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#### **Key Points:**

- Consistent with DNS, microstructure data show Ri<sub>f</sub> ≈ 0.2 for Re<sub>B</sub> < O(100)</li>
- Consistent with DNS, covariance-derived fluxes show that Ri<sub>f</sub> varies with Re<sub>B</sub> for Re<sub>B</sub> > O(100)
- Consideration of different studies shows that Ri<sub>f</sub> in general depends on Re<sub>B</sub>, but in a way that must depend on other parameters as well

#### **Supporting Information:**

· Supporting Information S1

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# Mixing Efficiency in the Presence of Stratification: When Is It Constant?

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**Abstract** The efficiency of the conversion of mechanical to potential energy, often expressed as the flux Richardson number,  $Ri_f$ , is an important determinant of vertical mixing in the ocean. To examine the dependence of  $Ri_f$  on the buoyancy Reynolds number,  $Re_B$ , we analyze three sets of data: microstructure profiler data for which mixing is inferred from rates of dissipation of turbulent kinetic energy ( $\varepsilon$ ) and temperature variance ( $\chi$ ) measured in the open ocean, time series of spectrally fit values of  $\varepsilon$  and covariance-derived buoyancy fluxes measured in nearshore internal waves, and time series of spectrally fit values of  $\varepsilon$  and  $\chi$  measured in an energetic estuarine flow. While profiler data are well represented by  $Ri_f \approx 0.2$  for  $1 < Re_B < 1,000$ , the covariance data have much larger values of  $Re_B$  and, consistent with direct numerical simulation results, show that  $Ri_f \sim Re_B^{-0.5}$ . The estuarine data have values of  $Re_B$  that fall between those of the other two data sets but also shows  $Ri_f \approx 0.2$  for  $Re_B < 5000$ . Overall, these data suggest that  $Ri_f$  is in general not constant and may be substantially less than 0.2 when  $Re_B$  is large, although the value at which the transition from constant to  $Re_B$ -dependent mixing may depend on additional parameters that are yet to be determined. Nonetheless, for much of the ocean,  $Re_B < 100$  and so  $Ri_f$  is constant there.

Plain Language Summary The efficiency of turbulent mixing, the rate at which mechanical energy of turbulence is converted into changes in potential energy, plays a central role in determining the dynamics of ocean circulation and the transport of carbon. This efficiency is commonly assumed to be constant, although there is evidence that it can depend on the strength of the turbulence, measured by the rate of dissipation of the turbulence energy, and the strength of the density stratification. Notably, ocean circulation models with variable efficiency produce different flows than do ones with constant efficiency. Using three oceanic data sets, including the large body of microstructure data acquired over the past 20 years, we analyze how efficiency varies with turbulence strength. Consideration of these data, and other published data, shows that mixing efficiency is, as commonly assumed, likely to be constant in much of the ocean. In contrast, in places that are highly turbulent, for example, very energetic currents, it might be relatively low. We show that at present, what controls the transition from constant to variable efficiency remains uncertain, although reanalysis of existing microstructure data in energetic parts of the ocean should help clarify the extent to which mixing efficiency varies in these regions.

### 1. Introduction

Turbulent mixing in the ocean is strongly affected by density stratification (Turner, 1973), behavior that is important to controlling distributions of water properties as well as functioning of many marine ecosystems. The extent to which turbulent mixing is affected by stratification can be represented by the flux Richardson number,  $Ri_f$ , defined by Ivey and Imberger (1991) as

$$Ri_{f} = \frac{B}{B + \varepsilon} \tag{1}$$

where B is the turbulent buoyancy flux and  $\varepsilon$  is the rate of dissipation of turbulent kinetic energy (TKE). Equation (1) generalizes Turner's (1973) definition for which  $B + \varepsilon$  is replaced by the rate of TKE production, P. In steady, homogeneous turbulence  $P = B + \varepsilon$ , whereas more generally  $B + \varepsilon$  represents the net supply of TKE including P, vertical divergence of TKE flux, and the rate of change of TKE with time.

