On the Probability and Spatial Distribution of Ocean Surface Currents

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ABSTRACT

Insights into the probability distribution of ocean currents are important for various applications such as the chance to encounter extreme events, which may affect, for example, marine construction, and for estimating the energy that can be extracted from the ocean. In addition, for devising better parameterizations for submesoscale mixing, which present climate models cannot resolve, one should understand the velocity distribution and its relation to the various forcing of surface ocean circulation. Here, the authors investigate the probability distribution of surface currents from the Gulf of Elat/Aqaba measured by high-frequency radar. Their results show that the distribution of ocean current speeds can be approximated by a Weibull distribution. Moreover, the authors demonstrate the existence of spatial variations of the scale and shape parameters of the Weibull distribution over a relatively small region of only a few kilometers. They use a simple surface Ekman layer model to investigate this spatial variability. They find that, when forced by local winds, this model does not reproduce the observations. The addition of Gaussian noise to the zonal and meridional components of the bottom geostrophic currents has only a slight effect on the surface current distribution. However, noise added to the components of the local wind (mimicking wind gusts) has a much greater effect on the distribution of surface currents, suggesting that wind spatial and temporal variability underlay the observed spatial variability of the parameters of the Weibull distribution.

1. Introduction

Ocean currents are the cumulative result of local and remote factors, including winds, buoyancy fluxes, tides, and many types of waves; the influence of these forces on ocean currents is not trivial. Although wind distribution has been studied extensively in the past (e.g., Seguro and Lambert 2000), the distribution of ocean currents has received only a little attention (Chu 2008). In this work, we analyze the probability distribution of ocean surface currents measured by high-frequency (HF) radar. We show that the distribution of surface ocean current speeds may be approximated by the Weibull distribution and that the parameters of the distribution vary over relatively small spatial scales of the order of a few kilometers. Using a simple surface Ekman layer model, we show that this variability may be linked to wind spatial and temporal variability.

The motivation behind deriving this distribution is as follows: 1) For many practical applications, it is necessary to know the current distribution, especially for predicting the probability of extremely severe currents, to more efficiently manage maritime trade, breakwaters, ports, etc. 2) There is a need to parameterize subgrid lateral ocean mixing in numerical models. Because of limited computer power, present-day ocean and climate models usually resolve processes on scales as small as a few kilometers and have to parameterize processes on smaller scales. To better parameterize submesoscale ocean mixing, we should know the probability distribution function of surface currents. Although it was shown before that the distribution of surface current speed follows the Weibull distribution (e.g., Chu 2008) on the mesoscale and larger scales, here we demonstrate this relation for the submesoscale. 3) Finally, knowledge of the distribution of the currents can serve as a benchmark for ocean models;...
that is, one can test whether these models reproduce the same statistics of the observed currents.

Previous studies have either used a limited number of point measurements and therefore had limited spatial and temporal sampling (e.g., Chu 2008) or used velocities from numerical models (Bracco et al. 2003). Other studies have used currents derived from satellite altimeters (Gille and Smith 1998, 2000; Chu 2009) and found that surface current speed follows the Weibull distribution; these satellite data were collected approximately every 5 days and had a spatial resolution of 1° × 1°. In addition, a recent study (Laws et al. 2010) presented surface velocity probability distribution functions but did not discuss the shape of the probability distributions. Here, we extract the distribution of surface currents using a dataset of surface currents measured by HF radar. This dataset is characterized by a long time series (one year) with fine temporal (half hour) and spatial (~300 m) resolutions. These submesoscale radar observations therefore fill an important gap between point measurements [by current meter or acoustic Doppler current profiler (ADCP)] and mesoscale data (a few tens of kilometers). As mentioned above, we show that surface current distribution may be approximated by the Weibull distribution. Mapping of the scale and shape parameters of the Weibull distribution over a domain scale of 10–20 km indicates significant changes in these distribution parameters. Using a simple model, we suggest that wind spatial and temporal variability underlies the observed spatial variability of the parameters of the Weibull distribution.

In the next section (section 2), we describe the study region and the dataset used. In section 3, we review a few characteristics of the Weibull distribution. The results are presented in section 4. A simple surface Ekman layer model is then used to study the origin of the distribution of surface currents (section 5). We conclude in section 6.

