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# Estimating longitudinal dispersion in rivers using Acoustic Doppler Current Profilers

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ABSTRACT

The longitudinal dispersion coefficient ($D$) is an important parameter needed to describe the transport of solutes in rivers and streams. The dispersion coefficient is generally estimated from tracer studies but the method can be expensive and time consuming, especially for large rivers. A number of empirical relations are available to estimate the dispersion coefficient; however, these relations are known to produce estimates within an order of magnitude of the tracer value. The focus of this paper is on using the shear-flow dispersion theory to directly estimate the dispersion coefficient from velocity measurements obtained using an Acoustic Doppler Current Profiler (ADCP). Using tracer and hydrodynamic data collected within the same river reaches, we examined conditions under which the ADCP and tracer methods produced similar results. Since dead zones / transient storage (TS) are known to influence the dispersion coefficient, we assessed the relative importance of dead zones in different stream reaches using two tracer-based approaches: (1) TS modeling which explicitly accounts for dead zones and (2) the advection–dispersion equation (ADE) which does not have separate terms for dead zones. Dispersion coefficients based on the ADE tend to be relatively high as they describe some of the effects of dead zones as well. Results based on the ADCP method were found to be in good agreement with the ADE estimates indicating that storage zones play an important role in the estimated dispersion coefficients, especially at high flows. For the river sites examined in this paper, the tracer estimates of dispersion were close to the median values of the ADCP estimates obtained from multiple datasets within a reach. The ADCP method appears to be an excellent alternative to the traditional tracer-based method if care is taken to avoid spurious data and multiple datasets are used to compute a distance-weighted average or other appropriate measure that represents reach-averaged conditions.


## 1. Introduction

The longitudinal dispersion coefficient ($D$) is an important parameter that describes the transport of solutes in streams and rivers. Accurate estimation of the dispersion coefficient is important from human health and public safety perspectives as the parameter is needed to predict contaminant concentrations near drinking water intakes and receiving water bodies such as lakes or oceans. Once a solute is released into the stream and becomes vertically and laterally well-mixed, longitudinal dispersion is the primary mechanism responsible for spreading the tracer plume and for reducing peak concentrations. The one-dimensional transport of solutes following the initial period of mixing can be described using the advection–dispersion equation (ADE) [1,2]:

$$\frac{\partial C}{\partial t} + U\frac{\partial C}{\partial x} = D\frac{\partial^2 C}{\partial x^2} \tag{1}$$

where $C$ is the solute concentration, $U$ is the mean flow velocity and $x$ and $t$ denote space and time respectively. The coefficient $D$ can be estimated using a number of empirical relations available in the literature [1,3,4]; however, these estimates are generally known to exhibit large variability. Dispersion estimates from tracer studies (which usually involve fitting the observed data to a solution of Eq. (1) for appropriate boundary and initial conditions) are generally believed to be more reliable; however, significant time and resources are needed to conduct tracer studies, especially on large rivers. An alternative approach, which is the main focus of this paper, is to estimate $D$ from the theory of shear-flow dispersion [1]:

$$D = -\frac{1}{A}\int_0^B u'(y)h(y)dy \int_0^y \frac{dy'}{D_y h(y')}\int_0^{y'} u'(y'')h(y'')dy'' \tag{2}$$

where $A$ is the channel cross-sectional area, $y$ is the transverse coordinate which varies from $y=0$ at one bank to $y=B$ at the other, $h(y)$ is the depth of flow at a given $y$ location, $D_y$ is the transverse mixing coefficient, $u'(y)=\overline{u}(y)-U$ is the deviation of the depth-averaged velocity $\overline{u}(y) = \int_0^{h(y)} u(y,z)dz$ from the mean velocity, $u(y,z)$ is the measured longitudinal velocity field, and $z$ is the vertical coordinate.

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Eq. (2) is based on several assumptions as described in [1,5] including one-dimensional flow (no vertical and transverse gradients in concentration, that is well-mixed). Although the theory for estimating the dispersion coefficient from the velocity field has been around for a long time, the single most limiting factor in the application of Eq. (2) in the past was the measurement of detailed velocity distribution and depth across the river. Significant time and resources are needed when instruments designed to make point-measurements (such as the Price-AA and Pygmy current meters) are used to measure the velocity fields in streams. However, this situation has changed with the advent of Acoustic Doppler Current Profilers (ADCP). While the ADCP technology itself is not new, early models of the instruments were geared towards oceanographic applications. Recent ADCP models designed for rivers, streams and other shallow inland water bodies can be used to quickly make velocity and bathymetry measurements over long distances with high accuracy and resolution. This new capability introduced the opportunity to address important questions involving inland water bodies [6–8] including the calculation of $D$ with relative ease using Eq. (2). However, there are several issues that need to be examined before comparing tracer estimates with ADCP results based on Eq. (2).

The dispersion coefficient estimated from the tracer data is often used as the “true” value to evaluate other methods. The tracer estimate represents the bulk, reach-averaged mixing strength in a given reach and is valid only for the particular stream reach and the flow conditions for which the experiment was conducted. The ADCP value, on the other hand, represents a “point estimate” along the length of the river. If the channel is fairly uniform and the transect represents the conditions in the entire reach, then the point estimate can be expected to represent reach-averaged conditions. If the river reach exhibits significant heterogeneity in properties, then a reach-averaged estimate can be calculated using a distance-weighted average as suggested by Rutherford[2]:

$$\overline{D} = \frac{1}{L}\sum_{i=1}^{n} D_i \Delta x_i \tag{3}$$

where $\overline{\mathrm{D}}$ is the reach-averaged dispersion coefficient, $\Delta x_i$ is the length of the sub-reach containing the ADCP transect at location $x_i$ (with value $D_i$) and $L$ is the total length of the river reach. A number of mechanisms including surface storage in dead zones (e.g., vegetation, woody debris) and solute exchange and retention within the hyporheic zone are known to produce an effect that is somewhat similar to the effects of dispersion in streams. The transient storage (TS) model [9,10], which describes the temporal trapping (and release) of solute particles in the dead zones is often used to describe transport when dead zones play an important role and the ADE cannot adequately describe the data. Ignoring lateral flow contributions into the channel due to groundwater, the TS model can be written as shown below [9,10].

$$\begin{aligned} &\frac{\partial C}{\partial t} + U\frac{\partial C}{\partial x} = D_S\frac{\partial^2 C}{\partial x^2} + \alpha(C_S - C) \\ &\frac{\partial C_S}{\partial t} = \alpha\frac{A}{A_S}(C - C_S) \end{aligned} \tag{4}$$

