Connection between encounter volume and diffusivity in geophysical flows

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Abstract: Trajectory encounter volume – the volume of fluid that passes close to a reference 8 9 fluid parcel over some time interval – has been recently introduced as a measure of mixing potential of a flow. Diffusivity is the most commonly used characteristic of turbulent diffusion. 10 We derive the analytical relationship between the encounter volume and diffusivity under the 11 assumption of an isotropic random walk, i.e. diffusive motion, in one and two dimensions. We 12 apply the derived formulas to produce maps of encounter volume and the corresponding 13 14 diffusivity in the Gulf Stream region of the North Atlantic based on satellite altimetry, and discuss the mixing properties of Gulf Stream rings. Advantages offered by the derived formula 15 for estimating diffusivity from oceanographic data are discussed, as well as applications to other 16 disciplines. 17

18 1. Introduction

The frequency of close encounters between different objects or organisms can be a fundamental 19 20 metric in social and mechanical systems. The chances that a person will meet a new friend or contract a new disease during the course of a day is influenced by the number of distinct 21 individuals that he or she comes into close contact with. The chances that a predator will ingest a 22 poisonous prey, or that a mushroom hunter will mistakenly pick up a poisonous variety, is 23 24 influenced by the number of distinct species or variety of prey or mushrooms that are encountered. In fluid systems, the exchange of properties such as temperature, salinity or 25 humidity between a given fluid element and its surroundings is influenced by the number of 26 other distinct fluid elements that pass close by over a given time period. In all these cases it is 27 best to think of close encounters as providing the *potential*, if not necessarily the act, of 28 29 transmission of germs, toxins, heat, salinity, etc...

In cases of property exchange within continuous media such as air or water, it may be most meaningful to talk about a mass or volume passing within some radius of a reference fluid element as this element moves along its trajectory. Rypina and Pratt (2017) introduce a trajectory encounter volume, *V*, the volume of fluid that comes in contact with the reference fluid parcel over a finite time interval. The increase of *V* over time is one measure of the mixing potential of the element, "mixing" being the irreversible exchange of properties between different water

- 36 parcels. Thus, fluid parcels that have large encounter volumes as they move through the flow
- 37 field have large mixing potential, i.e., an opportunity to exchange properties with other fluid
- 38 parcels, and vice versa.
- In order to formally define the encounter volume V, Rypina and Pratt (2017) subdivide the entire
- 40 fluid into infinitesimal fluid elements with volumes dV_i , and define the encounter volume for
- 41 each fluid element to be the total volume of fluid that passes within a radius R of it over a finite
- 42 time interval $t_0 < t < t_0 + T$, i.e.,

43
$$V(\vec{x}_0; t_0, T, R) = \lim_{dV_i \to 0} \Sigma_i \, dV_i.$$
 (1)

In practice, for dense uniform grids of trajectories, $\vec{x}_k(\vec{x}_{0k}; t_0, T), k = 1, ..., K$, where t_0 is the starting time, T is the trajectory integration time, and \vec{x}_{0k} is the trajectory initial position satisfying $\vec{x}(\vec{x}_0, t_0; T = 0) = \vec{x}_0$, both the limit and the subscript in the above definition (1) can be dropped. In this case, the encounter volume can be approximated by

$$48 \quad V \approx N \,\delta V, \tag{2}$$

49 where the *encounter number*,

50
$$N(\vec{x}_{0ref}; t_0, T, R) = \sum_{\substack{k=1 \ k \neq ref}}^{K} I(\min(|\vec{x}_k(\vec{x}_{0k}; t_0, T) - \vec{x}_{ref}(\vec{x}_{0ref}; t_0, T)|) \le R),$$
 (3)

is the number of trajectories that come within a radius R of the reference trajectory, 51 $\vec{x}_{ref}(\vec{x}_{0ref}; t_0, T)$, over a time $t_0 < t < t_0 + T$. Here the indicator function I is 1 if true and 0 if 52 false, and K is the total number of particles. As in Rypina and Pratt (2017), we define encounter 53 volume based on the number of encounters with different trajectories, not the total number of 54 encounter events (see the schematic diagram of trajectory encounters in Fig. 1). Rypina and Pratt 55 (2017) discuss how the encounter volume can be used to identify Lagrangian Coherent 56 Structures (LCS) such as stable and unstable manifolds of hyperbolic trajectories and regions 57 foliated by the KAM-like tori surrounding elliptic trajectories in realistic geophysical flows. A 58 detailed comparison between the encounter volume method and some other Lagrangian methods 59 60 of LCS identification, as well as the dependences on parameters, t_0 , T, R and on grid spacing (or on the number of trajectories, K), and the relative advantages of different techniques, was given 61 in Rypina and Pratt (2017). The interested reader is referred to that earlier paper for details. The 62 current paper is concerned only with the question of finding the connection between the 63 64 encounter volume and diffusivity, rather than identifying LCS.

Given the seemingly fundamental importance of close encounters, it is of interest to relate metrics such as V to other bulk measures of interactions within the system. For example, in some cases it may be more feasible to count encounters rather than to measure interactions or property

exchanges directly, whereas in other cases the number of encounters might be most pertinent to

the process in question but difficult to measure directly. In many applications, including ocean 69 turbulence, the most commonly used metric of mixing is the eddy diffusivity, κ , a quantity that 70 relates transport of fluid elements by turbulent eddies to diffusion (LaCasce, 2008; Vallis, 2006; 71 Rypina et al., 2015; Kamenkovich et al., 2015). The underlying assumption is that the eddy field 72 73 drives downgradient tracer transfer, similar to molecular diffusion but with a different (larger) 74 diffusion coefficient. This diffusive parameterization of eddies has been implemented in many non-eddy-resolving oceanic numerical models. The diffusivity can be measured by a variety of 75 means, including dye release (Ledwell et al., 2000; Sundermeyer and Ledwell, 2001; Rypina et 76 77 al., 2016), surface drifter dispersion (Okubo, 1971; Davis, 1991; LaCasce, 2008, La Casce et al., 2014; Rypina et al. 2012; 2016), and property budgets (Munk, 1966). In numerical models κ is 78 often assumed constant in both time and space, or related in some simplified manner to the large-79 80 scale flow properties (Visbeck, 1997).