Equation (1) is advantageous in that  $\varepsilon$  can be estimated with shear profilers (see, e.g., Gregg et al., 2018), and B can be computed from estimates of  $\chi$ , the rate of dissipation of temperature variance, as

$$B; \left(\frac{\partial T}{\partial z}\right)^{-2} \frac{\chi}{2} N^2 \tag{2}$$

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where N is the buoyancy frequency and T is the depth (z)-variable mean density profile (Osborn & Cox, 1972). Additionally, B defined by equation (2) is a good estimate of mixing efficiency because it measures irreversible mixing as opposed to covariance-based values of B, which can include both reversible and irreversible processes (Caulfield & Peltier, 2000). Nonetheless, for the most part, following Osborn (1980), microstructure-based measurements of ocean mixing have assumed that  $Ri_f = 0.17$  and computed mixing rates solely from measurements of  $\varepsilon$ , although Osborn carefully argues that 0.17 is only an upper bound on  $Ri_f$ .

Gregg et al. (2018) argue that because estimates of vertical mixing based on  $Ri_f = 0.17$  do not differ significantly from values inferred from tracer dispersion (e.g., Ruddick et al., 1997), "... observations should continue to be scaled with [0.17] until observations, laboratory experiments, and numerical simulations converge on a more accurate formulation." However, this view overlooks the body of evidence that shows that  $Ri_f$  can be substantially less than 0.17 when turbulence is energetic and stratification is weak. The direct numerical simulations (DNSs) of stratified shear flows reported in Shih et al. (2005), as well as laboratory experiments (Barry et al., 2001), microstructure profiling (Bouffard & Boegman, 2013), and direct measurements of B in nearshore breaking internal waves (Davis & Monismith, 2011; Walter et al., 2014), show relationships of the form:

$$Ri_f = C \operatorname{Re}_8^{-1/2} \tag{3}$$

where the buoyancy Reynolds number, Reg, is defined as (Gibson, 1980)

$$Re_{B} = \frac{\varepsilon}{vN^{2}} \tag{4}$$

when  $Re_B > O(100)$ . C varies from 1.5 (Shih et al., 2005) to 4 (Bouffard & Boegman, 2013). When  $Re_B < O(100)$ ,  $Ri_f$  is found to be a constant  $\leq$ 0.25. As noted by de Lavergne et al. (2016) and Mashayek et al. (2017), a dependence of  $Ri_f$  on  $Re_B$  of this type may be significant in determining the importance of internal wave breaking to the general circulation. Nonetheless, not all data taken with large values of  $Re_B$  obey equation (3). In particular, estimates of  $Ri_f$  reported by Holleman et al. (2016) for an energetic estuarine flow (median  $Re_B \approx 2,000$ ) have a median value of  $Ri_f = 0.21$ .

Motivated by the differences between the results cited by Gregg et al. (2018) showing  $Ri_f \approx 0.17$ , and the various experiments and observations that show  $Ri_f$  ( $Re_B$ ), we examined the constancy of  $Ri_f$  using the Scripps Institute of Oceanography database of microstructure profiler observations (Waterhouse et al., 2014). In this database there are eight data sets that include both  $\varepsilon$  and  $\chi$ , and so can be used to compute  $Ri_f$ . As we will show below, these data, which mostly have  $Re_B < O(100)$ , strongly support the contention that in general  $Ri_f$  is constant. In contrast, a composite of four data sets in which buoyancy fluxes were measured directly and for which  $Ri_f$  ( $Re_B$ ) follows equation (3) is characterized by much higher values of  $Re_B$  ( $Re_B$ ) and much smaller values of  $Ri_f$  ( $Re_B$ ) follows equation (3) is characterized by much higher values of  $Re_B$  ( $Re_B$ ) and much smaller values of  $Ri_f$  ( $Re_B$ ) follows equation (3) is characterized by much higher values of  $Re_B$  ( $Re_B$ ) follows equation (3) is characterized by much higher values of  $Re_B$  ( $Re_B$ ) follows equation (3) is characterized by much higher values of  $Re_B$  ( $Re_B$ ) follows equation (3) is characterized by much higher values of  $Re_B$  ( $Re_B$ ) follows equation (3) is characterized by much higher values of  $Re_B$  ( $Re_B$ ) follows equation (3) is characterized by much higher values of  $Re_B$  ( $Re_B$ ) follows equation (3) is characterized by much higher values of  $Re_B$  ( $Re_B$ ) follows equation (3) is characterized by much higher values of  $Re_B$  ( $Re_B$ ) follows equation (3) is characterized by much higher values of  $Re_B$  ( $Re_B$ ) follows equation (3) is characterized by much higher values of  $Re_B$  ( $Re_B$ ) follows equation (3) is characterized by much higher values of  $Re_B$  ( $Re_B$ ) for  $Re_B$  (

