New strategies for measuring rates of environmental processes in rivers, lakes, and estuaries

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Abstract: A central goal in limnology is measurement of physical, biogeochemical, and biological process rates. We can measure process rates from the temporal and spatial patterns they create in a measured variable, and we use 3 approaches for making those measurements: the fixed-site approach for detecting temporal pattern at a location, the snapshot approach for detecting spatial pattern at an instant in time, and the flow path approach for detecting temporal pattern as it changes through space. To compare and contrast these approaches, we present patterns in temperature collected simultaneously based on all 3 approaches. Translating these patterns into process rates requires different assumptions for each approach, and these assumptions lead to uncertainty in process rates. We propose that these assumptions and related uncertainty can be reduced by making simultaneous measurements based on all 3 approaches. Each approach fills gaps in the spatial and temporal patterns measured by the others, and these patterns can be combined to derive a process rate. We develop a conceptual theory to support this strategy for measuring process rate based on 2 criteria: the mixing time of a water body and the analytical limitations of the measurement. This new strategy for measuring process rates in aquatic environments has the potential to increase the resolution of rate measurements, reduce their uncertainty, and enhance limnologists' ability to resolve process rates from an increasing flow of environmental data.
Key words: Lagrangian, Eulerian, synoptic, environmental sensing, physical mixing, aquatic biogeochemistry, reference frames, ecosystem ecology, estuarine biogeochemistry

MEASUREMENT APPROACHES IN LIMNOLOGY

The study of streams, rivers, lakes, and estuaries is entering a new era. Our science is being transformed from one challenged to collect sufficient data to measure a process to one that is generating so many signals that we need to discern what those signals mean. The quantity, breadth, frequency, and resolution of data continue to grow with increasing use of miniaturized sensors, real-time measurements, and autonomous platforms. These technologies tempt us to imagine a future in which limnologists can measure the rate of many processes simultaneously at almost any scale in near real-time, an ideal situation for managers and scientists. However, this growing stream of data brings with it the problem of detecting the signal we seek from the noise of overlapping spatiotemporal scales. Here, we show how limnologists can more fully measure and resolve the rates of processes that cause spatiotemporal patterns by using combinations of alternative measurement approaches.

In an observational approach, limnologists study environmental processes by first measuring a *variable*, and repeating the measurement over time or space. The differences in the value of the variable over time or space are interpreted as *patterns* that they create. From the combination of patterns and an understanding of first principles (e.g., photosynthesis, turbulence), we infer *rates of processes*. These process rates (e.g., biological production, photolytic oxidation, mortality, reaction kinetics) are a fundamental pursuit of limnologists.

The starting point of limnology is generating patterns of variables from which to most accurately discern rates of processes. This step requires limnologists to decide which pattern will best inform their interpretation: a pattern over

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space, a pattern over time, or some combination. Limnologists have generated tremendous insights through their analysis of temporal patterns—repeated observations over time at a fixed location (e.g., water temperature data from an anchored buoy). A 2nd measurement approach is to document purely spatial patterns at a point in time: 'snapshots' of variables (e.g., satellite images of water temperature). A 3rd measurement approach is to generate a single, simultaneous temporal and spatial pattern from the change in a variable collected along a flow path (e.g., water temperature data generated by a drifting buoy). To decide which approach or combination of approaches to use, we must consider the underlying reference frame for each approach and its limitations for inferring process rate from temporal and spatial pattern.

Fixed-site approach (Eulerian reference frame)

Beginning in the 1950s, fixed-site time series of variables in aquatic ecosystems became the backbone of a new era of ecosystem-based research in which variables were interpreted as holistic measures of a spatially bounded system (e.g., a freshwater spring; Odum 1957). When applied to rivers, the watershed defined the ecosystem boundaries and fixed-site measurements provided integrated measures of mass output from the watershed (Likens et al. 1967). These measurement approaches correspond conceptually with the Eulerian reference frame in which fluxes are observed as they pass a point over time (Fig. 1, Table 1). This Eulerian reference frame is particularly well-suited to quantify changes in a process rate over time because it allows integration (i.e., homogenization) of spatial variability (Doyle and Ensign 2009).