Because the purpose of the diffusivity coefficient κ is to quantify the intensity of the eddy-81 82 induced tracer transfer, i.e., the intensity of mixing, it is tempting to relate it to the encounter volume, V, which quantifies the mixing potential of a flow and thus is closely related to tracer 83 mixing. Such an analytical connection between the encounter volume and diffusivity could 84 potentially also be useful for the parameterizations of eddy effects in numerical models. The 85 main goal of this paper is to develop a relationship between V and κ in one and two dimensions. 86 Specifically, we seek an analytical expression for the encounter volume, V, i.e., the volume of 87 fluid that passed within radius R from a reference particle over time, as a function of κ . The 88 relationship is not as straightforward as one might first imagine, but can nevertheless be written 89 down straightforwardly in the long-time limit. This is opportune, since the concept of eddy 90 diffusivity is most relevant in the long-time limit. 91

92 2. Connection between encounter volume and diffusivity

93 This problem was framed in mathematical terms in Rypina and Pratt (2017), who outlined some

94 initial steps towards deriving the analytical connection between encounter volume and diffusivity

but did not finish the derivation. In this section, we complete the derivation.

96 2.1. Main idea for the derivation

97 Let us start by considering the simplest diffusive random walk process in one or two dimensions, 98 where particles take steps of fixed length Δx in random directions along the x-axis in 1D or 99 along both x- and y-axes in 2D, respectively, at fixed time intervals Δt .

100 The single particle dispersion, i.e., the ensemble-averaged square displacement from the 101 particle's initial position, is $D_{1D} = \langle (x - x_0)^2 \rangle$ and $D_{2D} = \langle (x - x_0)^2 + (y - y_0)^2 \rangle$ in 1D 102 or 2D, respectively. For a diffusive process, the dispersion grows linearly with time, and the 103 constant proportionality coefficient related to diffusivity. Specifically, $D_{1D} = 2\kappa_{1D}t$ with 104 $\kappa_{1D} = \Delta x^2 / (2\Delta t)$, and $D_{2D} = 4K_{2D}t$ with $\kappa_{2D} = \Delta x^2 / (4\Delta t)$. 105 It is convenient to consider the motion in a reference frame that is moving with the reference 106 particle. In that reference frame, the reference particle will always stay at the origin, while other 107 particles will still be involved in a random walk motion, but with a diffusivity twice that in the 108 stationary frame, $\kappa^{moving} = 2\kappa^{stationary}$ (Rypina and Pratt, 2017).

109 The problem of finding the encounter number then reduces to counting the number of randomly 110 walking particles (with diffusivity κ^{moving}) that come within radius *R* of the origin in the 111 moving frame. This is related to a classic problem in statistics – the problem of a random walker 112 reaching an absorbing boundary, usually referred to as "a cliff" (because once a walker reaches 113 the absorbing boundary, it falls off the cliff), over a time interval from 0 to *t*.

114 In the next section we will provide formal solutions; here we simply outline the steps to 115 streamline the derivation. We start by deriving the appropriate diffusion equation for the 116 probability density function, $p(\vec{x}, t)$, of random walkers in 1D or 2D:

117
$$\frac{\partial p}{\partial t} = \kappa \nabla^2 p. \tag{4}$$

118 We place a cliff, $\overrightarrow{x_c}$, at the perimeter of the encounter sphere, i.e., at a distance *R* from the 119 origin, and impose an absorbing boundary condition at a cliff,

$$120 \quad p(\overrightarrow{x_c}, t) = 0, \tag{5a}$$

which removes (or "absorbs") particles that have reached the cliff (see Fig. 2 for a schematic diagram). We then consider a random walker that is initially located at a point $\overline{x_0}$ outside the cliff at t = 0, i.e.,

124
$$p(\vec{x}, t=0) = \delta(\vec{x} - \vec{x_0}),$$
 (5b)

and we write an analytical solution for the probability density function satisfying Eqs. (4-5),

126
$$G(\vec{x}, t; \vec{x_0}, \vec{x_c}),$$
 (6)

that quantifies the probability to find a random walker initially located at $\vec{x_0}$ at any location \vec{x} outside of the cliff at a later time t > 0. In mathematical terms, *G* is the Green's function of the diffusion equation.

130 The survival probability, which quantifies the probability that a random walker initially located 131 at $\overline{x_0}$ at t = 0 has "survived" over time t without falling off the cliff, is

132
$$S(t; \overrightarrow{x_0}, \overrightarrow{x_c}) = \int G(\overrightarrow{x}, t; \overrightarrow{x_0}, \overrightarrow{x_c}) d\overrightarrow{x},$$
 (7)

where the integral is taken over all locations outside of the cliff. The encounter, or "nonsurvival", probability can then be written as the conjugate quantity,

135
$$P_{en}(t; \overrightarrow{x_0}, \overrightarrow{x_c}) = 1 - S(t; \overrightarrow{x_0}, \overrightarrow{x_c}),$$
(8)

which quantifies the probability that a random walker initially located at $\overrightarrow{x_0}$ at t = 0 has reached, or fallen off, the cliff over time *t*. This allows one to write the encounter volume, i.e., the volume occupied by particles that were initially located outside of the cliff and that have reached the cliff by time *t*, as

140
$$V(t; \overrightarrow{x_c}) = \int P_{en}(t; \overrightarrow{x_0}, \overrightarrow{x_c}) d\overrightarrow{x_0}$$
, (9)

141 where the integral is taken over all initial positions outside of the cliff.

142

143 2.2. 1D case

144 Consider a random walker initially located at the origin, who takes, with a probability $\frac{1}{2}$, a fixed 145 step Δx to the right or to the left along the x-axis after each time interval Δt . Then the probability 146 to find a walker at a location $x = n\Delta x$ at after (m + 1) steps is

147
$$p(n\Delta x, (m+1)\Delta t) = 1/2[p((n-1)\Delta x, m\Delta t) + p((n+1)\Delta x, m\Delta t)].$$
(10)

148 Using a Taylor series expansion in Δx and Δt , we can write down the finite-difference 149 approximation to the above expression as

$$p(x,t) + \Delta t \frac{\partial p}{\partial t} = \frac{1}{2} \left[p(x,t) - \Delta x \frac{\partial p}{\partial x} + \frac{\Delta x^2}{2} \frac{\partial^2 p}{\partial x^2} + p(x,t) + \Delta x \frac{\partial p}{\partial x} + \frac{\Delta x^2}{2} \frac{\partial^2 p}{\partial x^2} + O(\Delta x^4) \right] =$$
$$= p(x,t) + \frac{\Delta x^2}{2} \frac{\partial^2 p}{\partial x^2} + O(\Delta x^4), \tag{11}$$

151 yielding a diffusion equation

152
$$\frac{\partial p}{\partial t} = \kappa \frac{\partial^2 p}{\partial x^2}$$
 (12)

153 with diffusivity coefficient $\kappa = \frac{\Delta x^2}{2\Delta t}$.