## 2. Methods

The microstructure profiler data we use come from the National Science Foundation-supported microstructure database curated by Dr. Amy Waterhouse and Prof. Jennifer McKinnon (https://microstructure.ucsd.edu). Specifically, we use profiles of salinity, temperature,  $\varepsilon$ , and  $\chi$  taken in studies of mixing below the thermocline reported at either 0.5- or 1-m intervals. Eight of the data sets in the archive have all four variables (see Table 1).  $N^2$  was computed from salinity and temperature using the EOS 80 Seawater toolbox, and the adiabatic leveling method of Bray and Fofonoff (1981), as recommended by the Microstructure working group (A. Waterhouse, personal communication, 2017). Points with  $N^2 \le 0$  were excluded from further analysis. Also, based on the work of St. Laurent and Schmitt (1999), to avoid regions in which double diffusion may be active, only points with  $0.5 < R_{\rho} < 2$  where  $R_{\rho} = \alpha (dT/dz)/\beta (dS/dz)$ , were used. These raw data were then averaged over 10 m using a moving average. B was computed using equation (2).

The second data set is a set of four studies of stratified nearshore flows that involved direct measurements of B via measurement of covariance of fluctuating densities and vertical velocities using acoustic Doppler velocimeters and conductivity and temperature sensors, and  $\varepsilon$  via inertial subrange fitting of vertical velocity spectra, both computed using 10-min averaging periods. The measurement protocols are described in



Table	1	
Mixina	Data	Sets

Data set	Study	Re <sub>B</sub> <sup>a</sup>	Ri <sub>f</sub> b	Segments <sup>c</sup>	Data source/PI
Microstructure	NATRE	18	0.2	31,248	K. Polzin
	BBTRE96/97	49	0.17	36,421	K.Polzin, L. St. Laurent, J. Toole
	SPAM1/2	8.9	0.27	26,781	G. Carter
	MIXET2	1.2	0.65	2281	G. Carter
	EXITS1	8.6	0.14	464	G. Carter
	GRAVILUCK	107	0.19	2529	L. St. Laurent and A. Thurnherr
Covariance	Various (see references in text)	9330	0.015	2,594	S. Monismith
Estuarine	Holleman et al. (2016)	1840	0.21	994	R. Holleman and W. R. Geyer

aValues of Re<sub>B</sub>. bRi<sub>f</sub> shown are median values for each data set. <sup>c</sup>For microstructure data, "segments" refers to 10 m bins in vertical profiles; for covariance data, segments refers to 10-min averaging periods; and for estuarine data, segments refers 20-s averaging periods, which represent ~30 m in the streamwise direction.