2. Measurements methods and studied region

a. Study region

The northern terminus of the Gulf of Eilat/Aqaba (referred to here as the gulf) is a nearly rectangular, deep (~700 m; Fig. 1a), and semienclosed basin in the northeast region of the Red Sea. The gulf is bounded by a desert mountain range that steers the persistent northerly wind along its main axis (Berman et al. 2003). The circulation in the gulf has wind-driven, tidal, and thermohaline components. The tidal component is dominated by the semi-diurnal (M2) peak forced by the flux of water through the Straits of Tiran (Genin and Paldor 1998; Monismith and Genin 2004; Manasrah et al. 2006). The surface flow is quite complex most of the time, although occasionally a large (much of the domain) spatially coherent eddy (Fig. 1b) fills much of the domain (Gildor et al. 2010).

Cold, dense water from the World Ocean cannot flow into the gulf because it is blocked by the shallow sill (137 m) near Bab el Mandeb and the shallow sill (240 m) of the Tiran Strait (Genin 2008). Consequently, stratification across the entire water column in the gulf is relatively weak and deep water forms in situ. The weak density stratification breaks down in winter as a result of surface cooling and evaporation, and deep water forms (Wolf-Vecht et al. 1992; Genin et al. 1995; Biton et al. 2008; Biton and Gildor 2011a). In February–March, we find vertical homogeneity in temperature and salinity reaching a depth of a few hundred meters and sometimes down to the bottom, with new stratification beginning to form in March (Wolf-Vecht et al. 1992). In summer, the gulf is stratified with an upper warm layer of up to 200-m depth overlying a homogeneous deeper layer (Biton and Gildor 2011b). Accordingly, the first baroclinic Rossby radius changes seasonally, ranging from 6 to 20 km.

The configuration and dimensions (6 km × 10 km basin) of the northern gulf (Fig. 1a) enables observation of surface currents at a very high spatial and temporal resolution using HF radar, rendering this gulf a unique natural laboratory for studying submesoscale mixing processes. The HF radars provide two-dimensional maps of surface currents every 30 min with a spatial resolution of about 300 m.

During most of the year, the wind in Eilat region blows from the north, with a small easterly component (see section 5). Rarely, there are strong southerly winds. During the summer, there is a strong diurnal cycle associated with the diurnal breeze cycle (Saaroni et al. 2004). Rare strong wind events may occur in the wintertime, usually during southern storms. On average, the wind is stronger during summer.

b. Current measurements by HF radar

In recent years, HF radar systems for current measurements (Barrick et al. 1985; Gurgel et al. 1999b), such as the SeaSonde (Hodgins 1994) or Wellen Radar (WERA; Gurgel et al. 1999a) have been used throughout the world, mainly to study coastal circulation. Most of these systems operate at a frequency of around 24 MHz or lower, observing from a few tens of kilometers up to more than a hundred kilometers, at a resolution of a few kilometers.

For the present study, we use measurements conducted by two 42-MHz SeaSonde HF radar systems installed in the Gulf of Eilat (see their locations in Fig. 1) in August 2005. Detailed description of the theory behind HF radar can be found in numerous articles (e.g., Gurgel et al. 1999b; Barrick et al. 1985). In short, the radar transmits radio waves and detects the signal backscattered by the
surface gravity waves, due to a Bragg resonance from those surface waves with a wavelength equal to one-half of the transmitted waves. The radial component of the phase speed of the incoming and outgoing waves causes a Doppler shift in the received spectrum compared to the transmitted spectrum. If the waves are superimposed on a current, the spectral peaks are further shifted. Based on the additional shift, it is possible to extract the radial velocity of the current. If two radar sites measure the radial velocity of a patch of water from two different angles, it is possible to calculate the surface velocity field.

Strictly speaking, the radar measures the currents at the top few tens of centimeters of the water column. However, comparison to measurements by an ADCP that were conducted during May 2006 demonstrate that the shear in the top few meters is usually small, and most of the time the surface currents represent the upper 10–20 m (Gildor et al. 2009). The currents measured by the ADCP and by the HF radar were found to be in good agreement. The surface current fields were filtered and interpolated to fill spatial gaps in the observation using the technique described by Lekien and Gildor (2009) and Lekien et al. (2004).