150

155 A Green's function for the 1D diffusion equation without a cliff is a solution with initial 156 condition $p(x, t = 0; x_0) = \delta(x - x_0)$ in an unbounded domain. It takes the form

157
$$G_{unbounded}(x,t;x_0) = \frac{1}{\sqrt{4\pi\kappa t}} e^{-\frac{(x-x_0)^2}{4\kappa t}}.$$
 (13)

158 A Green's function with the cliff (see Fig. 2 for a schematic diagram), for a solution to the 159 initial-value problem with $p(x, t = 0; x_0) = \delta(x - x_0)$ in a semi-infinite domain, $x \in [-\infty; x_c]$, with an absorbing boundary condition at a cliff, $p(x = x_c, t; x_0) = 0$, can be constructed by the method of images from two unbounded Green's functions as

162
$$G(x,t;x_0,x_c) = \frac{1}{\sqrt{4\pi\kappa t}} \left(e^{-\frac{(x-x_0)^2}{4\kappa t}} - e^{-\frac{(x-(2x_c-x_0))^2}{4\kappa t}} \right).$$
(14)

163 It follows from (7-9) that the survival or non-encounter probability is

164
$$S(t; x_0, x_c) := \int_{-\infty}^{x_c} G(x, t; x_0, x_c) dx = Erf[\frac{x_c - x_0}{2\sqrt{\kappa t}}],$$
 (15)

the encounter probability is

166
$$P_{en}(t; x_0, x_c) = 1 - S(t) = 1 - Erf\left(\frac{x_c - x_0}{2\sqrt{\kappa t}}\right),$$
 (16)

167 and the encounter volume is

168
$$V(t;x_c) = \int_{-\infty}^{x_c} P_{en}(t;x_0,x_c) dx_0 = \int_{-\infty}^{x_c} \left(1 - Erf\left[\frac{x_c - x_0}{2\sqrt{\kappa t}}\right]\right) dx_0 = \frac{2}{\sqrt{\pi}}\sqrt{\kappa t}.$$
 (17)

169 The above formula accounts for the randomly walking particles that have reached the cliff from 170 the left over time t. By symmetry, if the cliff was located to the right of the origin, the same 171 number of particles would be reaching the cliff from the right, so the total encounter volume is

172
$$V(t;x_c) = \frac{4}{\sqrt{\pi}}\sqrt{\kappa t}.$$
 (18)

173 Note that formula (18) gives the encounter volume, i.e., the volume of fluid coming within radius 174 *R* from the origin, in a reference frame moving with the reference particle, so the corresponding 175 diffusivity in the right-hand side of (18) is $\kappa^{moving} = 2\kappa^{stationary}$.

176 2.3. 2D case

177 Consider a random walker in 2D, who is initially located at the origin and who takes, with a 178 probability of 1/4, a fixed step of length Δx to the right, left, up or down after each time interval 179 Δt . Then the probability to find a walker at a location $x = n\Delta x$, $y = m\Delta y$ at time $t = (l + 1)\Delta t$ 180 is

181
$$p(n\Delta x, m\Delta y, (l+1)\Delta t) = \frac{1}{4} \left[p((n-1)\Delta x, m\Delta y, l\Delta t) + p((n+1)\Delta x, m\Delta y, l\Delta t) + p(n\Delta x, (m-1)\Delta y, l\Delta t) + p(n\Delta x, (m+1)\Delta y, l\Delta t) \right].$$
 (19)

183 Using a Taylor series expansion in Δx , Δy and Δt , the finite-difference approximation leads to a 184 diffusion equation

185
$$\frac{\partial p}{\partial t} = \kappa \left(\frac{\partial^2 p}{\partial x^2} + \frac{\partial^2 p}{\partial y^2} \right)$$
(20)

- 186 with diffusivity coefficient $\kappa = \frac{\Delta x^2}{4\Delta t}$.
- 187 To proceed, we need an analytical expression for the Green's function of Eq. (20) with a cliff at a 188 distance *R* from the origin, i.e., a solution to the initial-value problem with $p(\vec{x}, t = 0; \vec{x_0}) =$ 189 $\delta(\vec{x} - \vec{x_0})$ for the above 2D diffusion equation on a semi-infinite plane $(r \ge R, 0 < \theta \le 2\pi)$, 190 bounded internally by an absorbing boundary (a cliff) located at r = R, so that p(r =191 $R, \theta, t; \vec{x_0}) = 0$ (see Fig. 2(right) for a schematic diagram). Here (r, θ) are polar coordinates.
- 192 Carlslaw and Joeger (1939) give the answer as

193
$$G(r,\theta,t;r_0,\theta_0,R) = u + w = \sum_{n=-\infty}^{\infty} (u_n(r,t;r_0,R) + w_n(r,t;r_0,R)) \cos n(\theta - \theta_0)$$
(21)

194 where $r_0 (\geq R)$, θ_0 denote the source location, and

195
$$\{u_n, w_n\} = L^{-1}\left\{\overline{u}_n, \overline{w}_n\right\} = \frac{1}{2\pi i} \lim_{T \to \infty} \int_{\gamma - iT}^{\gamma + iT} e^{st}\left\{\overline{u}_n, \overline{w}_n\right\} ds$$

196 are the inverse Laplace transforms of

197
$$\bar{u}_n = \frac{1}{2\pi\kappa} \begin{cases} I_n(qr)K_n(qr_0), R < r < r_0 \\ I_n(qr_0)K_n(qr), r > r_0 \end{cases} \text{ and } \bar{w}_n = -\frac{I_n(qR)}{K_n(qR)} K_n(qr_0)K_n(qr) \tag{22}$$

- 198 with $q = \sqrt{\frac{s}{\kappa}}$.
- 199 The survival probability (from Eq. (7)) is

200
$$S(t; r_0, R) = \int_{R^2} G(\vec{x}, t; \vec{x_0}, R) d^2 \vec{x} = \int_0^{2\pi} \int_R^{\infty} \sum_{n=-\infty}^{\infty} (u_n + v_n) \cos n(\theta - \theta_0) r \, dr \, d\theta =$$

201 $2\pi \int_R^{\infty} (u_0 + v_0) r \, dr.$ (23)

Next, we take the Laplace transform of the survival probability and write it in terms of a Laplacevariable *s* as