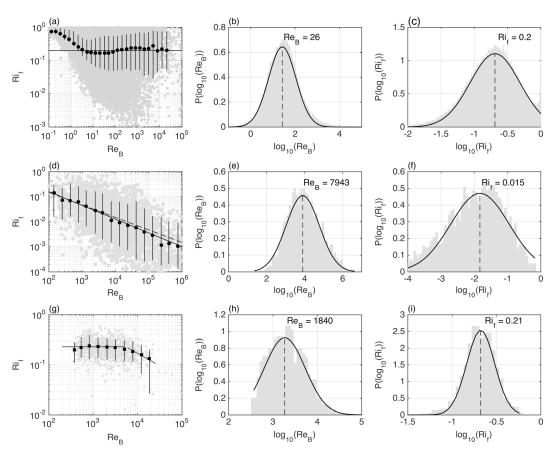
details in Davis and Monismith (2011) and Walter et al. (2014), where results for flow dynamics, mixing, etc., are also given. In addition to these two data sets, we also include two other similar data sets, the first from internal tides propagating over a Red Sea coral reef (Dunckley, 2012) and the second from shoaling internal tides in Mamala Bay (Squibb, 2014). Instrumentation and data processing used in these latter two studies were identical to those used in Davis and Monismith (2011) and Walter et al. (2014). In all cases errors in estimation of  $\varepsilon$  and B were generally less than 27% and 57%, respectively, for any single averaging period, giving a maximum uncertainty in any single value of  $Ri_f$  of 60%; that is,  $Ri_f$  was between 40% and 160% of the measured value (Davis & Monismith, 2011), while relatively large, this is still smaller than the scatter in  $Ri_f$  shown below for the covariance data. To eliminate possible variability associated with small values of  $N^2$  (cf. Gregg et al., 2018], data with  $N^2 < 2 \times 10^{-5}$  s<sup>-2</sup> (corresponding to  $dT/dz \sim 0.01^\circ/m$ ) were excluded from the analysis we present here. It is important to note that in all four cases,  $Ri_f$  can be fit with equation (3). Detailed analysis of these four data sets will be presented elsewhere.

A third data set that we consider is that of Holleman et al. (2016), who measured both  $\varepsilon$  and  $\chi$  in a strongly sheared and stratified estuarine flow using an array of acoustic Doppler velocimeters and conductivity and temperature sensors deployed from a moving boat. Holleman et al. determined  $\varepsilon$  and  $\chi$  using spectral fitting, and B was then computed using equation (2).

# 3. Results

The microstructure profiler data shown in Table 1 represent approximately 100,000 segments falling primarily in the ranges  $0.1 < Re_B < 10^4$  and  $10^{-3} < Ri_f < 1$  (Figures 1a and 1c). The bulk of the data come from NATRE (Toole et al., 1994), from the two Brazil Tracer Release programs (St. Laurent et al., 2001) and from the Samoan Passage programs (Alford et al., 2013). Remarkably, binning the data by  $Re_B$  shows that for  $Re_B > 10$ , approximately where one may expect a transition from internal waves to active turbulence (Gibson, 1980), the median value of  $Ri_f \approx 0.17$ , as first suggested by Osborn (1980), and as found by Shih et al. (2005) for  $10 < Re_B < 60$ . The confidence intervals determined by bootstrapping (Efron & Tibshirani, 1993; not shown) are essentially zero, except at the largest values of  $Re_B$ , where there are few points. Surprisingly,  $Ri_f$  increases with decreasing Re<sub>B</sub> when  $Re_B < 10$ , reaching a maximum of nearly  $Ri_f \approx 0.7$  when  $Re_B \approx 0.1$ . As seen in the laboratory experiments of Davies Wykes and Dalziel (2014), this value of  $Ri_f$  has been shown to be nearly maximal and is typically found for turbulence produced by convection. It is possible that this result is an experimental artifact since these low values of  $Re_B$  correspond to small values of  $\varepsilon$  and  $\chi$ , which may not be well resolved by the profiler sensors (Polzin & Montgomery, 1998), or because the flow is undergoing transition to turbulence (Smyth et al., 2001). More generally, flows with  $Re_B < 1$  are not likely turbulent (Brethouwer et al., 2007) and so data with  $Re_B < 1$  may not properly represent vertical mixing. Likewise, for large values of  $Re_{Br}$   $\varepsilon$ and  $\gamma$  may be under-resolved because the shear probe and thermistor spatial resolutions are larger than the Kolmogorov and Batchelor scales, respectively.