3. The Weibull distribution

The Weibull probability density function (PDF) is defined for positive values, $x > 0$, as

$$f(x; k, \lambda) = \frac{k}{\lambda} \left( \frac{x}{\lambda} \right)^{k-1} e^{-\left( \frac{x}{\lambda} \right)^k},$$

(1)

where $\lambda$ and $k$ are two positive parameters. The term $\lambda$ is the scale parameter of the distribution, and $k$ is the shape parameter. The cumulative Weibull distribution function is given by

$$F(x; k, \lambda) = 1 - e^{-\left( \frac{x}{\lambda} \right)^k}.$$  

(2)

Many studies have indicated that the distribution of wind speed can be represented by the Weibull distribution (e.g., Monahan 2006, 2010). Because the main driving force of surface currents seems to be the wind, one can expect to find a relation between the wind distribution and the surface current speed distribution. Given the $k$ and $\lambda$ parameters, it is possible to find the moments of the distribution $\langle x^m \rangle$,

$$\langle x^m \rangle = \lambda^m \Gamma\left(1 + \frac{m}{k}\right),$$

(3)

where $\Gamma$ is the gamma function. Thus, given a time series, it is sufficient to calculate the first and second moments and from them to find the Weibull distribution ($k$ and $\lambda$) parameters. This is done by numerically solving

FIG. 1. (a) The bathymetry map of the Gulf of Eilat. (b) The flow field at 1100 UTC 29 Nov 2005 observed by two HF radar stations (marked by 1 and 2). The shape of the domain is nearly rectangular, and it has only one open boundary. Note the large-scale pattern of the flow. The gray square indicates the location of the time series presented in Fig. 2a. The X indicates the location of the wind speed time series presented in Fig. 5a.
the transcendental equation for $k(x)^{2}/(x^{2}) = 1^{2}(1 + 1/k)/\Gamma(1 + 2/k)$ and by using the first moment (the mean) and the estimated $k$ to find $\lambda$. Alternatively, it is possible to estimate the shape $k$ parameter from the slope of the hazard function of the Weibull distribution $f(x)/[1 - F(x)] = (k/\lambda)(x/\lambda)^{k-1}$ on a log–log plot; then, the standard error and the correlation coefficient $R^2$ can be calculated based on the linear regression. We use both procedures to verify the variability in the Weibull distribution parameters and to allow the computation of the uncertainty of these parameters. Other studies have suggested even simpler approximations to find the scale and shape parameters (Monahan 2006; Chu 2008).

Naively, one would try to associate the Weibull distribution of the surface current to the Weibull distribution of the winds. However, this association is problematic because the wind stress (and not the wind speed), which is roughly proportional to the square of the wind speed, forces the ocean surface. The square (or even cube) transformation yields a much different Weibull distribution described by smaller $k$ parameter compared to that of the wind.

A special case of the Weibull distribution (with $k = 2$), the Rayleigh distribution, has been shown analytically to be associated with winds (Monahan 2006) and currents (Chu 2008). Still, we wish to explain the general shape of the Weibull distribution in a more intuitive way. Generally speaking, a Weibull distribution (or distribution close to Weibull) can arise when the magnitude of two independent random variables is considered; that is, $s = \sqrt{x^2 + y^2}$, where $x$ and $y$ are random variables. The general shape of the Weibull distribution is low probability for low ($s \rightarrow 0$) and high ($s \gg 0$) values and maximum probability in between. These general characteristics are because both variables have to be small to obtain a small magnitude $s$, a case that has low probability. The same is
true for high values. However, many more combinations exist to yield intermediate values. The outcome distribution is one with a shape similar to Weibull distribution. When the two variables have (independent) Gaussian distributions, the distribution for the magnitude $s$ is Rayleigh (Monahan 2006; Chu 2008).

4. Results

A representative example of surface current speed is shown in Fig. 2a. This current speed time series (which spans one year) possesses erratic and complex fluctuations. The distribution of this time series is shown in Figs. 2b,c,
where the Weibull distribution with $\lambda = 14.4$ cm s$^{-1}$ and $k = 1.85$ can fit this distribution; the standard error of $k$ is 0.05 and $R^2 = 0.97$. These parameters fall in the range of parameters reported in a recent publication (Chu 2009).