204
$$\overline{S}(s,r_{0},R) = \int_{0}^{\infty} e^{-st} S(t;r_{0},R) dt = 2\pi \int_{R}^{\infty} (\overline{u_{0}} + \overline{w_{0}}) r dr = \frac{1}{\kappa} \int_{R}^{r_{0}} I_{0}(qr) K_{0}(qr_{0}) r dr + \frac{1}{\kappa} \int_{r_{0}}^{\infty} I_{0}(qr_{0}) K_{0}(qr) r dr - \frac{1}{\kappa} \int_{R}^{\infty} \frac{I_{0}(qR)}{K_{0}(qR)} K_{0}(qr) K_{0}(qr_{0}) r dr.$$
(24)

206 Using
$$\int r I_0(r) dr = r I_1(r)$$
 and $\int r K_0(r) dr = -r K_1(r)$, and $\lim_{x \to \infty} x K_1(x) = 0$ we find
207

$$\begin{aligned} &\overline{S}(s;r_{0},R) = \\ &209 \quad \frac{1}{\kappa}K_{0}(qr_{0})\left[\frac{r}{q}I_{1}(qr)\right]\Big|_{R}^{r'} + \frac{1}{\kappa}I_{0}(qr_{0})\left[-\frac{r}{q}K_{1}(qr)\right]\Big|_{R}^{\infty} - \frac{1}{\kappa}\frac{I_{0}(qr_{0})}{K_{0}(qR)}K_{0}(qr_{0})\left[-\frac{r}{q}K_{1}(qr)\right]\Big|_{R}^{\infty} = \\ &210 \quad \frac{1}{\kappa}\Big\{\frac{r_{0}}{q}\Big(I_{1}(qr_{0})K_{0}(qr_{0}) + I_{0}(qr_{0})K_{1}(qr_{0})\Big) - \frac{a}{q}\frac{K_{0}(qr_{0})}{K_{0}(qR)}\Big(I_{1}(qR)K_{0}(qR) + I_{0}(qR)K_{1}(qR)\Big)\Big\}. \end{aligned}$$

211 But
$$I_1(x)K_0(x) + I_0(x)K_1(x) = \frac{1}{x}$$
 so

212
$$\overline{S}(s;r_0,R) = \frac{1}{\kappa} \left(\frac{1}{q^2} - \frac{1}{q^2} \frac{K_0(qr_0)}{K_0(qR)} \right) = \frac{1}{s} \left(1 - \frac{K_0(qr_0)}{K_0(qR)} \right).$$
(26)

From (8), the encounter probability $P_{en}(t; \vec{x_0}, R) = 1 - S(t; \vec{x_0}, R)$, and from (9) the encounter volume is

215
$$V(t;R) = \int_{R^2} P_{en} d^2 \overrightarrow{x_0} = \int_0^{2\pi} \int_R^{\infty} P_{en} r_0 dr_0 = 2\pi \int_R^{\infty} [1 - S(t;r_0,R)] r_0 dr_0.$$
(27)

216 We now take the Laplace transform of the encounter number to get

217
$$\bar{V}(s;R) = \int_0^\infty e^{-st} V(t;R) dt = 2\pi \int_R^\infty \left[\frac{1}{s} - \overline{S}(s;R)\right] r_0 dr_0 = 2\pi \int_R^\infty \frac{K_0(qr_0)}{K_0(qR)} \frac{r_0}{s} dr_0 = 2\pi R K_1(qR) = 2\pi R K_1(qR) = 2\pi R K_1(qR)$$

218
$$\frac{2\pi}{sK_0(qR)} \left[-\frac{r_0}{q} K_1(qr_0) \right] \Big|_R^{\infty} = \frac{2\pi R}{sq} \frac{K_1(qR)}{K_0(qR)} = \frac{2\pi R}{s^{3/2} \kappa^{-\frac{1}{2}}} \frac{K_1(\sqrt{\kappa}K)}{K_0(\sqrt{\frac{s}{\kappa}R})},$$
(28)

219 where we used
$$\int_0^\infty e^{-st} dt = \frac{1}{s}$$
, $\int K_0(z) z \, dz = -zK_1(z)$, and $\lim_{z \to \infty} K_1(z) = 0$.

The explicit connection between the encounter volume and diffusivity is thus given by the inverse Laplace transform of the above expression (28),

222
$$V(t;R) = L^{-1}\{\bar{V}(s;R)\}.$$
 (29)

Although numerically straightforward to evaluate, a non-integral analytic form does not exist for this inverse Laplace transform. To better understand the connection between V and κ and the growth of V with time, we next look at the asymptotic limits of small and large time. The small-*t* limit is transparent, while the long-*t* limit is more involved.

- 227 (a) small-*t* asymptotics
- 228 In the small-*t* limit, the corresponding Laplace coordinate *s* is large, giving

229
$$\bar{V}(s;R) \sim 2\pi R \kappa^{\frac{1}{2}} \frac{1}{s^{3/2}}$$
 (30)

because $\lim_{z\to\infty} \frac{K_1(z)}{K_0(z)} = 1$. Noting that $L^{-1}\left\{s^{-\frac{3}{2}}\right\} = \frac{2\sqrt{t}}{\sqrt{\pi}}$, the inverse Laplace transform of the above gives the following simple expression connecting the encounter number and diffusivity at short times:

233
$$V(t;R) \xrightarrow{t \to 0} 4R\sqrt{\pi} \sqrt{\kappa t}.$$
 (31)

234 (b) large-*t* asymptotics

In the large-*t* limit, the Laplace coordinate *s* is small and the asymptotic expansions K_0 , K_1 take the form

237
$$lim_{z\to 0}K_0(z) = -\gamma - \ln\left(\frac{z}{2}\right) + O\left(\left(\frac{z}{2}\right)^2 \ln\left(\frac{z}{2}\right)\right),$$
 (32)

238
$$lim_{z\to 0}K_1(z) = \frac{1}{z} + \frac{z}{2} \left[ln\left(\frac{z}{2}\right) + \gamma - \frac{1}{2} \right] + O(z^3 ln z),$$
 (33)

239 giving

240
$$\lim_{s \to 0} \bar{V}(s; R) = -\frac{4\pi\kappa}{s^2 \ln(\tau s)} - \frac{\pi R^2}{s} + O\left(\frac{1}{s \ln(\tau s)}\right),$$
 (34)

241 where

242
$$\tau = \frac{R^2 e^{2\gamma}}{4\kappa}.$$
 (35)