Rapid development of in situ sensing and communications technology has simplified the fixed-site approach and transformed it from discrete measurements to continuous time series. Sensors continue to decrease in size, cost, and power consumption, while accuracy and temporal resolution continue to increase. For example, within the last 20 y NO_3^- sensors have progressed from ion-selective electrodes to optics (Pellerin et al. 2016) with highly sensitive microelectrodes on the horizon (Gartia et al. 2012). Chemical variables are now measured on the order of minutes and physical variables can be measured every second. Progress in wireless communication (Rundel et al. 2009) and emerging technology in wireless power (Park et al. 2013) have paralleled innovations in sensing, thereby giving the fixed-site approach a strong foothold.

The fixed-site approach has 3 limitations in terms of elucidating rates of processes from measured changes in variables (Table 2). First, the size of the 'box' (distance between 2 measurement points, or the space represented by a single point) constrains the spatial scale that can be considered; no space smaller than the size of the bounded measurements is directly observable. For instance, dissolved O_2 measured up- and downstream of a pool–riffle sequence would provide information on ecosystem metabolism of that sequence, but the interpreter would not know whether the temporal signature was the result of the processes occurring in the pool, in the riffle, or both. The 2nd problem is that the fixed-site approach requires bounding the system (i.e., the boundaries of the box) a priori, and ecosystem boundaries may not be as sharp or discernible as are typically imagined (Post et al. 2007).

The 3rd limitation is related to the assumption of the homogeneity of the system within the black box of a fixed-site measurement. Temporal changes are assumed to represent the cumulative effect of all processes occurring within the box and are identical regardless of measurement location within the box. This assumption is valid if all of the particles or solutes through that space are well-mixed such that a sampling point integrates variability in temporal and spatial processes. However, if the pathways by which particles or solutes travel through the bounded space are not well-mixed, then what appears as a temporal signature may in fact be the peculiarities (i.e., spatial variability) of a particular flow path through a system that is conceptualized as homogenous. This limitation of fixed-site measurements often is cited to explain temporal variation in fixed-site data. Van de Bogert et al. (2012, p. 1690) explained such flow path variation in lake dissolved O_2 measurements: ". . . some of the variation reflects . . . physical processes causing the sensor to measure a parcel of water with differing metabolic and physical histories for some portions of the day." In summary, spatial variability in process may be manifest or interpreted as temporal variability in measured variables.

Snapshot approach (synoptic reference frame)

In the same way that the Eulerian reference frame homogenizes space to maximize temporal insights, the synoptic reference frame homogenizes time to maximize spatial insights (Fig. 1). In its purest form, synoptic data capture spatial patterns in a variable without any intervening temporal pattern: remote sensing and coordinated spatial grab sampling (Dent and Grimm 1999) are examples of synoptic data. The spatial resolution of synoptic data can be imagined as a pixel that represents the spatially weighted average of a variable within the pixel space. The power of synoptic data for limnology is the ability to measure a spatial pattern (and the underlying spatial pattern in process rate) without the influence of a temporal pattern affecting the variable between measurements.

Recent technological advancements are enabling snapshot measurements at scales not previously possible with satellite remote sensing (Table 1). Distributed fiber-optic temperature sensors are widely used to collect snapshot temperature data along a river axis over hundreds of meters with a resolution at the centimeter scale, while airplane