Here $C$ and $C_S$ are the solute concentrations in the main channel and the storage zones, $A$ and $A_S$ are the sizes of the main channel and storage zones, and $\alpha$ is an exchange rate between the main channel and the dead zones. $D_S$ denotes the dispersion coefficient in the TS model. The subscript “S” is used to indicate the fact that the dispersion coefficients estimated using the ADE and TS models are generally different for the same river reach and flow conditions. Since the TS model has additional terms for the dead zones, the coefficient $D_S$ represents only the shear-flow contribution while the ADE estimates of dispersion tend to be higher as $D$ includes the effects of dead zones to some extent [11]. Therefore, by comparing the dispersion coefficients obtained from the TS and ADE models, we may be able to assess the relative contributions of dead zones (or storage zones) in different stream reaches. This approach was used for stream reaches where detailed tracer breakthrough data were available to run both models.

Fischer et al. [1] numerically evaluated Eq. (2) for both laboratory flumes as well as natural streams and compared their results with tracer estimates (see Table 5.3 in [1]). Their velocity measurements were made using standard current meters. Carr and Rehmann [5] recently evaluated Eq. (2) using the velocity and bathymetry measurements obtained from ADCPs and compared their estimates with tracer results for ten US rivers. Half of their ADCP values were found to be within 50% of the values from tracer studies, and 85% were within a factor of 3. They concluded that the ADCP method was at least as accurate as the best empirical formula considered in their work. While these results are encouraging, a few questions remain unanswered. First, if the ADCP estimates are only as good as the best empirical relations (which generally produce numbers within an order of magnitude of the tracer value) then the ADCP method is not very attractive since it is easier to use the empirical relations. Second, the tracer data used in [5] spanned a period of nearly three decades (1967 to 1991) while the ADCP measurements coved the period from 2000 to 2004. Changes in both channel cross-section and (local) slope are possible in the period following the tracer studies which could potentially influence the results. In addition, different approaches were used to estimate $D$ from the tracer data — from a routing method [2] to fitting a line to the variance obtained from the tracer breakthrough curve [1] to modeling the tracer response curve as a scalene triangle [12]. These methods are known to produce different results when applied to the same river reach under similar flow conditions introducing additional sources of uncertainty into the comparison between ADCP and tracer methods. Noting that the tracer-based values of $D$ have their own sources of error and uncertainty, it is important to understand if the ADCP method has the ability to produce numbers that are comparable to the tracer values, especially when using multiple/repeated transect data at the same site, a procedure that tends to average errors involved in the data. This is one of the questions we will attempt to answer in this paper. In many stream ecosystem studies the primary interest is not in dispersion but in other processes (e.g., biogeochemical processes, mortality/loss rates of bacteria or viruses, storage zone sizes and reaction rates) but accurate values of $D$ are still needed to adequately describe these processes. If the ADCP method has the potential to produce dispersion values that are as accurate as the tracer method (in a fraction of the time taken to plan and conduct a dye release experiment), then the result has important implications for studies involving stream and river ecosystems. The aims of this paper, therefore, are (a) to contribute additional tracer and ADCP datasets in support of the analysis reported in Carr and Rehmann [5] focusing, as far as possible, on datasets collected at the same time and (b) to systematically examine the effects of different post-processing methods on the dispersion results since raw ADCP data usually contain noise which depends on the river characteristics and the operating conditions of the instrument. Finally we will examine the limitations of the ADCP method to better understand conditions under which the method can produce reliable values of the dispersion coefficient.

## 2. Materials and methods

Data from a total of 505 ADCP transects collected from seven rivers in the states of Ohio, Indiana and Michigan were used in the present study. In addition, nearly ten tracer studies have been conducted on some of the rivers. Details of the rivers are summarized in Table 1 and maps of the sites showing the locations of the ADCP transects are shown in Fig. 1. Out of the seven rivers, simultaneous tracer and ADCP data were collected for three rivers (Ohio River, Grand River and Burns Waterway). For one river (Red Cedar River) tracer data were collected during

**Table 1**
Physical characteristics of the rivers and comparion of tracer and ADCP estimates of the dispersion coefficient.

| River | $W$ (m) | $H$ (m) | $u^*$ (m/s) | $Q$ (m$^3$/s) | $D$ (m$^2$/s) | |
|---|---|---|---|---|---|---|
| | | | | | Tracer[a] | ADCP |
| Burns Ditch | 20.59 | 1.48 | 0.18 | 2.14 | 0.12 | 0.16 |
| Muskegon River | 70.03 | 0.98 | 0.24 | 48.41 | NA | 4.37 |
| Thornapple River | 44.57 | 1.94 | 0.17 | 4.90 | NA | 0.12 |
| Ohio River | 471.25 | 4.96 | 0.061 | 1405.0 | 80.80 | 107.0 |
| St. Clair River | 553.26 | 7.92 | 0.083 | 4999.0 | 53.5[e] | 65.5 |
| Grand River | 59.25 | 1.26 | 0.15 | 63.00 | NA | 7.15 |
| Grand River | 68.59 | 0.98 | 0.21 | 80.00 | 11.00[b] | 11.80 |
| Red Cedar River | 12.66 | 0.62 | 0.11 | 2.70 | 0.74[c] | 0.71 |
| Red Cedar River | 24.68 | 0.97 | 0.14 | 19.80 | 2.58[d] | 1.50 |

NA = not available.
[a] ADE (method B).
[b] Discharge $Q = 91$ m$^3$/s.
[c] $Q = 2.06$ m$^3$/s.
[d] $Q = 19.06$ m$^3$/s.
[e] $Q = 4902$ m$^3$/s.