We now need to take an inverse Laplace transform of \overline{V} . The second term in the right-hand side gives $L^{-1}\left\{\frac{\pi R^2}{s}\right\} = \pi R^2$. Llewelyn Smith (2000) discusses the literature for inverse Laplace transforms of the form $(s^{\alpha} \ln s)^{-1}$ for small *s*. For our problem, the discussion in Olver (1974, Chap. 8, §11.4) is the most helpful approach. His result (11.13), discarding the exponential term which is not needed here, shows that the inverse Laplace transform of $(s^2 \ln s)^{-1}$ has the asymptotic expansion

249
$$L^{-1}\left\{\frac{1}{s^2 \ln s}\right\} \xrightarrow{t \to \infty} - t\left(\frac{1}{\ln t} + \frac{1-\gamma}{(\ln t)^2} + O((\ln t)^{-3})\right).$$
 (36)

Using $L^{-1}{F(\tau s)} = \frac{1}{\tau}f(t/\tau)$, we thus obtain the desired connection between the encounter number and diffusivity at long times:

252
$$V(t;R) \xrightarrow{t \to \infty} 4\pi\kappa t \left(\frac{1}{\ln\frac{t}{\tau}} + \frac{1-\gamma}{\left(\ln\frac{t}{\tau}\right)^2} \right) - \pi R^2 + O\left(\frac{t}{\left(\ln\frac{t}{\tau}\right)^3}\right) + O\left(\frac{1}{\ln\frac{t}{\tau}}\right).$$
(37)

253 Physically, the time scale τ (Eq. (35)) defines the time at which the dispersion of random 254 particles, $D = 4\kappa\tau$, is comparable to the volume of the encounter sphere, ie., $R^2 e^{2\gamma} \cong \pi R^2$ in 255 2D. Thus for $t \gg \tau$, particles are coming to the encounter sphere "from far away."

For practical applications, it is sufficient to only keep the leading order term of the expansion, yielding a simpler connection between encounter number and diffusivity,

258
$$V(t;R) \xrightarrow{t \to \infty} \frac{4\pi\kappa t}{\ln\frac{t}{\tau}} + O\left(\frac{t}{\left(\ln\frac{t}{\tau}\right)^2}\right).$$
(38)

259 Note again that the diffusivity in the right-hand side of Eqs. (28-29), (31) and (38) is 260 $\kappa^{moving} = 2\kappa^{stationary}$.

261 2.4. Numerical tests of the derived formulas in 1d and 2d

Before applying our results to the realistic oceanic flow, we numerically tested the accuracy of 262 the derived formulas in idealized settings by numerically simulating a random walk motion in 1D 263 and 2D, as described in the beginning of subsections 2.1 and 2.2, respectively. We then 264 265 computed the encounter number and encounter volume using definition (2-3), and compared the result with the derived exact formulas (18) and (28-29) and with the asymptotic formulas (31) 266 and (38). Note that although formulas (28-29) are exact, the inverse Laplace transform still needs 267 to be evaluated numerically and thus is subject to numerical accuracy, round-off errors etc.; these 268 numerical errors are, however, small, and we will refer to numerical solutions of (28-29) as 269 270 "exact," as opposed to the asymptotic solutions (31) and (38).

The comparison between numerical simulations and theory is shown in Fig. 3. Because the 271 numerically simulated random walk deviates significantly from the diffusive regime over short 272 $(\leq O(100\Delta t))$ time scales, the agreement between numerical simulation and theory is poor at 273 those times in both 1D and 2D. Once the random walkers have executed > 100 time steps, 274 275 however, the dispersion reaches the diffusive regime, and the agreement between the theory (red) and numerical simulation (black) rapidly improves for both 1D and 2D cases, with the two 276 277 curves approaching each other at long times. In 2D, the long-time asymptotic formula (38) works 278 well at long times, $t \gg \tau$, as expected. The 2D short-time asymptotic formula (green) agrees well 279 with the exact formula (red) at short times but not with the numerical simulations (black) for the same reason as discussed above, i.e., because the numerically simulated random walk has not yet 280 reached the diffusive regime at those times. 281

282 3. Application to the altimetric velocities in the Gulf Stream region

Sea surface height measurements made from altimetric satellites provide nearly global estimates 283 284 of geostrophic currents throughout the World Oceans. These velocity fields, previously distributed by AVISO, are now available from the Copernicus Marine and Environment 285 286 Monitoring Service (CMEMS) website (http://marine.copernicus.eu/), both along satellite tracks and as a gridded mapped product in both near-real and delayed time. Here we use the delayed-287 time gridded maps of absolute geostrophic velocities with ¹/₄ deg spatial resolution and temporal 288 step of 1 day, and focus our attention on the Gulf Stream extension region of the North Atlantic 289 Ocean. There, the Gulf Stream separates from the coast and starts to meander, shedding cold-290 291 and warm-core Gulf Stream rings from its southern and northern flanks. These rings are among 292 the strongest mesoscale eddies in the ocean. However, their coherence, interaction with each other and with other flow features, and their contribution to transport, stirring and mixing are still 293 not completely understood (Bower et al., 1985; Cherian and Brink, 2016). 294

295 Maps showing the encounter volume for fluid parcel trajectories in the region, and the corresponding diffusivity estimates (Fig. 4) could be useful both for understanding and 296 interpreting the transport properties of the flow, as well as for benchmarking and 297 parameterization of eddy effects in numerical models. In our numerical simulations, trajectories 298 299 were released on a regular grid with $dx = dy \approx 10$ km on 11 Jan 2015 and were integrated forward in time for 90 days using a fifth-order variable-step Runge-Kutta integration scheme 300 with bi-linear interpolation between grid points in space and time. The encounter radius was 301 chosen to be R = 30 km in both zonal and meridional directions, i.e., about a third of a radius of 302 303 a typical Gulf Stream ring. Similar parameter values were used in Rypina and Pratt (2017), although our new simulation was carried out using more recent 2015 velocities instead of 1997 304 as in that paper. 305

306 The encounter volume field, shown in the top left panel of Fig. 4, highlights the overall 307 complexity of the flow and identifies a variety of features with different mixing potential, most 308 notably several Gulf Stream rings with spatially small low-V (blue) cores and larger high-V (red) peripheries. Although the azimuthal velocities and vorticity-to-strain ratio are large within the 309 rings, the coherent core regions with inhibited mixing potential are small, suggesting that the 310 *coherent* transport by these rings might be smaller than anticipated from the Eulerian diagnostics 311 such as the Okubo-Weiss or closed-streamline criteria (Chelton et al., 2011; Abernathey and 312 313 Haller, 2017). On the other hand, the rings' peripheries, where the mixing potential is elevated compared to the surrounding fluid, cover a larger geographical area than the cores. Thus, while 314 rings inhibit mixing within their small cores, the enhanced mixing on the periphery might be 315 their dominant effect. This is consistent with the results from Rypina and Pratt (2017), but a 316 317 more thorough analysis is needed to test this hypothesis. Notably, the encounter number is also large along the northern and southern flank of the Gulf Stream jet, with two separate red curves 318 running parallel to each other and a valley in between (although the curves could not be traced 319 continuously throughout the entire region). This enhanced mixing on both flanks of the Gulf 320 Stream Extension current is reminiscent of chaotic advection driven by the tangled stable and 321 unstable manifolds at the sides of the jet (del-Castillo-Negrete and Morrison, 1993; Rogerson et 322 al., 1999; Rypina et al., 2007; Rypina and Pratt, 2017), and is also consistent with the existence 323 324 of critical layers (Kuo, 1949; Ngan and Sheppard, 1997).