The distributions of  $Re_B$  and  $Ri_f$  can be examined in more details by plotting histograms of the data (Figures 1b and 1c). Given that both variables vary over multiple decades, examination of the distributions of logarithms is appropriate. Here too, a second remarkable feature of the profiler data set emerges: both

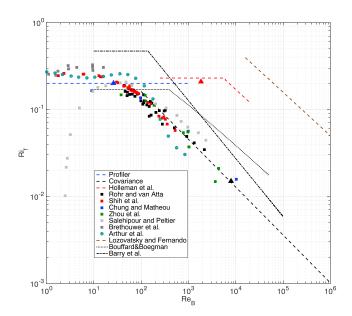


**Figure 1.**  $Ri_f$  and  $Re_B$  for three turbulent mixing data sets.  $Ri_f$  as a function of  $Re_B$  is given for (a) microstructure profiler data, (d) covariance data, and (g) estuarine data of Holleman et al. (2016). The closed symbols represent median values of  $Ri_f$  with error bars showing 10th and 90th percentiles of the data in each bin. The solid lines represent fits to the binned data, whereas the dashed line in (d) is the relation found by Shih et al. (2005). Histograms of (b, e, and h)  $Re_B$  and (c, f, and i)  $Ri_f$  are also given for the same three data sets. In each of these panels the solid lines show least squares fits to lognormal distributions with histograms and fits are scaled so that the integral of the lognormal fitted pdf is 1.

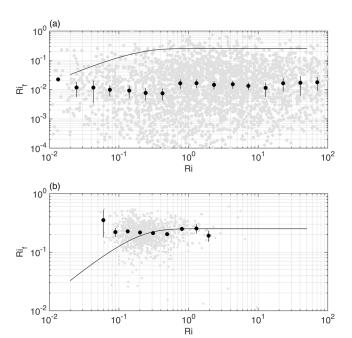
 $Ri_f$  and  $Re_B$  are distributed lognormally, despite good reasons to believe that this should not be the case (Yamazaki & Lueck, 1990). This lognormality holds for each of the data sets individually (see the supporting information) and also is seen in the float data presented by Salehipour et al. (2016). As seen in Figure 3, the median value of  $Re_B = 26$  (Salehipour et al. find  $Re_B \approx 30$ ), and the median value of  $Ri_f = 0.2$ , behavior that is consistent with the results of Shih et al. (2005) for  $Re_B < 60$ .

The results of the four covariance data sets paint a somewhat different picture. These data are characterized by a clear dependence on  $Re_B$ , much large values of  $Re_B$ , that is,  $100 < Re_B < 10^6$ , and somewhat smaller values of  $Ri_f$ , that is,  $10^{-5} < Ri_f < 1$  (Figures 1d and 1f). Least squares fitting of  $Ri_f$  binned by quarter decades of  $Re_B$  shows that  $Ri_f = 2 Re_B^{-0.55}$  ( $r^2 = 0.96$ ), which is remarkably close to the Shih et al. (2005) relation (Figure 1d). These data also show the lognormality seen in the profiler data, with the median value of  $Re_B = 7943$  and the median value of  $Ri_f = 0.015$ . Thus, the covariance data set describes much more energetic turbulence than does the profiler data, and, consistent with the results of Shih et al. (2005), has much lower mixing efficiencies.

In contrast, the estuarine data set of Holleman et al. (2016) has  $Ri_f \approx$  constant for somewhat higher values of  $Re_B$  than does the covariance data set (Figure 1g), although there is also a decrease of  $Ri_f$  with  $Re_B$  for  $Re_B > 5,000$ . These data have a range of values of  $Re_B$  that lie between those of the profiler data sets and those of the covariance data sets (Figure 1h). Like the other data, the probability density function of  $Re_B$  is well described by the lognormal distribution. Agreeing well with the profiler data (but not the covariance data), the median value of the estuarine data is  $Ri_f = 0.21$ , and, as seen with the two other data sets, is distributed lognormally (Figure 1i).



