocean. This demonstrates the viability of simple 1D models for nearshore water quality prediction and transport of other tracers such as larvae, sediment, or microplastics. Two wave-derived velocity formulas were tested using wave properties from an offshore location. Given the range of wave properties in this region over the twelve-month model period, nearshore tracer evolution could be estimated well using the small angle, weak current approximation, but not with the linear friction approximation. Running the same 1D model using a linear friction model for velocity produced dye distributions with considerably less model skill than the small angle, weak current model. The effect of a small inlet and shoal at the TJRE on alongshore transport was examined. However, model performance was unaffected by the TJRE for values of dye that were above a beach advisory threshold,  $C_{\text{BAC}} = 5 \times 10^{-4}$ . Only when small (inconsequential from a human health perspective) dye concentrations were considered did model performance decrease by 10% north of the TJRE. Because this 1D wave-advection model can be run with a wave buoy or a wave forecast model, it could be used for real-time or forecasts of tracer transport in other coastal regions. The simplicity, speed, and accuracy of this 1D nearshore model are evidence that a similar modeling technique could be implemented in place of or in concert with a full hydrodynamic model for public health websites and ensemble studies where full hydrodynamic models may be impractical. Moreover, it can be combined with other existing tracer transport models that focus on shelf-circulation to better represent the fate of tracers along the shoreline.

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 812 sented in plots is available at DOI:10.5281/zenodo.6544844. 1D model output and SD  
 813 Bight model extracted and processed nearshore data is in the process of being made pub-  
 814 licly available on the UCSD Digital collections library, and will have a citable DOI be-  
 815 fore publication of this manuscript.

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