summer 2002 while ADCP data were collected for similar flows between 2003 and 2006. Similarly, ADCP data for the St. Clair River were collected by USGS staff in 2002 while tracer data were collected in 2009. No tracer data are available for two rivers (Muskegon River and Thornapple River) but estimates from the ADCP method and empirical relations are shown for comparison. Where conditions warranted we ran multiple transects at the same location and at multiple locations within the same river reach. Details of the tracer study and modeling for the Grand River and Red Cedar River are available in [8,13]. Tracer and ADCP data for the Ohio River (only ADCP data for the St. Clair River) were collected by USGS staff and details are available in [14,15]. A continuous dye release was conducted on the Portage Burns waterway on June 21, 2008 using Rhodamine WT. Although the aim of the tracer study was to understand nearshore processes in Lake Michigan, concentration-time data collected within the stream were used to estimate a dispersion coefficient by fitting an analytical solution for continuous release [16] to the data. For the Ohio River, Rhodamine WT was released at one of the banks and the tracer did not completely mix within the study reach. Breakthrough data are not available in the form of concentration versus time data; however, concentration values are reported within the channel cross-section (at different depths and distances from the bank) for several different stations. We computed the cross-sectional average concentration at different stations and fitted the spatial data to the unsteady ADE to compute a dispersion coefficient. This method will likely introduce some error since the tracer was not fully mixed to justify the use of one-dimensional ADE; however, the estimated dispersion coefficient described the mean concentration values at different stations accurately after the first few sampling locations. Three dye studies were conducted on the St. Clair River by Applied Science Inc., Detroit, Michigan between August 17 and 20, 2009 (average discharge: 4902 m$^3$/s) for the Great Lakes Observing System (GLOS). Rhodamine-WT dye was released near Sarnia, Ontario/Marysville, Michigan and the dye plumes were tracked as they traveled downstream. ADCP and tracer estimates reported in this paper are based on data collected between the following two locations: (82.4635 W, 42.9059 N) and (82.4766 W, 42.7889 N).

Two ADCPs manufactured by Teledyne-RD Instruments, Poway, California (1200 or 600 kHz Workhorse Rio Grande) were used for field data collection. Data were collected by mounting the ADCP on a trimaran (an OceanScience Riverboat™ with housing for electronics and radio modems to communicate with a land-based laptop) and towing the vessel across the river perpendicular to the direction of flow either from a bridge or behind a small motor boat. During an ADCP ping, the boat travels a certain distance along the transect and the corresponding water column is called an ensemble. The width of this ensemble depends on the ping rate and the boat velocity (typically 0.2–0.5 m/s in this work). The ADCP measures three-dimensional water velocities from vertical segments of the water column and each of the segments is referred to as a bin. Simultaneously, the ADCP measures the bottom depth of the river and the boat velocity relative to the river bed. After each transect is completed we obtain a 2D field of 3-dimensional water velocities for a given $x$ (longitudinal) location $\vec{v}(y,z) = (v_N, v_E, v_Z)$ where $v_N$ and $v_E$ are the North and East velocity components in Earth coordinates and $v_Z$ the vertical velocity component at location($y$, $z$) where $y$ and $z$ denote the transverse and vertical coordinates respectively. The measurement of $\vec{v}(y,z)$ by ADCP is equivalent to deploying a dense array of velocimeters throughout the cross-sectional area. When the ADCP has trouble tracking the bottom for a particular ping, potentially caused by abrupt changes in depth, too fast a boat speed or other factors (e.g., combination of boat speed and water velocity), the instrument reports a 'bad ensemble' which is an invalid column in the data array. In this paper, we use the bad ensembles reported by the WinRiver software (Teledyne RD Instruments, Poway, CA). The ADCP data were processed carefully after collection including smoothing and removal of bad ensembles. The bad ensembles are discarded, which is equivalent to using the data from the nearest valid ping to estimate the distance traveled during the bad ensemble. This is the approach used in WinRiver to calculate discharge. General principles of ADCP operation and post-processing for moving-vessel measurements are described in Dinehart and Burau [6], Simpson [17] and Muste et al. [18]. Apart from bad ensembles, some bins in a good ensemble may also report bad velocity readings (e.g., when data do not meet the echo intensity, correlation or other thresholds or when readings from the four beams differ significantly). In the final datasets, the bad bins were replaced by using nearest neighbor interpolation.

Noise is almost always present in the ADCP data due to the transient turbulent nature of the flow. In order to reduce the effect of random noise on the dispersion estimates, we have considered smoothing the vertical velocity profile before evaluating Eq. (2). Muste [18] described the need for such smoothing and discussed several techniques such as fitting a power law (Eq. (5)) or a logarithmic profile (Eq. (6)) to the data in an ensemble:

$$\frac{u}{u^*} = a\left(\frac{z}{z'}\right)^m \quad (5)$$

$$\frac{u}{u^*} = \frac{1}{k}\ln\left(\frac{u^* z}{\nu}\right) + B \quad (6)$$

where $z$ is the vertical coordinate measured from the bottom, $z'$ is a characteristic length [18], $u^*$ is the shear velocity, $k$ is the von Karman constant, $\nu$ is the kinematic viscosity of water and $a$,$m$,$B$ are fitting parameters. We will assess the effect of using these two smoothing formulations on the dispersion coefficients in a later section. In addition to profile smoothing, we have considered two alternative approaches for orienting the velocities before evaluating Eq. (2). In the first approach, which is used in [5], the water velocities are projected onto the main direction of river flow (streamwise direction). The main direction of the flow is calculated as:

$$\vec{V} = \sum_{i=1}^{n} \sum_{j=tb(i)}^{db(i)} \vec{v}(i,j) \quad (7)$$

where $\vec{V} = (V_N, V_E)$ is the cross-sectional average velocity vector, $tb(i)$ and $db(i)$ are, respectively, the top good bin and bottom good bin of the ensemble $i$. The velocities are then projected as:

$$u = \frac{\vec{v}\cdot\vec{V}}{|\vec{V}|^2}\vec{V} \quad (8)$$

where $u$ is the projected water velocity and the width of the ensemble, $\Delta y$, is similarly projected to the diagonal direction to $\vec{V}$. In the second