Next, we derive the statistics of the distribution at each grid cell and at the different seasons (Fig. 3); half-hourly data provide enough data points for such an analysis. As mentioned above (section 2a), the water column in the gulf varies significantly between a stratified water column season (roughly between April and November) and a mixed water column season (roughly between December and March). This has significant effects on the dynamics. For example, near the coast, the tidal signal is strong in the stratified season and almost absent in the mixed season (Berman et al. 2003; Monismith and Genin 2004). It is therefore interesting to look at the spatial and seasonal variability of the shape and scale parameters of the Weibull distribution.

The shape parameter is clearly larger in the middle of the domain and smaller along the periphery, for both summer and winter (Fig. 3, left). This might be the result of proximity to the coast, which limits the cross-shore component of the velocity. The maximal value is around 2 (i.e., nearly the same as that of the Rayleigh distribution), but it can be as low as 1. Interestingly, the domain with maximum value shifts northward during the winter. As for the scale parameter (Fig. 3, middle), as expected it exhibits a similar pattern as for the mean ocean current field (Fig. 3, right). The results are consistent with previous studies that indicated greater current speed during the summer; here, however, we identify the location of this maximum at the southernmost (and deepest) part of the domain. This is somehow expected because the northerly winds (and hence the wind-driven component of the currents) speed up at farther distances from the northern coast of the gulf.

In Table 1, we summarize the results by performing a spatial mean for the fields shown in Fig. 3 and for the zonal and meridional currents components. Here, it is clear that during summer the currents are more intense than during winter. In addition, the shape parameter $k$ is larger during summer. The mean current direction during winter is $-180^\circ$ clockwise from the north, whereas during summer it is $-191^\circ$. However, the mean zonal current during summer is more than threefold higher than that of winter, which is consistent with the more persistent currents during summer. The annual-mean values are closer to the summer values because the gulf is stratified throughout the year, except during winter. Note that, because only the surface currents are considered here, the current mean vector does not necessarily equal to the net inflow/outflow at the southern open boundary of the gulf but rather mainly represents the mean wind action on the current.

We also estimated the uncertainty of the $k$ shape parameter of the annual time series based on the Hazard function, as described section 3; we indicate this parameter by $k_{\text{hazard}}$ and the $k$ parameter that is based on the first and second moments by $k_{\text{moment}}$. Although the $k_{\text{hazard}}$ shown in Fig. 4a exhibits a similar pattern to that of $k_{\text{moment}}$ shown in Fig. 3a, there are noticeable differences between the two. The difference between these two is shown in Fig. 4d. In general, $k_{\text{moment}}$ is larger than $k_{\text{hazard}}$, where in most of the domain the absolute difference is less than 0.1, validating the spatial variability shown in Fig. 3a. In Fig. 4b, the standard error of $k_{\text{hazard}}$ is presented, where it is clear that the estimated error is less than 0.15; not surprisingly, the standard error exhibits close similarity to the difference $k_{\text{hazard}} - k_{\text{moment}}$ shown in Fig. 4d. In Fig. 4c, the $R^2$ values of $k_{\text{hazard}}$ are presented, and it is clear that, throughout most of the domain, $R^2$ is larger than 0.6, where the lower values are located close to the shore.

In some places, the difference $k_{\text{hazard}} - k_{\text{moment}}$ (shown in Fig. 4d) is twofold higher than the standard error (shown in Fig. 4b). This fact together with the systematic lower $k_{\text{hazard}}$ compared to $k_{\text{moment}}$ indicates that Weibull distribution may not be the optimal fit for all ocean currents. This issue will be further discussed elsewhere.

5. A simple Ekman surface layer model

We used the model (and setting) described below in a previous study of temporal correlations in the Gulf of Elat (Ashkenazy and Gildor 2009). However, below we briefly describe the model for the sake of clarity.