325

We now apply the asymptotic formula (38) to convert the encounter volume to diffusivity. 326 Because equation (38) is not invertible analytically, we converted V to κ numerically using a 327 look-up table approach. More specifically, we used (38) to compute theoretically-predicted V 328 values at time T=90 days for a wide range of κ 's spanning all possible oceanographic values for 329 0 to $10^9 \ cm^2/s$, and we used the resulting look-up table to assign the corresponding κ values to 330 V values in the 3^{rd} row of Fig. 4. Note that, instead of the long-time asymptotic formula (38) (as 331 in in the 3rd row of Fig. 4), it is also possible to use the exact formulas (28-29) to convert V to κ 332 via a table look-up approach. The resulting exact diffusivities, shown in the 2nd row of Fig. 4, are 333 similar to the long-time asymptotic values (3rd row). Because both exact and asymptotic formulas 334

were derived under the assumption of a diffusive random walk, neither should work well in regions with a non-diffusive behavior. The asymptotic formula has the advantage of being simpler and it also provides for a numerical estimate of the "long-time-limit" time scale, τ , shown in the bottom row of Fig. 4

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As expected, the diffusivity maps in the 2nd and 3rd rows of Fig. 4, which resulted from 340 converting V to κ using (28-29) or (38), respectively, have the same spatial variability as the V-341 map, with large κ at the peripheries of the Gulf Stream rings and at the flanks of the Gulf Stream 342 and small κ at the cores of the rings, near the Gulf Stream centerline and far away from the Gulf 343 Stream current, where the flow is generally slower. The diffusivity values range from 344 $O(10^5) \ cm^2/s$ to $O(10^7) \ cm^2/s$. Using the 1971 Okubo's diffusivity diagram and scaling law, 345 $\kappa_{Okubo}[cm^2/s] = 0.0103 \ l[cm]^{1.15}$, our diffusivity values correspond to spatial scales from 346 10 km to 650 km, thus spanning the entire mesoscale range. This is not surprising considering 347 the Lagrangian nature of our analysis, where trajectories inside the small (< 50 km) low-348 349 diffusion eddy cores stay within the cores for the entire integration duration (90 days), whereas trajectories in the high-diffusivity regions near the ring peripheries and at the flanks of the Gulf 350 Stream jet cover large distances, sometimes $> 650 \ km$, over 90 days. 351

352

353 The performances of the exact and asymptotic diffusive formulas vary greatly throughout the domain, with better/poorer performances in high-/low-V areas. This is because in the low-V 354 areas, the behavior of fluid parcels is non-diffusive, so the diffusive theoretical formulas work 355 poorly. The breakdown of the long-time asymptotic formula is evident in the 4th row of Fig. 4, 356 which shows the corresponding long-time scales, τ (from Eq. (35)), throughout the domain. As 357 suggested by our 2D random walk simulations, the long-time asymptotic diffusive formula only 358 works well when $t \gg \tau$, but in reality τ values are < 9 days (1/10 of our integration time) only in 359 the highest-V regions, and are much larger everywhere else, reaching values of \cong 90 days within 360 the cores of the Gulf Stream rings. More detailed comparison between theory, both exact and 361 asymptotic, and numerical V(t) is shown in Fig. 5 for 3 reference trajectories that are initially 362 located inside the core, on the periphery, and outside of a Gulf Stream ring (black, red, and blue, 363 364 respectively) centered at approximately 36.8N and 60W. Clearly, the diffusive theory works 365 poorly for the trajectory inside the eddy core (black curve). The agreement is better for the blue and even better for the red curves, corresponding to trajectories outside and on the periphery of 366 the eddy, although deviations between the theory and numerics are still visible, raising questions 367 368 about the general validity of the diffusive approximation in ocean flows on time scales of a few months. 369

370

The non-diffusive nature of the parcel motion over 90 days is because ocean eddies have finite length- and time-scales, so a variety of different transport regimes generally occurs before separating parcels become uncorrelated and transport becomes diffusive, as in a random walk. At

very short times the motion of fluid parcels is largely governed by the local velocity shear, so the

resulting transport regime is ballistic, i.e., $D \propto T^2$ and $V \propto T$ (Rypina and Pratt, 2017). At longer 375 times, when velocity shear can no longer be assumed constant in space and time, the regime may 376 transition to a local Richardson regime (i.e., $D \propto t^3$), where separation at a given scale is 377 governed by the local features of a comparable scale (Richardson 1926; Bennett 1984; Beron-378 379 Vera and LaCasce 2016), or to a non-local chaotic-advection spreading regime (i.e., $D \propto$ $\exp(\lambda t)$, where separation is governed by the large scale flow features (Bennett 1984; Rypina et 380 al. 2010; Beron-Vera and LaCasce 2016). The kinetic energy spectrum of a flow indicates 381 382 whether a local or non-local regime will be relevant. The chaotic transport regime is generally expected to occur in mesoscale-dominated eddying flows, such as, for example, AVISO velocity 383 fields, over time scales of a few eddy winding times. At times long enough for particles to 384 sample many different flow features, such as Gulf Stream meanders or mesoscale eddies in the 385 386 AVISO fields, the velocities of the neighboring particles become completely uncorrelated, and transport finally approaches the diffusive regime. With the mesoscale eddy turnover time being 387 on the order of several weeks, it often takes longer than 90 days to reach the diffusive regime. 388 389