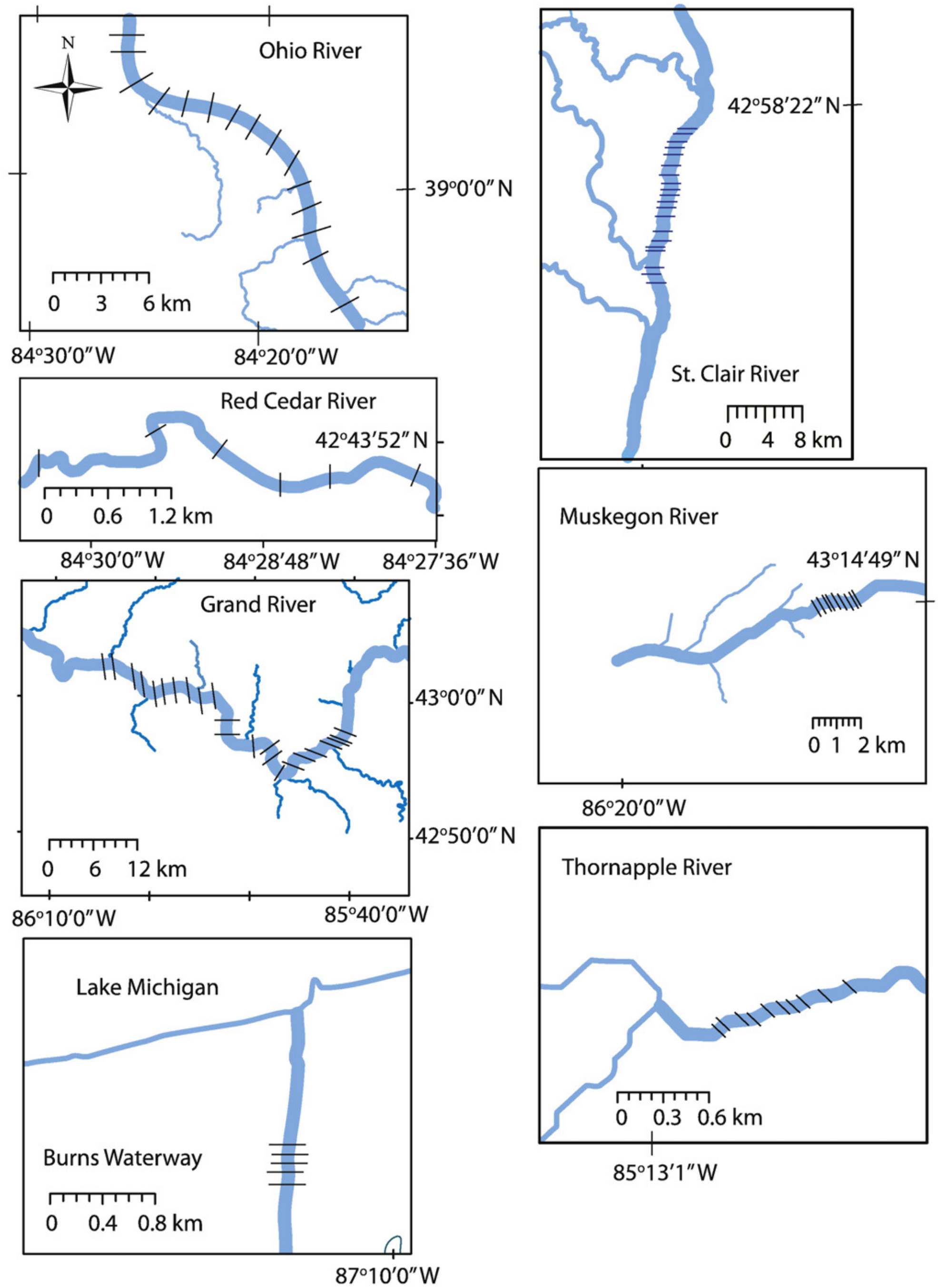


**Fig. 1.** Maps of the rivers showing locations of ADCP transects.

approach, $u$ is simply projected to the normal direction of the transect track, $\vec{n}$, similar to the way the ADCP evaluates discharge:

$$u = \vec{v} \cdot \vec{n} = \frac{q}{a} = \frac{\left(\vec{v} \times \vec{v_b}\right) \cdot \vec{k}\,\Delta t}{\Delta y} \tag{9}$$

Here $\vec{n}$ is the unit vector normal to the transect, $\vec{k}$ is the unit vector in the vertical direction, $q$ is the fractional discharge, $\vec{v_b}$ is the boat velocity vector, $a$ is the fractional area, $\Delta t$ and $\Delta y$ are the elapsed time and distance for the ensemble. It is clear from Eq. (2) that the success of the ADCP method depends on accurate approximation of the transverse dispersion coefficient $D_y$. An expression for $D_y$ based on experimental results is given by Fischer et al. [1]:

$$D_y \approx C' H U^* \tag{10}$$

where $C'$ is a constant, normally taken as 0.145 for straight uniform channels, $H$ is the mean depth, $U^*$ is the mean shear velocity, and $u^*$ is the local shear velocity, which is computed as $u^* = \sqrt{gRS}$ where $g$ is the acceleration due to gravity, $R$ is the hydraulic radius and $S$ is the channel slope evaluated using local measurements of bed elevations. The other formula for $D_y$ that was previously used in [3] and [19] and in our work is:

$$D_y = \theta U^* h(y) \tag{11}$$

$$\theta = \left[0.145 + \frac{1}{3520}\left(\frac{U}{U^*}\right)\left(\frac{B}{H}\right)^{1.38}\right]$$
$$U^* = \int_0^B u^*(y)dy \qquad (12)$$
$$H = \int_0^B h(y)dy$$

where $H$ is the cross-sectionally averaged depth, $h(y)$ is the local depth and $U^*$ denotes the average friction velocity (obtained by numerically integrating the local friction velocity over the channel cross-section). After $D_y$ is computed from Eq. (11), Eq. (2) can be numerically integrated. Repeated ADCP transects have been collected at various locations under different flow conditions in order to assess the variability in the ADCP method. The ADE and TS models were solved numerically using a compact finite difference method. Details of the numerical method and the parameter estimation procedures are available in [8,13].

## 3. Results and discussion

Before computing the dispersion coefficient using Eq. (2), we examined the ADCP datasets to identify potential issues that could lead to a violation of the assumptions involved in Eq. (2). We examined the depth-averaged velocity profiles in the transverse direction to identify recirculating or secondary flow regions. We also examined the number of bad ensembles as a per cent of the total number of ensembles. Datasets with a large percent of bad ensembles were not used for estimating the dispersion coefficient. Results from typical ADCP surveys are shown in Fig. 2 in which the variable plotted is the velocity magnitude $\sqrt{v_E^2 + v_N^2 + v_Z^2}$ as a function of the depth and width of the channel. Channel characteristics in all stream reaches are such that the width-to-depth ratio $(B/H) > 10$. The raw velocity data obtained from the ADCPs were conditioned by orienting (rotating) the velocities and smoothing the vertical profiles. Fig. 3 shows the vertical velocity profiles in two large rivers (Ohio and St. Clair). Power law and logarithmic profiles were fitted to the raw ADCP data. We found that the logarithmic relation described the data better for the larger rivers such as the St. Clair River in our work (especially closer to the bottom boundary layer). As described earlier, we have examined two approaches for orienting the velocities (rotating the velocities in the streamwise direction and projecting them along a direction that is normal to the transect track). These two methods can be expected to produce different results in regions with strong secondary flows. These two methods together with the three profile smoothing methods (power law, log law and no smoothing) yielded a total of six cases. Assuming that the tracer estimate of the dispersion coefficient in a given reach represents a reasonable averaged measure of dispersion in that reach, the relative "error" in the ADCP estimates for individual transects was calculated for all six cases and the results are displayed as box plots in Fig. 4 for the Grand River. Results indicate that the method of orienting the velocities has a relatively larger influence on the dispersion results than the method used for profile smoothing. The reason is that in evaluating Eq. (2) only the mean velocity in the water column is used (which is relatively insensitive to the smoothing technique). For the Grand River datasets used to generate Fig. 4, log law smoothing with velocity projection in the streamwise direction gave the best (closest to the tracer) results.