Among the three main factors (winds, tides, and buoyancy) that affect the circulation in the gulf, the winds seem to have the largest influence on surface currents. We thus concentrate on the wind’s effect on the upper ocean layer. We use the classical model proposed by Ekman (1905) to study the probability distribution of upper ocean currents.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Annual $\pm$ 0.19</th>
<th>Winter $\pm$ 0.20</th>
<th>Summer $\pm$ 0.20</th>
</tr>
</thead>
<tbody>
<tr>
<td>$k$</td>
<td>1.66 $\pm$ 0.19</td>
<td>1.63 $\pm$ 0.20</td>
<td>1.84 $\pm$ 0.20</td>
</tr>
<tr>
<td>$\lambda$</td>
<td>11.0 $\pm$ 2.3</td>
<td>8.35 $\pm$ 2.10</td>
<td>11.39 $\pm$ 2.50</td>
</tr>
<tr>
<td>$u$</td>
<td>$-0.63 \pm 1.22$</td>
<td>0.02 $\pm$ 1.03</td>
<td>$-0.81 \pm 1.25$</td>
</tr>
<tr>
<td>$v$</td>
<td>$-3.38 \pm 1.60$</td>
<td>$-1.37 \pm 1.27$</td>
<td>$-4.22 \pm 1.88$</td>
</tr>
<tr>
<td>$\sqrt{u^2 + v^2}$</td>
<td>9.88 $\pm$ 2.08</td>
<td>7.51 $\pm$ 1.88</td>
<td>10.14 $\pm$ 2.21</td>
</tr>
</tbody>
</table>
The original model of Ekman (1905) has both time-dependent and time-independent analytical solutions under constant winds and constant interior currents. However, because we are forcing the model by the variable wind of the gulf (Fig. 5a), we solve the model numerically. In particular, the following set of equations is solved:

\[
\frac{\partial u}{\partial t} - f(v - v_g) = \nu \frac{\partial^2 u}{\partial z^2} \quad \text{and} \quad (4)
\]

\[
\frac{\partial v}{\partial t} + f(u - u_g) = \nu \frac{\partial^2 v}{\partial z^2}. \quad (5)
\]

where \( u \) and \( v \) are the zonal and meridional velocities, \( u_g \) and \( v_g \) are the zonal and meridional bottom geostrophic velocities, \( f \) is the local (constant) Coriolis parameter, and \( \nu = 0.01 \text{ m}^2 \text{ s}^{-1} \) is the eddy viscosity coefficient. Here, we ignore the nonlinear advection terms, the lateral (x and y) dynamics, the basin topography, and the dependence of \( \nu \) on depth. The water density is set to be constant. At the surface, the ocean is forced by the wind through the wind stress as follows:

\[
\frac{\partial u}{\partial z} \bigg|_{z=0} = \frac{\tau}{\nu \rho_o}. \quad (6)
\]
where \( \rho_w = 1028 \text{ kg m}^{-3} \) is the water density and \( \tau = (\tau_x, \tau_y) \) is the wind stress vector given by

\[
\tau = \rho_a C_D U u,
\]

where \( u = (u_x, v_y) \) is the wind vector composed of the zonal and meridional wind components, \( U = \sqrt{u_x^2 + v_y^2} \) is the wind speed, and \( \rho_a = 1.3 \text{ kg m}^{-3} \) is the air density.

The term \( C_D \) is the drag coefficient and \( C_D = 10^{-3} \) for \( U \leq 6.2 \text{ m s}^{-1} \) and \( C_D = (0.6094 + 0.063U) \times 10^{-3} \) for \( U > 6.2 \text{ m s}^{-1} \) (after Gill 1982). The Coriolis parameter is chosen to be that of the gulf: that is, \( f = 7.16 \times 10^{-5} \text{ s}^{-1} \). Additionally, we chose an upper ocean layer depth of \( H = 50 \text{ m} \), a vertical resolution of \( \Delta z = 0.5 \text{ m} \), and an integration time step of \( \Delta t = 10 \text{ s} \). We used hourly wind data from Eilat airport, collected between October 2005 and September 2006 (Fig. 5a), to force the ocean; this time period coincides with the surface currents analyzed above. The wind data was interpolated linearly to provide wind data for the model at each time step. The interior ocean currents were modified to study the dependence of the probability distribution on these currents.