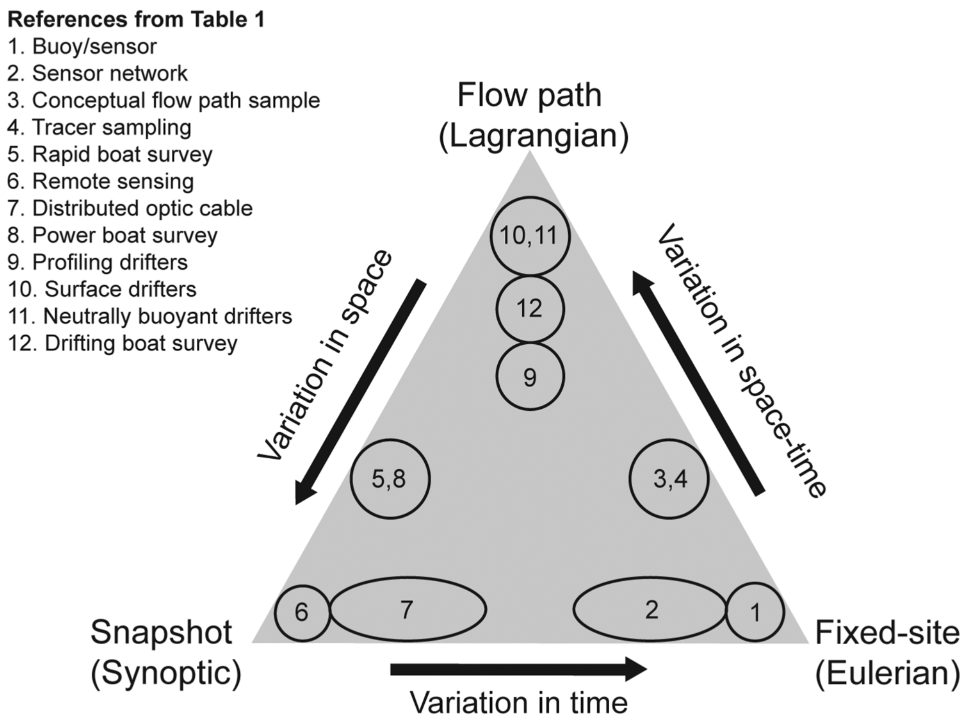

Figure 1. Triad (ternary diagram) of measurement frameworks with examples from Table 1 plotted qualitatively in this measurement space.

and drone-mounted thermal infrared radiometers can map temperature patterns longitudinally and laterally at high spatial resolution (Deitchman and Loheide 2012, Vatland et al. 2015). Drones are enabling a range of snapshot measurements of variables, including chlorophyll, turbidity, and dissolved organic matter (e.g., Fichot et al. 2016). Vessel-based snapshot sampling uses both wet-chemistry and sensor-based variable measurements (Croswell et al. 2012, Crawford

Table 1. Examples of methods and representative studies using fixed-site, snapshot, and flow path approaches.

Approach	Reference	Water body	Process	Method (numbers refer to Fig. 1)
Fixed-site	Houser et al. 2015	Upper Mississippi, Wisconsin, USA	Ecosystem metabolism	1. Stationary buoy/sensor
	Hunt et al. 2012	Mitchell River, Australia	Ecosystem metabolism	2. Stationary sensor network
	Newbold et al. 1981	Walker Branch, Tennessee, USA	N and P uptake	3. Stationary sampling with Lagrangian concept (e.g., nutrient spiraling)
	Bohlke et al. 2004	Sugar Creek, Indiana, USA	Denitrification	4. Stationary sampling with conservative tracers
Snapshot	Crawford et al. 2014	Lake Mendota, Upper Mississippi, others	Characterization of C and N sources, sinks	5. Synoptic survey from boat (e.g., FLAME)
	Bosc et al. 2004	Global ocean	Primary production	6. Remote sensing (e.g., seaWIF)
	Vogt et al. 2010	River Thur, Switzerland	Groundwater–stream exchange	7. Distributed fiber optic temperature sensors
	Croswell et al. 2012	Neuse River, North Carolina	Air–water CO_2 exchange	8. Synoptic survey from boat (e.g., Dataflow)
Flow path	Riser and Johnson 2008	Pacific Ocean	O_2 production	9. Profiling drifters (e.g., ARGO)
	Gattuso et al. 1996	Great Barrier Reef	Coral metabolism	10. Surface drifters
	This study	Neuse River	O_2 dynamics	11. Drifters (e.g., HydroSphere)
	Hensley et al. 2014	Florida springs	Autotrophic NO_3 uptake	12. Drifting survey from boat

Table 2. Comparison of the information gained and limitations of fixed-site, snapshot, and flow path measurement approaches.