To quantify the uncertainty in the dispersion coefficient obtained from a single ADCP transect relative to an average value from multiple transects in a reach, we collected repeated transect data at different locations in a reach. We then plotted all the ADCP results for a given reach against the tracer result for that reach in Fig. 5(a). The variability in the ADCP estimates within a given reach is shown using box plots and colors indicate different rivers. For the Red Cedar River, ADCP and tracer data are shown for reach A, a 1.4 km reach as described in [8]. Tracer data were collected for flow rates 19.06, 16.82, 14.41 and 2.49 $m^3/s$ and tracer values of dispersion are marked in Fig. 5(a) for all the four flow rates. Several ADCP datasets were collected within the same reach for flow rates 19.98, 3.6 and 4.7 $m^3/s$ and the dispersion values are shown using box plots (the $X$-axis labels mark the locations of the box plots). For the Grand River, tracer and ADCP data are shown for reaches 2 and 3 as described in [13]. The combined reach is approximately 23.8 km long which explains the larger variability in the ADCP estimates shown in Fig. 5(a). In other words, some of the variability reflects the longitudinal variation of the dispersion coefficient. Tracer values for Grand River plotted in the figure represent average values for reaches 2 and 3. For the Ohio River all the transect data reported in [14] are included to generate the box

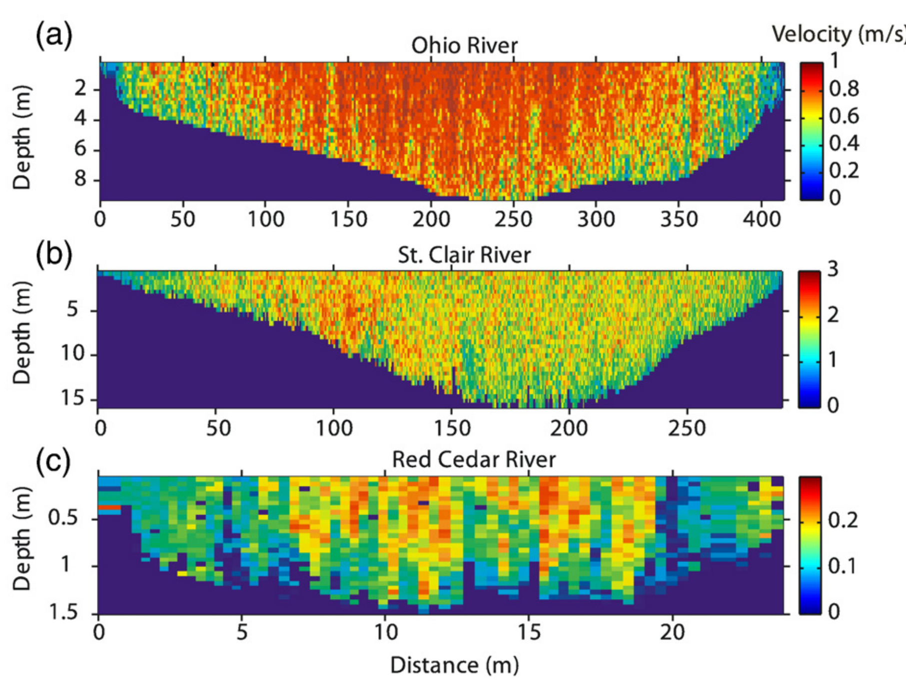


**Fig. 2.** Data from typical ADCP transects (observed mean velocity fields) used for computing the longitudinal dispersion coefficients.

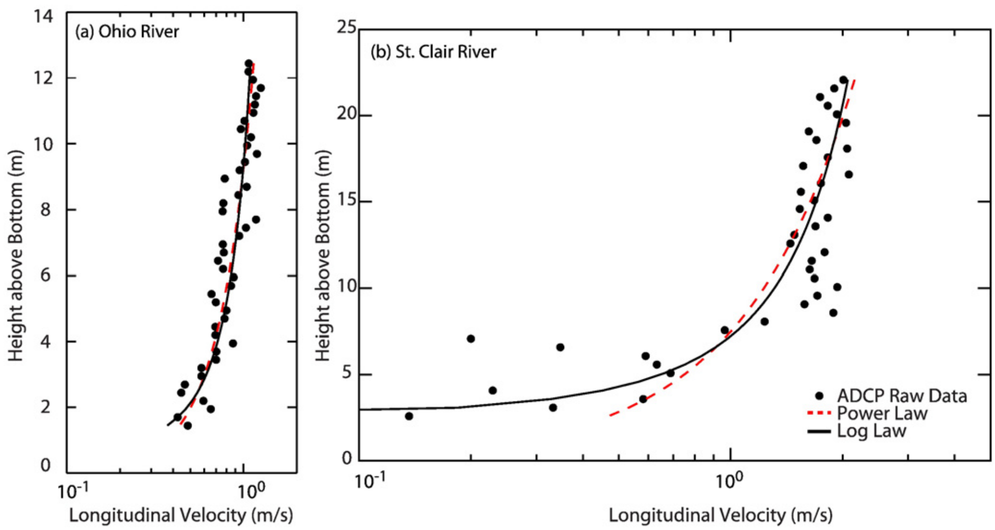


**Fig. 3.** Vertical velocity profiles in the Ohio and St. Clair Rivers showing the effect of fitting a power law (black lines) and logarithmic profiles (dashed lines). The raw data from the ADCP are shown using symbols.

plots and lengths of the river reaches are shown in Fig. 1. ADCP data for the remaining rivers came from a single reach as shown in Fig. 1.