In Fig. 5, we present the Gulf of Eilat wind data used in the model and the corresponding simulated surface current time series; in this simulation, we assumed zero interior geostrophic currents. As expected, the surface current responds nonlinearly to the wind according to Eq. (7); for periods where the winds were stronger, the currents were much stronger. In addition, the probability distribution of both the winds and surface currents are shown in Fig. 6. Here, the wind speed probability distribution seems to follow the Weibull distribution, whereas the currents distribution function has a stretched tail, leading to a relatively small shape exponent, \( k \approx 1.09 \), of the Weibull distribution; note that the Weibull distribution with \( k = 1 \) reduces to exponential distribution. Such a small \( k \) is inconsistent with the observations shown in Figs. 2 and 3. The probability distributions of each component of the wind and simulated current are also depicted in Fig. 6. The annual mean ± one standard deviation of the zonal and meridional wind velocities is \(-1.45 \pm 1.58 \text{ m s}^{-1} \) and \(-4.15 \pm 3.29 \text{ m s}^{-1} \), indicating north-northeastern winds. These probability distribution functions do not follow Gaussian distribution as is usually assumed (e.g., Chu 2009). This preferred wind direction resulted in preferred direction of the simulated surface currents (Fig. 6); the mean ± one standard deviation of the simulated surface currents are \(-3.17 \pm 5.71 \text{ cm s}^{-1} \) and \(-1.86 \pm 5.19 \text{ cm s}^{-1} \) such that the mean surface current vector is oriented 40.34° to the right of the wind, roughly consistent with the 45° of the theoretical prediction. The distribution of modeled ocean zonal and meridional surface currents is approximately exponential (linear on semilog curves), with different exponents for positive and negative values.

The observations shown in Fig. 3 indicate that there is a spatial variability of the scale and shape parameters of the Weibull distribution, \( \lambda \) and \( k \). Because we used the Eilat surface wind (assuming that this wind time series represents the entire domain under consideration), we studied the model behavior under different bottom current scenarios.

When using different temporally constant bottom geostrophic currents, we obtained surface currents that are “riding” on the bottom currents, such that there is a minimum current speed that is larger than zero (depending on the magnitude of the bottom speed). This resulted in a probability distribution that is different from the Weibull distribution and even different from the more generalized shifted Weibull distribution,

\[
f(x; k, \lambda, \theta) = \frac{k}{\lambda} \left( \frac{x - \theta}{\lambda} \right)^{k-1} e^{-\left(\frac{x - \theta}{\lambda}\right)^k},
\]

for \( x > \theta \). Such a distribution is inconsistent with the observations shown above and thus rules out the possibility that the magnitude of the bottom currents underlies the spatial variability of the parameters of the Weibull distribution.

We next assumed that the bottom zonal and meridional currents are Gaussian distributed about zero. Similar to the above, the surface water is forced by the wind of
Eilat but the noise amplitudes of the bottom currents are varied. The results are shown in Fig. 7a, and it is clear that even large fluctuations of the bottom currents have little effect on the surface current shape parameter. Moreover, the shape parameter is much smaller than the observed ones (shown in Fig. 3). It is thus unlikely that the fluctuations of the bottom surface underlay the spatial variability of the shape parameter of the Weibull distribution shown in Fig. 3.

Previous studies (Chu 2009) showed that, when the zonal and meridional wind components are Gaussian distributed, the ocean currents are Rayleigh distributed. Motivated by this, we forced the model by artificially generated winds whose components are Gaussian distributed (Fig. 7b). We estimated the $k$ exponent for different values of amplitude of bottom current noise (where the zonal- and meridional-mean current are zero) and found that the exponent varied from $\sim 1.9$ to $\sim 2$. These numerical results are different from the analytical prediction of Chu (2008); as for zero bottom currents (without noise added to them), the mean $k$ ± one standard deviation is $k \approx 1.9 \pm 0.01$ (i.e., well below $k = 2$), whereas the analytical prediction was of $k = 2$. This difference may be attributed to the fact that Eq. (7) was ignored in the analytical derivation of Chu (2008) or to the fact that the analytical derivation of Chu (2008) referred to the depth integrated (mean) currents.

Fig. 6. (a) The probability distribution of the zonal (circles) and meridional (squares) winds of Eilat airport. Note the preferred northerly wind direction and that the distributions are not Gaussian. (b) The distribution of the wind speed (diamond) time series shown in Fig. 5a. The solid line indicates the Weibull distribution fit. (c) As in (a), but for the simulated surface currents. Here, the distributions are approximately exponential (linear on semilog plot) but with different exponents for positive and negative values. (d) As in (b), but for the simulated surface currents. The tail of the distribution is almost exponential. The solid line indicates the Weibull fit to the distribution (with $k \approx 1.1$). The vertical dotted lines in (a)–(d) indicate the mean values.