**Figure 2.** Schematic of different observations of  $Ri_f$  and  $Re_B$ . Symbols as given in the legend. Curves for "Profiler," "Covariance," and "Holleman et al" represent the fits and  $Re_B$  ranges seen in Figure 1, with the large triangles showing the median values of  $Ri_f$  and  $Re_B$  for each of these three data sets. Other field data are from Lozovatsky and Fernando (2013) (atmospheric boundary layer) and Bouffard and Boegman (2013). DNS data are from Shih et al. (2005), Chung and Matheou (2012), Zhou et al. (2017), Salehipour and Peltier (2015), Brethouwer et al. (2007), and Arthur et al. (2017). Lab data for homogeneous shear are from Rohr and van Atta (1987), and for homogeneous un sheared, stirred turbulence from Barry et al. (2001).



**Figure 3.**  $Ri_f$  as a function of Ri for (a) covariance data and (b) estuarine data of Holleman et al. (2016). The closed symbols are quarter-decade bin averages with error bars determined by bootstrapping. The solid line in each figure is the formula given by Vennaygamoorthy and Koseff (2016):  $Ri_f = 0.25(1 - \exp[-7Ri])$ .

Holleman et al. (2016) argued that the reduced values of  $Ri_f$  at large values of  $Re_B$  seen in their data were an effect of boundary proximity (see also Scotti & White, 2016). However, the reduction in  $Ri_f$  at large Re<sub>B</sub> appears to reflect the fact that the highest values of Re<sub>B</sub> coincide with smallest values of  $(z/L_O)$ , for z the height above the bed and  $L_O = (\varepsilon/N^3)^{0.5}$  the Ozmidov length (Turner, 1973). Indeed, for values of  $Re_B$  where there are data with both  $(z/L_O)$  <10 or >10 (the cutoff used by Holleman et al.),  $Ri_f$  does not appear to depend on  $(z/L_O)$  (see the supporting information). These two points also hold for the covariance data (see the supporting information). Large values of Reg mostly occur for small values of  $(z/L_O)$ , and  $Ri_f$  ( $Re_B$ ) tends to not depend separately on  $(z/L_O)$ . It should be noted that the two data sets have somewhat different values of  $(z/L_O)$ : For the Holleman et al. data  $1 < (z/L_O) < 50$ with a median value of 9, whereas for the covariance data,  $0.05 < (z/L_O) < 100$  with a median value of 3.8. In both cases, the issue is that  $L_O$  and  $Re_B$  involve the same variables ( $\varepsilon$  and  $N^2$ ) and so are themselves well correlated.

#### 4. Discussion

From the standpoint of statistical averages, it is clear that much of the ocean below the mixed layer, at least as far as it has been sampled by microstructure profilers, and, as argued by Gregg et al. (2018), is well characterized by  $Ri_f = 0.2$ , albeit with substantial variability. Given that a majority of these data have  $10 < Re_B < 100$ , the regime where  $Ri_f$  is expected to be constant, this result is consistent with the findings of Shih et al. (2005) as well as others (e.g., Barry et al., 2001). In contrast, the covariance data all have  $Re_B > 100$ , and, per Shih et al. (2005), fall in the regime described by equation (3) and so  $Ri_f$  should be substantially less than 0.2, as observed.

For  $Re_B > 100$ , the covariance data appear to agree closely with the DNS results for homogeneous shear of Shih et al. (2005) and Chung and Matheou (2012); the DNS of Kelvin-Helmholtz instabilities of Salehipour and Peltier (2015); the DNS of stratified Couette flow reported by Zhou et al. (2017), albeit only in the center of their channel; and laboratory results for stratified, homogeneous stratified shear flows given by Rohr and van Atta (1987), that is, as seen in their Figure 7a. Moreover, countering the concern of various authors (e.g., Gregg et al., 2018) that the Shih et al. DNS results are affected by numerical artifacts, Figure 2 shows that the Rohr and van Atta experimental data, for which the length scales are not limited by the channel size nor are the smallest scales under-resolved, are remarkably close to the DNS results of Shih et al. Thus, it is clear that the Shih et al. results represent the steady, homogeneous shear limit of mixing by stratified turbulence and that the turbulence seen in the four covariance data sets appears to conform best to the dynamics of this limiting flow case.