Two different tracer estimates of dispersion are plotted in Fig. 5(a) — in the first approach TS modeling (Eq. 4) was used to estimate the dispersion coefficient. In the second approach, the tracer data were fitted to a solution of the ADE to obtain the dispersion coefficient. There are additional details associated with the tracer methods that are important to understand the comparisons shown in Fig. 5. Observed tracer data can be modeled in two different ways. In the first approach (method A), tracer mass is injected into the stream at $x = 0$ and model parameters are estimated by minimizing the deviation between simulated and observed concentrations at the downstream sampling stations. In this method, parameters (e.g., $D$) estimated for reach 1 represent average conditions between the injection site and the first sampling location; however, parameters estimated for reach 2 represent conditions for *both* reaches 1 and 2 and so on. In the second approach (method B), upstream conditions in the form of concentration versus time data observed at the first sampling location are specified at the beginning of reach 2, therefore parameters estimated for reach 2 represent conditions in reach 2 only. While using the TS model for relatively small rivers, our experience indicates that the two approaches produce almost identical results [8]. However, this situation is different while using the ADE for large rivers. We found that methods A and B produced widely different results for large rivers. This is not surprising since the ADE does not have a separate term for the dead zones. Therefore, the dispersion term in the ADE tends to capture the effects of dead zones as well. As a result, if method A is used with the ADE in large rivers, the cumulative effects of dead zones as travel time increases could produce dispersion estimates that are unreasonably high compared to the local/point estimates from the ADCP. For the Grand River, for example, the TS estimates of the dispersion coefficient in the four reaches are 2.16, 1.6, 4.2 and 1.39 $m^2/s$ respectively while the values based on the ADE using method A are 3.5, 27.72, 56.54 and 112.3 $m^2/s$ respectively. Results from the ADE obtained using method B in the same reaches (using the same initial mass) are 3.5, 13.05, 15.02, and 4.92 respectively. The ADE estimates shown in Fig. 5(a) were obtained using method B in which parameters estimated for a reach represent conditions only in that reach. ADE model results based on method A were significantly higher and therefore not included in Fig. 5. We notice that the ADCP and tracer estimates are in good agreement as the flow rate changes over four orders of magnitude. In addition, the tracer estimate is closer to the median value of the dispersion coefficients obtained from the ADCP method indicating that it is beneficial to obtain multiple datasets within the reach. These results establish the ADCP method as a reliable alternative to the tracer method. From Fig. 5(a) it appears that the difference between the TS and ADE estimates increases with flow indicating that dead zones play an important role at high flows. This was observed clearly for the Red Cedar River and the Grand River during our field studies (e.g., Fig. 10 in[8]). At high flows, the low lying areas near the banks of the river were filled with stagnant water that contributed additional storage. This additional storage was not available during low flow conditions. For low flows, the difference between the two models (TS and ADE) is not as high for the river sites considered in this paper and the dispersion coefficient from the TS model is in good agreement with the ADCP estimates. These comparisons indicate that the ADCP estimates of dispersion include the effects of dead zones as well. The ADCP measures velocities in both fast and slow moving regions of the river. There are no guidelines in the literature on what constitutes a dead zone (e.g., regions where velocities

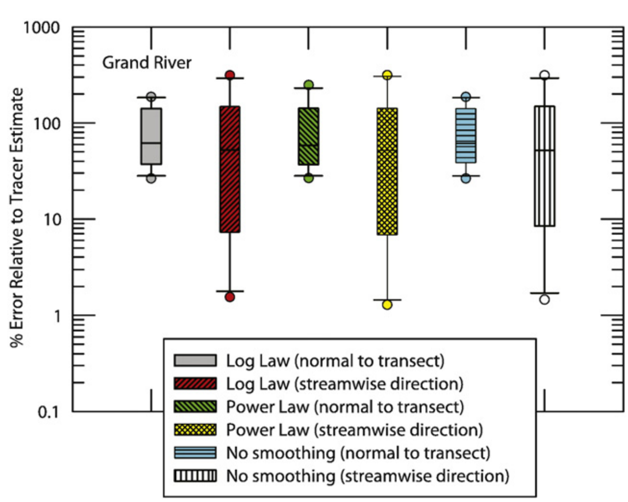


**Fig. 4.** Effects of smoothing (logarithmic, power law or no smoothing) and velocity projection methods (rotating velocities in the streamwise direction or projecting them in a direction normal to the transect track) on the dispersion estimates from ADCPs.