Approach	Information gained	Limitations
Fixed-site	1. Temporal change in a process rate upstream	1. Requires knowledge of transport time scale (e.g., velocity, mixing) to calculate a process rate
	2. Physicochemical variability in a mixing length upstream	2. Spatially integrated measure of physical and biological process rates
	3. Temporal change in rate integrates spatial variability	3. Cannot differentiate spatially unique process rates or lateral inputs from a change in process rate over time
Snapshot	1. Reach-scale process rate expressed over distance	1. Requires knowledge of transport time scale (e.g., velocity, mixing) to calculate a process rate
	2. Temporal change in a process rate expressed over distance	2. Spatially integrated measure of physical and biological process rates
	3. Process rate and change without the influence of mixing variability	3. Cannot differentiate a temporal change in rate from the process rate expressed over space
Flow path	1. Process rate occurring over a discrete flow path	1. The flow path measured may not reflect reach-average conditions
	2. Spatiotemporal variability over a discrete flow path	2. The flow path may not adequately follow the relevant scale of water movement
	3. Location of discontinuities (e.g., lateral inputs)	3. Cannot separate temporal and spatial variability in process rate

et al. 2014, Hensley et al. 2014). In practice, the ability of vessel-based sampling to collect a snapshot independently of temporal variability between points is limited by speed and, therefore, represents a hybrid of measurement approaches (Fig. 1).

Inferring process rates from snapshot measurements is limited in 2 ways (Table 2). First, spatial differences in the rate of a process cannot be separated from temporal changes in the process rate as water moves across the field of observation. For example, a hot spot of chlorophyll in an estuary could indicate a persistent location of high plankton growth rate or water flow patterns that cause phytoplankton to accumulate in that particular location. Inability to detect temporal change in process rates from snapshot data is the reciprocal of the fixed-site limitation of parsing spatial differences from process-rate changes over time.

Second, spatial patterns in snapshot data can reflect a legacy of process rates that occurred in the past, and this legacy affects interpretation of process rates. For example, Hensley et al. (2014, p. 1168) summarized how the time of day a snapshot was taken affected interpretation of autotrophic NO_3^- removal from a profile along a river reach: ". . . as profile length increases so do effects of temporally varying removal." In summary, snapshot data enable interpretation of spatial changes in process rates but not how those rates occur over time.

Flow path approach (Lagrangian reference frame)

The variation between particular flow paths, or even histories, of water are the focus for the Lagrangian reference frame, which allows direct measurement of the movement of objects with the measurement of changes in variables associated with those objects over time (Fig. 1). In theory, the Lagrangian reference frame follows the movement of an object that is not geographically fixed, but instead referenced only to its change in position over time (Doyle and Ensign 2009). To some extent, this approach removes the need for arbitrary, human-defined boundaries of the ecosystem under study (Post et al. 2007). In practice, the flow path approach serves the practical purpose of transporting measuring equipment spatially and coupling variable changes with the transport time scales of water. This coupling of variables with transport enables measurement of specific process rates that are unique to specific flow paths. Unbundling the average process rate in a river into the rate occurring in backwaters vs a deep channel, for example, would be a powerful capability in limnology. Hensley et al. (2014, p. 1168) expressed the benefit of the flow path method this way (when applied to studying biogeochemical hotspots along a river): "Whereas an Eulerian reference frame aggregates reach-scale processes, using a Lagrangian-based approach disaggregates these processes and helps identify removal hot spots and their attendant controls."

Flow path measurements are being conducted by using manned vessels to track water moving at an average surface-flow velocity and to measure concentration changes (Table 1; Hitchcock et al. 2004, Dagg et al. 2005, Gruberts et al. 2012, Gruberts and Paidere 2014). Floating instrument platforms also are being used to mount sensors and enable deployment to capture flow path variability in process rates in lakes (Stocker and Imberger 2003), rivers (Spencer et al. 2014), and estuaries (Schacht and Lemckert 2007, Mullarney and Henderson 2013, Landon et al. 2014). Un-instrumented drifters are being used to track the movement of water parcels (MacMahan et al. 2009, Oroza et al. 2013, Wu et al. 2015), and the flow path of individual particles can be measured with tracers (Kemp et al. 2010). 'Pseudo-Lagrangian' techniques can be used to analyze fixed-site data based on temporal offsets that mimic the elapsed time in water travel, as in the 2-station, open-water metabolism method (Odum 1956), grab sampling methods (Brown et al. 2009), nutrient-uptake measurements (Stream Solute Workshop 1990), and other analytical methods (Imberger et al. 1983). Only recently have autonomous, free-drifting, sensor-based measurements been developed to measure flow paths in a passive 3-dimensional framework.