The Holleman et al. (2016) data for  $Ri_f$  also make a transition to a dependence on  $Re_B$ , albeit at a much higher value of  $Re_B$  than what is seen in any of the other lab or oceanic data sets, that is, 70 (Shih et al., 2005), 200 (Barry et al., 2001), and 400 (Bouffard & Boegman, 2013). Moreover, stable atmospheric boundary layers (SABL) that satisfy Monin-Obukhov scaling (e.g., Grachev et al., 2015) do not show a unique relationship of the form  $Ri_f = f(Re_B)$ , although any individual



data set might show such a relation (Scotti & White, 2016). Indeed, the SABL data of Lozovatsky and Fernando (2013) do satisfy equation (3), except that the constant of proportionality *C* is much larger than values seen in DNS and oceanic studies.

There is no reason to believe that any of the different data sets have methodological biases that would explain why they differ. Thus, as argued by Scotti and White (2016) and Gregg et al. (2018),  $Ri_f$  cannot depend only on  $Re_B$ . Indeed, Salehipour et al. (2016) follow this approach and choose  $Ri_f = g$  (Ri,  $Re_B$ ), where the gradient Richardson number  $Ri = N^2/S^2$ . As seen in Figure 3, neither the covariance nor the estuarine data appear to depend systematically on Ri. In particular, they do not match the function  $Ri_f$  (Ri) described in Vennaygamoorthy and Koseff (2016), a function that fits Pi0 the Shih et al. (2005) DNS data and the SABL data of Lozovatsky and Fernando (2013) reasonably well. Unfortunately, the microstructure database does not include values of Ri, so no conclusions can be drawn as to its importance for the profiler data. On the other hand, it is striking that the covariance data include a much wider range of values of Ri (0.01 to 100) than does the Shih et al. DNS (0.16 to 1) yet Pi1 yet Pi2 is nearly identical in the two cases.

More generally, depending on which other dimensional variables are thought to be important, for example, S, the Buckingham Pi theorem (e.g., Street et al., 1996) specifies the number of dimensionless variables that may serve to define  $Ri_f$ . That is, if there are n variables, which likely would only have units of meters and seconds,  $Ri_f$  could at most depend on (n-3) dimensionless variables. Thus, if the only relevant variables are B,  $\varepsilon$ , v, and  $N^2$ , then  $Ri_f$  must be only a function of  $Re_B$ . If S, TKE, k, and turbulent length scale  $I_t$  are also thought to be important, then three other parameters upon which  $Ri_f$  could depend would be Ri, the Froude number  $Fr_k = \varepsilon/Nk$  (Maffioli et al., 2016), and  $Fr_t = (L_O/L_t)^{2/3}$  (Ivey & Imberger, 1991). We note that few data sets include S and fewer still include k; neither is reported in the microstructure database. However, the covariance data set also differs significantly in  $Fr_k$  values from those of Shih et al. (2005), so would produce different  $Ri_f$  ( $Fr_k$ ) functional relationships (not shown), suggesting that  $Ri_f$  ( $Fr_k$ ) is not likely to be universal either. If  $L_t$  is taken to be the Thorpe scale, the length scale of overturns seen in profiles, it could be calculated from microstructure data, although for weak stratification, it could be highly dependent on sensor noise. This would be worth exploring in the future, especially given that the Thorpe scale and the Ellison scale, the scale defined by time series of the fluctuating density (Ivey et al. 2018), are closely correlated, thus facilitating comparable analysis of both types of data.