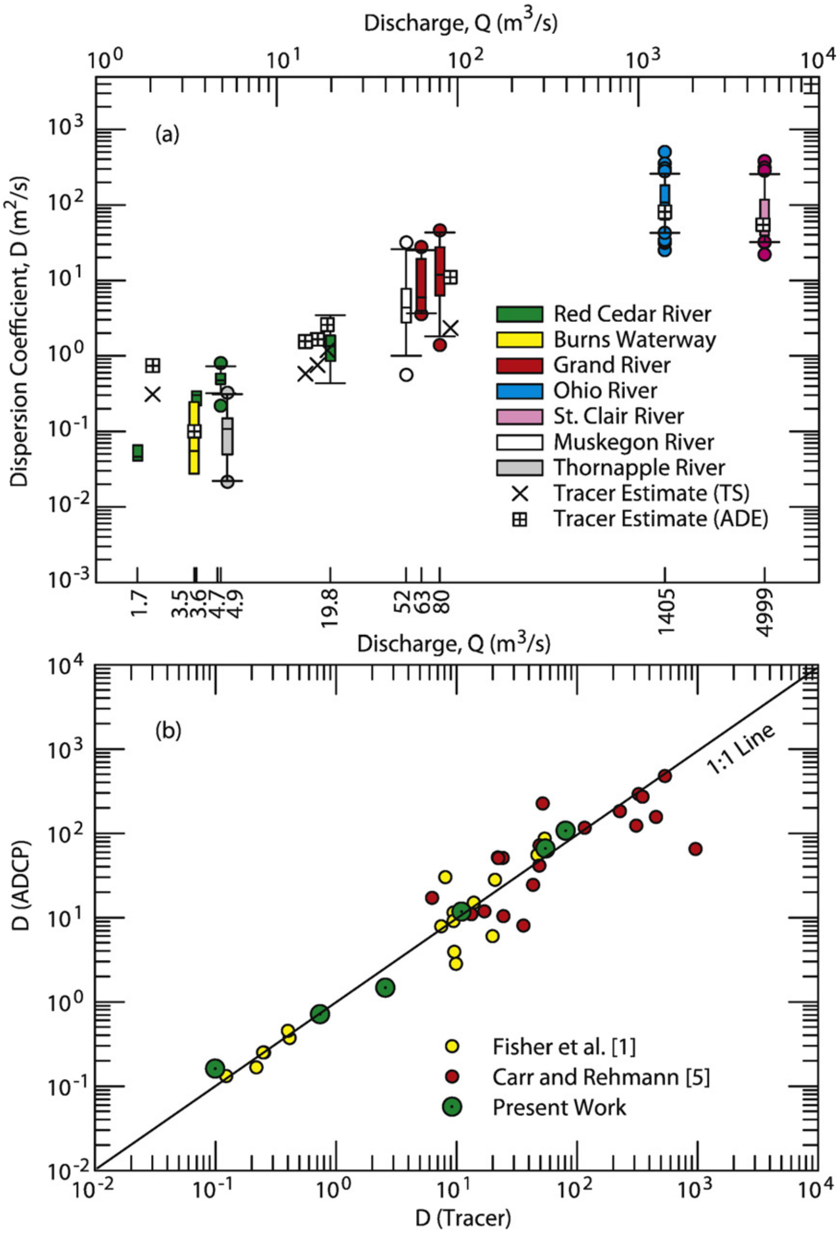


**Fig. 5.** Comparisons between ADCP and tracer estimates of the dispersion coefficient: (a) Box plots denote the variability in $D$ estimated using the ADCP method within a given river reach. Tracer estimates based on the ADE and the transient storage modeling are shown using different symbols. (b) Comparisons between the ADCP and tracer estimates plotted on top of similar results reported in the literature. For the data of Fischer et al. [1], $D$(ADCP) represents values obtained using conventional current meters.

fall below a certain threshold value). In an earlier paper [8] we explored the idea of separating the flow field measured using an ADCP into relatively fast and slow moving regions using wavelet decomposition. We were successful in estimating the size of surface storage zones ($A_S/A$) based on ADCP data and estimates compared favorably with results from a tracer-based method (TS modeling) for both high and low flows. Our results support the fact that the dispersion coefficients estimated by the ADCP method include contributions from dead zones.

The median dispersion values from repeated transect data shown in Fig. 5(a) are plotted against the tracer values in Fig. 5(b). In cases where tracer and ADCP data were obtained on different days, linear interpolation was used to obtain the ADCP estimates corresponding to the tracer values. For comparison, we also plot values reported in the literature, including data from Carr and Rehmann [5] and Fischer et al. [1]. The lower end of the tracer values shown in Fig. 5(b) comes from either the laboratory flume data reported by Fischer et al. [1] or the relatively smaller rivers such as the Burns Waterway or the Red Cedar River (present work).

Results from individual datasets for all rivers are plotted in Fig. 6(a) against some of the well known empirical relations available in the literature including the relations of Fischer (p. 136 in [1]), Seo and Cheong [4] and Deng et al. [3]. The ADCP method generally produces estimates that are comparable to the results from the empirical relations; however ADCP and tracer values are generally lower. The deviation ($\Delta D/D_{\mathrm{ADCP}}$) where $\Delta D = (D_{\mathrm{ADCP}} - D_{\mathrm{Empirical}})$ between the ADCP values and those from empirical relations is displayed using box plots in Fig. 6(b) for all three empirical relations considered. Comparisons with empirical relations showed that results based on the relation of Fischer [1] matched more closely with the ADCP estimates. A Kruskal–Wallis one-way ANOVA test on ranks indicated that the three groups had statistically significant differences ($p \leq 0.001$) among their median values. Further analysis using Tukey's multiple

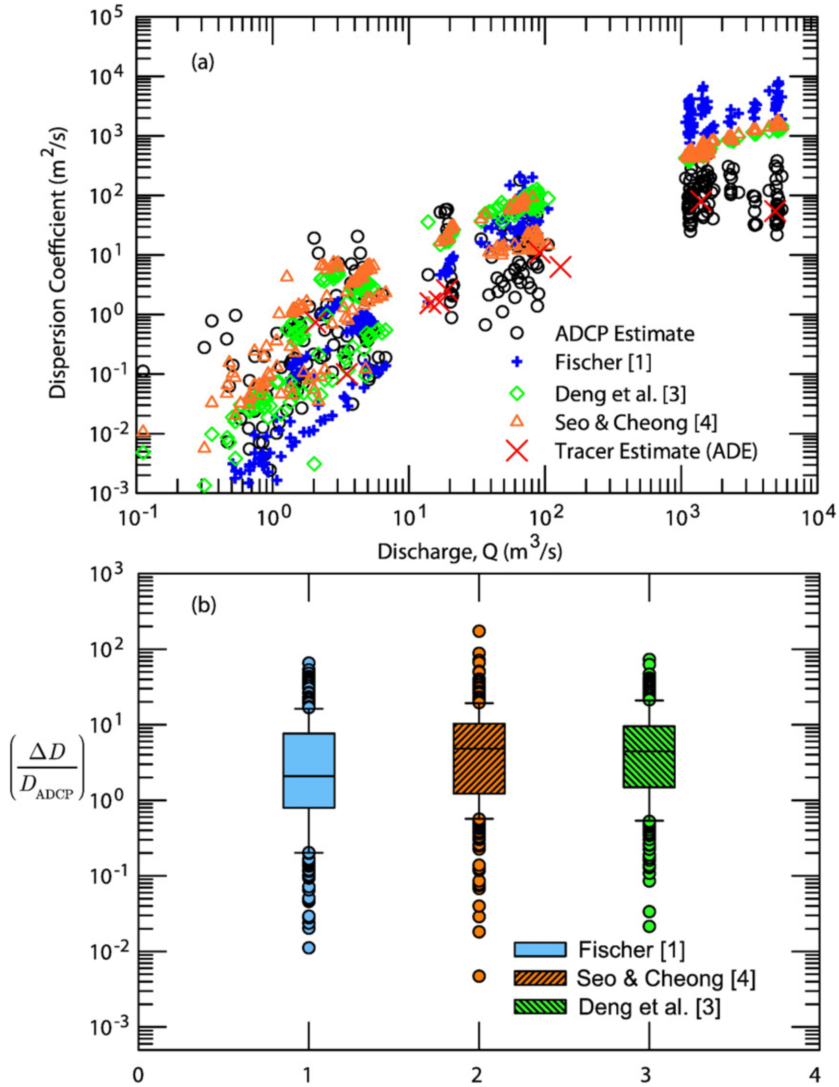


**Fig. 6.** Comparison of ADCP estimates of the dispersion coefficient with tracer estimates and results from empirical relations. (b) Box plots showing the deviation between estimates of *D* based on the ADCP method and empirical relations.

pairwise comparison procedure reported that the relation of Fischer [1] was responsible for the observed difference and that differences in the results based on the Seo and Cheong[4] and Deng et al. [3] relations were not statistically significant.