- 390 A number of diffusivity estimates other than Okubo's have been made for the Gulf Stream extension region (e.g., Zhurbas and Oh, 2004; LaCasce, 2008; Rypina et al., 2012; Abernathey 391 and Marshall, 2013; Klocker and Abernathey, 2014; or Cole et al., 2015). These estimates are 392 based on surface drifters (Zhurbas and Oh, 2004, LaCasce, 2008; Rypina et al., 2012), satellite-393 observed velocity fields (Abernathey and Marshall, 2013; Klocker and Abernathey, 2014, 394 395 Rypina et al., 2012), and Argo float observations (Cole et al., 2015), and they use either the spread of drifters or the evolution of simulated or observed tracer fields to deduce diffusivity. 396 The resulting diffusivities are spatially varying and span 2 orders of magnitude, from 2×10^4 397 m^2/s in the most energetic regions in the immediate vicinity of the Gulf Stream and its 398 extension, to $10^3 m^2/s$ in less energetic areas, to $200 m^2/s$ in the coastal areas of the Slope Sea. 399 Diffusivity estimates vary significantly depending on the initial tracer distribution used 400 401 (Abernathey and Marshall, 2013) and depend on whether the suppression by the mean current 402 has been taken into account (Klocker and Abernathey, 2014). The diffusivity tensor has also been shown to be anisotropic, with a large anisotropy ratio near the Gulf Stream (Rypina et al., 403 2012). Data resolution and coverage, as well as the choice of time and length scales also play a 404 role in defining κ value (Cole at al., 2015). All of these issues complicate the reconciliation of 405 406 different diffusivity estimates. Nevertheless, ignoring these complications for a moment, and avoiding the smallest diffusivities in those geographical areas of Fig. 4 where the diffusive 407 approximation is invalid, our $O(10^3 m^2/s)$ encounter-volume-based diffusivity estimates tend to 408 be in the middle of the range of available estimates for the western North Atlantic. Although not 409 410 inconsistent with other estimates, the encounter volume method did not predict diffusivities to reach values of $10^4 m^2/s$ anywhere within the considered geographical domain. 411
- 412

Because the action of the real ocean velocity field on drifters or tracers is generally not exactly
diffusive, all methods simply fit the diffusive approximation to the corresponding variable of

interest, such as particle dispersion, tracer variance, or, in our case, encounter volume. The analytic form of the diffusive approximation is, however, different for different variables and different flow regimes. For example, for a diffusive random walk regime, dispersion grows linearly with time, whereas the growth of the encounter volume is non-linear, as defined by eq. (38). This generally leads to different diffusivity estimates resulting from different methods. In other words, the diffusivity value that fits best to the observed particle dispersion at 90 days does

- 421 not necessarily provide the best fit to the observed encounter volume at 90 days, and vice versa.
- 422

423 To illustrate this more rigorously, we consider a linear strain flow,

 $\begin{aligned} u &= \alpha \, x, \\ 424 \qquad \qquad v &= -\alpha \, y, \end{aligned}$

425 with a constant strain coefficient α . The particle trajectories are given by $x = x_0 e^{\alpha t}$, $y = y_0 e^{-\alpha t}$ 426 where x_0, y_0 are particles initial positions. The dispersion of a small cluster of particles that are

427 initially uniformly distributed within a small square of side length 2dx is

428
$$D = \langle (X - \bar{X})^2 + (Y - \bar{Y})^2 \rangle,$$

where $X = x - x_0$ and $Y = y - y_0$ are displacements of particles from their initial positions and the overbar denotes the ensemble mean. Since the linear strain velocity remains unchanged in a reference frame moving with a particle, without loss of generality we can restrict our attention to a cluster that is initially centered at the origin, so $\bar{X} = \bar{Y} = 0$. In the long time limit, when $e^{\alpha t} \gg 1 \gg e^{-\alpha t}$, the dispersion becomes

 $D = 2/3dx^3e^{2\alpha t}.$

435 If one is using a diffusive fit,

 $436 D = 4\kappa_D t,$

437 to approximate diffusivity, then the resulting diffusivity is

$$\kappa_D = \frac{dx^3 e^{2\alpha t}}{6t}$$

438 On the other hand, the encounter volume for the linear strain flow is

- $V = 2\alpha R^2 t,$
- 440 whereas the long-time diffusive fit is
- 441
- 442 yielding

$$\kappa_V = -\frac{\alpha R^2 Product Log(-\frac{\pi e^{2\gamma}}{2\alpha t})}{2\pi}$$

 $V=\frac{4\pi\kappa_V t}{\ln t/\tau},$

443

444 where the function ProductLog(z) is a solution to $z = we^w$. Because κ_D is exponential in time, 445 while κ_V is not, κ_D always becomes larger than κ_V at large *t*.

446

Of course, real oceanic flows are more complex than the simple linear strain example. However,for flows that are in a state of chaotic advection, exponential separation between neighboring

449 particles will occur and the dispersion will grow exponentially in time, as in the linear strain example. Although we do not have a formula for the encounter volume for a chaotic advection 450 regime, the linear strain example suggests that the encounter volume growth will likely be slower 451 than exponential. Thus, for a chaotic advection regime, the dispersion-based diffusivity could be 452 453 expected to be larger than the encounter-volume-based diffusivity. This can potentially explain the smaller encounter-volume-based diffusivity values in Fig. 4 compared to other available 454 estimates from the literature. Numerical simulations (not shown) using an analytic Duffing 455 oscillator flow, which features chaotic advection, indeed produced smaller encounter-volume-456 based diffusivity than dispersion-based diffusivity, in agreement with our arguments above. The 457 AVISO velocities are dominated by the meso- rather than submeso-scales, and the 90-day time 458 interval is about a few mesoscale eddy winding times, thus this flow satisfies all the pre-459 requisites for the chaotic advection to occur. Finally, the particle trajectories that we used to 460 produce Fig. 4 can be grouped into small clusters (we are using encounter radius R=30 km as a 461 462 cluster radius for consistency) to estimate their dispersion and infer diffusivity from its slope. Consistent with our arguments above, the resulting dispersion-based diffusivities in Fig. 6 are 463 larger than the encounter-volume-based diffusivities in Fig. 4 and reach values $O(10^4 m^2/s)$ in 464 the energetic regions of the Gulf Stream and its extension, in agreement with the previous 465 diffusivity estimates from the literature. In applications where the number of encounters is a 466 more important quantity than the spread of particles, the encounter-volume-based diffusivity 467 might be a more appropriate estimate to use. 468