Finally,  $L_t$  could be assumed to be proportional to the height, z, above a solid boundary, as in Monin-Obukhov theory (Grachev et al., 2015), although as seen above, neither of the two data sets for which  $z/L_O$  was available could dependence of  $Ri_f$  on  $z/L_O$  be differentiated from dependence on  $Re_B$ . In any case, it is possible that  $Ri_f$  is dependent on more than local, instantaneous conditions; for example, besides parameters like  $Re_B$ ,  $Ri_f$  may also depend on how the given flow was established or is maintained (Mashayek et al., 2017).

The difference between  $Ri_f = 0.2$  and  $Ri_f \approx 2$   $Re_B^{-0.5}$  (taking an approximate average of the various values of C in equation (3) from the various published studies) can be significant when  $Re_B$  is large. For example, microstructure data reported by Mead Silvester et al. (2014) in the Antarctic Circumpolar Current have  $Re_B = 0(10^6)$  (T. Rippeth, personal communication, 2017) implying values of  $Ri_f$  that would be 100 times smaller than the value of 0.2 seen in much of the profiler data. Unfortunately,  $\chi$  is not likely to be resolved directly in energetic regions like this or in bottom boundary layers like that studied by Nash et al. (2004). However, the method described by Bluteau et al. (2017) in which  $\chi$  is determined from profiler data by fitting of temperature and salinity variations may be a useful way of inferring  $\chi$ , and thus for inferring  $\mu$  for portions of the ocean for which  $\mu$  cannot be measured directly. Indeed, it appears that at present, the best way forward would be to apply the approach of Bluteau et al. to existing data sets from energetic parts of the ocean where  $\mu$  is large, for example, bottom boundary layers (Nash et al. (2004) or strong current systems (Mead Silvester et al., 2014).

The profiler data, as well as all of the DNS results shown in Figure 2, including DNS studies of stirred stratified turbulence by Brethouwer et al. (2007) and of breaking internal waves by Arthur et al. (2017), and excepting those of Salehipour and Peltier (2015), show constancy of  $Ri_f$  for  $1 < Re_B < 10$ , a regime where the irreversible mixing can differ considerably from the covariance-based buoyancy flux (Vennaygamoorthy & Koseff, 2016). A nonzero  $Ri_f$  is unexpected given that  $B \approx 0$  might be expected for these conditions. The behavior for Salehipour and Peltier's results for  $Re_B < 10$  may reflect the fact that  $Ri_f$  and  $Re_B$  were computed using



volume averages, which can differ from averages calculated with local values of N, etc. (cf. Arthur et al., 2017). In any case, the small  $Re_B$  regime clearly deserves further attention.

#### 5. Conclusions

We agree with the assertion of Gregg et al. (2018) that this issue of constancy or variability of  $Ri_f$  is not settled. However, examination of data not considered by Gregg et al. shows that there is clear evidence that  $Ri_f$  can vary with  $Re_B$  such that  $Ri_f$  is small when  $Re_B$  is large in the fashion described by Shih et al. (2005). Indeed, the general structure of  $Ri_f(Re_B)$  that emerges from presently available data is one in which  $Ri_f(Re_B)$  has a constant portion for  $Re_B$  less than some transitional value and then decays approximately like  $Re_B^{-1/2}$  for larger values of  $Re_B$ . At a minimum, all the data sets agree that  $Ri_f \approx 0.2$  for  $Re_B < O(100)$ . In agreement with Shih et al., the covariance data sets show the  $Ri_f \sim Re_B^{-0.5}$  for  $Re_B > 100$ , whereas the estuarine data of Holleman et al. (2016) show a transition to  $Ri_f \sim Re_B^{-0.5}$  near  $Re_B \approx 5,000$ . Overall, these results suggest that while  $Ri_f$  is not constant and does depend on  $Re_B$ , it does not uniquely depend of  $Re_B$ . In terms of inferring mixing from dissipation data in energetic portions of the ocean, it remains to be determined what sets the value of  $Re_B$  for the transition from constant  $Ri_f$  to a functional relationship of the form  $Ri_f \sim Re_B^{-1/2}$  occurs. Nonetheless, for much of the ocean interior  $Re_B < 100$  and so  $Ri_f$  is constant there.

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