Examination of our ADCP data indicated that there was a correlation between the quality of the dispersion estimates and the per cent bad ensembles in the transect data. Estimated dispersion numbers were found to be unrealistically high when the per cent bad ensembles exceeded about 12%. Bad ensembles can occur when communication is interrupted, when aquatic vegetation or large debris enters the field of the transducer beams or when a change in the ADCP operating conditions is warranted. A large number of bad ensembles could potentially influence the discharge measurement which can be a problem in itself. In fact, we found that whenever the ADCP discharge from a transect deviated significantly from its "true" value (e.g., value from a nearby USGS gauge or the average discharge value based on multiple transects), the estimated ADCP dispersion coefficient for that transect also deviated significantly from the tracer estimate. Fig. 7 shows typical depth-averaged velocity profiles (Fig. 7a, b and c) and the computed discharge and the dispersion coefficient as a function of per cent bad ensembles within the same reach for the Grand River. Symbols show the raw ADCP data and trend lines based on LOESS smoothing are also plotted (no attempt was made to fit the profile to satisfy the no-slip condition at the two banks). Examination of the velocity profiles can help isolate datasets that could potentially lead to a violation of the assumptions involved in Eq. (2).

## 4. Conclusions

As improved understanding of stream solute transport processes leads to better models and new approaches [11,20,21], there is an imperative need for independent, field-based estimates of the dispersion coefficient to constrain model parameters. The ADCP method of estimating the dispersion coefficient appears to be an excellent alternative to the tracer approach if care is taken to identify spurious data and repeated transects are used to estimate $\overline{D}$ (or another appropriate measure that represents average conditions within the stream reach). Our results indicate that a measure of *D* based on multiple transects is more reliable than a value obtained from a single transect. For the river reaches in our work, the median value of the dispersion coefficients obtained from multiple datasets was found to be closer to the tracer estimate based on the ADE (using method B as described earlier). Our comparisons indicate that the ADCP method measures the influence of dead zones on the dispersion coefficient as does the estimate from the ADE. The ADCP method has its share of limitations including the inability to make measurements close to the banks and in shallow stream reaches. In addition, the

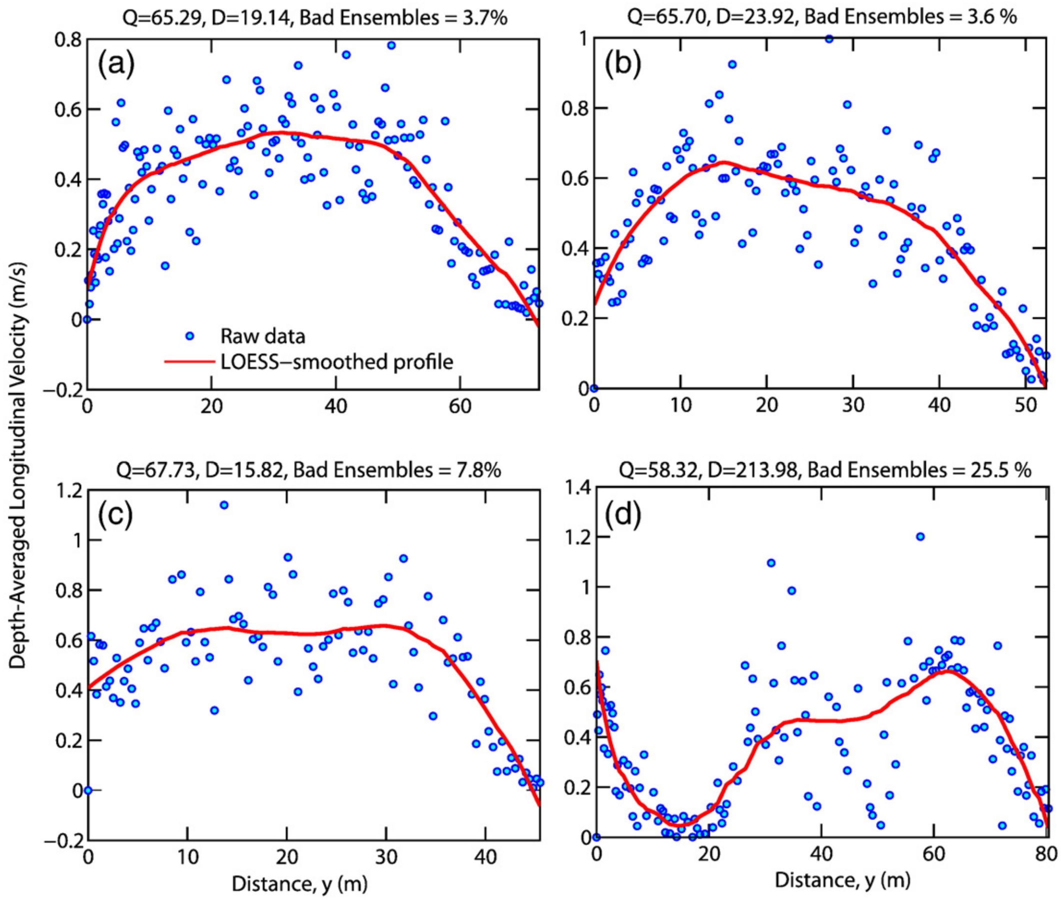


**Fig. 7.** Depth-averaged longitudinal velocity ($u$) profiles plotted as a function of the transverse coordinate $y$.

method is not suitable for stream reaches dominated by meander bends, recirculating regions or secondary flows. Recent ADCP models using smaller sensor heads, small (~5 cm) blanking distances and bin sizes and multiple acoustic frequencies (with features such as frequency hopping) have the potential to further improve our ability to estimate dispersion in streams and rivers. Additional datasets (including simultaneous tracer and ADCP data) and analyses are needed to further assess the relative strengths of this approach, especially for large rivers.

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