469

470 In the left panels of Fig. 4 we used the full velocity field to advect trajectories, so both the mean 471 and the eddies contributed to the resulting encounter volumes and the corresponding 472 diffusivities. But what is the contribution of the eddy field alone to this process? To answer this question, we have performed an additional simulation in the spirit of Rypina et al. (2012), where 473 474 we advected trajectories using the altimetric time-mean velocity field, and then subtracted the resulting encounter volume, V_{mean} , from the full encounter number, V. The result characterizes 475 the contribution of eddies, although strictly speaking $V_{eddy} \neq V - V_{mean}$ because of non-476 linearity. Note also that because we are interested in the Lagrangian-averaged effects of eddies 477 following fluid parcels, V_{eddy} cannot be estimated by simply advecting particles by the local 478 eddy field alone (see an extended discussion of this effect in Rypina et al., 2012). Not 479 surprisingly, the eddy-induced encounter volumes (upper right panel of Fig. 4) are smaller than 480 the full encounter numbers, with the largest decrease near the Gulf Stream current, where both 481 the mean velocity and the mean shear are large. In other geographical areas, specifically at the 482 483 peripheries of the Gulf Stream rings, the decrease in V is less significant, so the resulting map retains its overall qualitative spatial structure. The same is true for the diffusivities in the 2nd and 484 3rd rows of Fig. 4. The overall spatial structure of the eddy diffusivity is preserved and matches 485 that in left panels, but the values decrease, with the largest differences near the Gulf Stream, 486 where some diffusivity values are now $O(10^6) \ cm^2/s$ instead of $O(10^7) \ cm^2/s$. In contrast, κ 487 only decreases, on average, by a factor of 2 (instead of an order of magnitude) near the 488

peripheries of the Gulf Stream rings. The long-time diffusive time scale τ generally increases, and the ratio t/τ generally decreases throughout the domain, but the long-time asymptotic formula (38) still works well in high-V regions, specifically on the peripheries of the Gulf Stream rings where τ is still significantly less than t.

- 493
- 494 4. Discussion and Summary

495 With many new diagnostics being developed for characterizing mixing in fluid flows, it is important to connect them to the well-established conventional techniques. This paper is 496 497 concerned with understanding the connection between the encounter volume, which quantifies 498 the mixing potential of the flow, and diffusivity, which quantifies the intensity of the downgradient transfer of properties. Intuitively, both quantities characterize mixing and it is natural to 499 expect a relationship between them, at least in some limiting sense. Here, we derived this 500 anticipated connection for a diffusive process, and we showed how this connection can be used 501 502 to produce maps of spatially-varying diffusivity, and to gain new insights into the mixing 503 properties of eddies and the particle spreading regime in realistic oceanic flows.

When applied to the altimetry-based velocities in the Gulf Stream region, the encounter volume 504 and diffusivity maps show a number of interesting physical phenomena related to transport and 505 mixing. Of particular interest are the transport properties of the Gulf Stream rings. The 506 materially-coherent Lagrangian cores of these rings, characterized by very small diffusivity, are 507 508 smaller than expected from earlier Eulerian diagnostics (Chelton et al., 2011). The periphery 509 regions with enhanced diffusivity are, on the other hand, large, raising a question about whether the rings, on average, act to preserve coherent blobs of water properties or to speed up the 510 mixing. The encounter volume, through the derived connection to diffusivity, might provide a 511 512 way to address this question and to quantify the two effects, clarifying the role of eddies in transport and mixing. 513

514 Our encounter-volume-based diffusivity estimates are within the range of other available 515 estimates from the literature, but are not among the highest. We provided an intuitive explanation 516 for why the encounter-volume-based diffusivities might be smaller than the dispersion-based 517 diffusivities, and we supported our explanation with theoretical developments based on a linear 518 strain flow, and with numerical simulations. We note that in problems where the encounters 519 between particles are of interest, rather than the particle spreading, the encounter-volume-based 520 diffusivities would be more appropriate to use than the conventional dispersion-based estimates.

Reliable data-based estimates of eddy diffusivity are needed for parameterizations in numerical models. The conventional estimation of diffusivity from Lagrangian trajectories via calculating particle dispersion requires large numbers of drifters or floats (LaCasce, 2008). It would be useful to have a technique that would work with fewer instruments. The derived connection between encounter volume and diffusivity might help in achieving this goal. Specifically, one could imagine that if an individual drifting buoy was equipped with an instrument that would 527 measure its encounter volume – the volume of fluid that came in contact with the buoy over time 528 t – then the resulting encounter volume could be converted to diffusivity using the derived 529 connection. This would allow estimating diffusivity using a single instrument.

530 In the field of social encounters, it is becoming possible to construct large data sets by tracking 531 cell phones, smart transit cards (Sun, et al. 2013), and bank notes (Brockmann, et al. 2006). As 532 was the case for the Gulf Stream trajectories, some of the behavior appears to be diffusive and 533 some not so. Where diffusive/random walk behavior is relevant, it may be easier to accumulate 534 data on close encounters rather than on other metrics using, for example, autonomous vehicles 535 and instruments that are able, through local detection capability, to count foreign objects that 536 come within a certain range.

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687 Fig. 1. Schematic diagram of trajectory encounters, showing trajectories of 9 particles, with dots indicating positions of particles at 3 time instances, at the release time, t_0 , and at two later times, $t_0 + T_1$ and $t_0 + T_2$. The reference trajectory and the encounter sphere are shown in black, trajectories that do not encounter the reference trajectory are in grey, and trajectories that encounter the reference trajectory are in green if the encounter occur at $t_0 + T_1$, and in blue if encounters occur at $t_0 + T_2$. Time slices are schematically shown by dashed rectangles, and the encounter number, N, is indicated at the top of each time slice.



709	Figure 2. Schematic diagram in 1D (left) and 2D (right). Hatched areas show semi-infinite domains outside of the cliff.
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721Figure 3. Comparison between theoretical expression (red, green, blue) and numerical estimates (black) of the encounter722volume for a random walk in 1D (left) and 2D (right). In both, $\kappa = 5$ and $\Delta t = 0.5$. In 2D, $\tau \approx 20$.



Figure 4. Encounter number (1st row), exact diffusivity (2nd row), long-time diffusivity (3rd row) and diffusive time-scale (4 th row) for the full flow (left) and for the eddy component of the flow (right). White shows land and thick black curve shows coastline. The encounter volume was computed on 11/01/2015 over 90 days with encounter radius of 30 km.



Figure 5. Comparison between numerically-computed V (solid) and the exact (dotted) and long-time diffusive formulas (dashed) with the corresponding κ for the 3 reference trajectories located in the core, periphery and outside (black, red, blue) of a Gulf Stream ring.



Figure 6. Dispersion-based diffusivity, κ_D .