As mentioned above, the surface wind data are hourly-mean data and were linearly interpolated to force the model with 10-s-resolution data. Thus, wind variability (and wind gusts) with a time scale of less than one hour is ignored. To mimic this variability, we added Gaussian white noise to the zonal and meridional wind components; here (Fig. 7c), the value of the $k$ exponent changed drastically as a function of the added noise amplitude, suggesting the fast wind temporal variability as a source for the spatial variability of the surface currents presented in Fig. 3. The gulf is surrounded by high mountains that
may lead to different wind variability inside this small region. In this sense, our attempts to capture the probability distribution characteristics using a single wind time series is a simplification. We note that, as the wind noise amplitude increases, the error bars also increase, together with the increase in $k$ as a function of the noise added to the bottom geostrophic currents. Here, $k$ is larger and varies more drastically as a function of the noise added to the bottom geostrophic currents. Previous study supports that conclusion: We conjecture that the deviation of the distribution from a Rayleigh distribution (obtained when the zonal and meridional components are independent, uncorrelated, and Gaussian distributed) is the manifestation of the deviation of the components from Gaussian distribution, implying the need to find better parameterization for ocean mixing than the simple eddy viscosity parameterization. Non-Gaussian distribution on the mesoscale was found before by Bracco et al. (2003). This also may be one of the reasons for the inability of the analyzed model to reproduce the observed Weibull distribution and its spatial variability. In addition, we repeated the experiment using Eilat wind but when changing the noise added to the wind components every half hour instead of every 10 s (which is the model integration step); the results are indicated by the dashed line in Fig. 7c. For low noise level, the estimated $k$ parameter is similar to the one obtained when using wind noise that is changed every 10 s, whereas, for high noise level, the estimated $k$ parameter is around 1.5 (compared to 1.8). This experiment indicates that the temporal variability of the noise and not just the noise amplitude is an important factor in affecting the distribution of surface currents.

6. Summary and discussion

We analyzed the probability distribution function of the surface current speed field in the northern part of the Gulf of Eilat and found that it can be approximated by the Weibull distribution. Surprisingly, we also found relatively large spatial variability of the shape and scale parameters that characterize the Weibull distribution. These parameters were different for summer and winter, where stronger winds and larger parameters were observed during the summer period.

We used the surface Ekman layer model to study the origin of this distribution and found that the shape exponent of the Weibull distribution is much smaller than the observed one. When adding Gaussian white noise to the wind field, this exponent became larger, suggesting that temporal wind gusts may be linked to the large spatial variability of this exponent.

Lateral small-scale ocean mixing parameterization is often done using diffusion-like parameterizations, with an “eddy diffusivity,” which is significantly larger than molecular diffusivity (and scales with the model’s resolution) but implies similar physical characteristics to that of molecular diffusion. Gildor et al. (2009) demonstrated the existence of submesoscale barriers to mixing, which suggest that ocean mixing is much more complex than implied by using lateral eddy diffusivity. Our present study supports that conclusion: We conjecture that the deviation of the distribution from a Rayleigh distribution (obtained when the zonal and meridional components are independent, uncorrelated, and Gaussian distributed) is the manifestation of the deviation of the components from Gaussian distribution, implying the need to find better parameterization for ocean mixing than the simple eddy viscosity parameterization. Non-Gaussian distribution on the mesoscale was found before by Bracco et al. (2003). This also may be one of the reasons for the inability of the analyzed model to reproduce the observed Weibull distribution and its spatial variability. In addition, the analyzed model (in which the viscosity coefficient is
assumed to be constant) lacks many oceanic processes that could alter the probability distribution. The lack of spatially varying wind field may also be a serious disadvantage of the suggested model. We believe that other, more realistic models should be challenged to reproduce the Weibull distribution of the ocean currents; preliminary analysis of a general circulation model of the gulf (forced by monthly-mean wind) yielded distributions of surface currents that are much different from the observed Weibull distribution.

The HF radar measurements that our analysis is based on represent the currents of the upper few tens of centimeters. Kim et al. (2011) analyzed the wavenumber spectra of HF radar data and showed that they are more indicative of two-dimensional turbulence rather than three-dimensional quasigeostrophic turbulence. This type of dynamics may not be captured by the Weibull distribution and possibly may be associated with the lateral variations in Weibull distribution parameters reported above.

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