In practice, the flow path measurement approach has 3 limitations for measuring process rates (Table 2). First, measurements reflect only 1 of a myriad of flow paths. The greater the difference in process rate among flow paths, the more flow paths must be measured to estimate an integrated process rate. Second, the physical scale of flow path measurement is limited to the size of the measurement device and its physical coherence with water movement. Third, each path may have a unique temporal signature.

Example of measurement using 3 approaches

Most of the research cited above relied on a single-measurement approach, and the contrasts and comparisons we have made between approaches are difficult to visualize. To better illustrate, compare, and contrast spatiotemporal patterns in a variable measured with each approach, we show temperature data collected simultaneously based on all 3 approaches along a river reach. Our brief description of the data focuses on spatiotemporal patterns.

Methods Data were collected in the Neuse River, which originates in the Piedmont of North Carolina, crosses the coastal plain, and terminates as a 5th-order river at the Pamlico Sound (Fig. 2A). We measured a 19-km reach of the river characterized by extensive coastal plain riparian floodplains, a gradient of 0.00005, and a channel ~80-m wide. Data were collected from 12 to 13 October 2015 when discharge at US Geological Survey (USGS) stream gage at the head of our study reach (Neuse River Fort Barnwell, North Carolina, 02091814) averaged 238 m^3/s.

Fixed-site, time-series data were collected at the up- and downstream ends of the study reach by HOBO sensors (Onset, Bourne, Massachusetts) attached to a dock ~50 cm below the water surface. Measurements were made for 24 h starting at midnight 12 October 2015. Snapshot data were collected with a temperature sensor (Campbell Scientific, Logan, Utah) attached to a powerboat driven the length of the study reach between 1015 and 1310 h on 13 October 2015 (Fig. 2B, C). Flow path data were collected with a HydroSphere (Planktos Instruments, Morehead City, North Carolina) adjusted for neutral buoyancy (Fig. 2D). The HydroSphere is an underwater, autonomous, drifting, spherical (0.5-m diameter) multisensor platform that monitors its position at the surface by a global positioning system (GPS) and emits a radio signal for tracking when submerged. The HydroSphere traveled the entire study reach submerged between 1300 and 2045 h on 12 October 2015. It profiled vertically through the water column as dictated by vertical mixing and was tracked from a boat by means of a directional antenna and radio receiver.

Results Temperature at the up- and downstream ends of the study reach showed a diurnal warming and cooling trend (Fig. 3A). Water entering the study reach from upstream warmed slightly over the 24-h period, whereas water exiting the reach showed net cooling. The flow path drifter showed that travel time between the upstream and downstream fixed-sites was 7.75 h. The initial and final flow path temperatures matched the fixed-site temperature. We presume this condition would occur regardless of the time the flow path measurements began. For example, if the drifter were released at the beginning of the measurement period (~19.4°C at 2400 h), it would measure ~19.0°C when it passed the downstream fixed-site at 0745 h. The flow path data also highlighted spatiotemporal variability in the reach that was not captured in fixed-site data.

The snapshot data reflect the spatial variation in warming along the reach during mid-day (Fig. 3B). Distinct decreases in surface water temperature occurred at 5 and 12 km, indicating mixing of cooler water into the channel. This mixing could have been a result of lateral or groundwater inflow or mixing within the water column. Flow path temperature was measured over a different period of time, but the vertical temperature gradient detected within the water column (Fig. 3C) provides useful information for interpreting the snapshot pattern. We presume that the 2 abrupt decreases in snapshot temperature resulted from turbulent mixing in the water column that brought cooler bottom water to the surface.

These data highlight complementarity of 3 simultaneously conducted measurement approaches for characterizing spatiotemporal patterns in a variable from which process rates could be derived. We will focus on this complementarity later in this review. First, we will explore how transport time scale and mixing, also highlighted in our temperature data, affect measurement of spatiotemporal patterns and process rates.

A THEORY FOR SELECTING A MEASUREMENT APPROACH

How do limnologists choose between these 3 approaches to measure the rate of a process in a particular ecosystem? Practical considerations include the types of sensors and as-

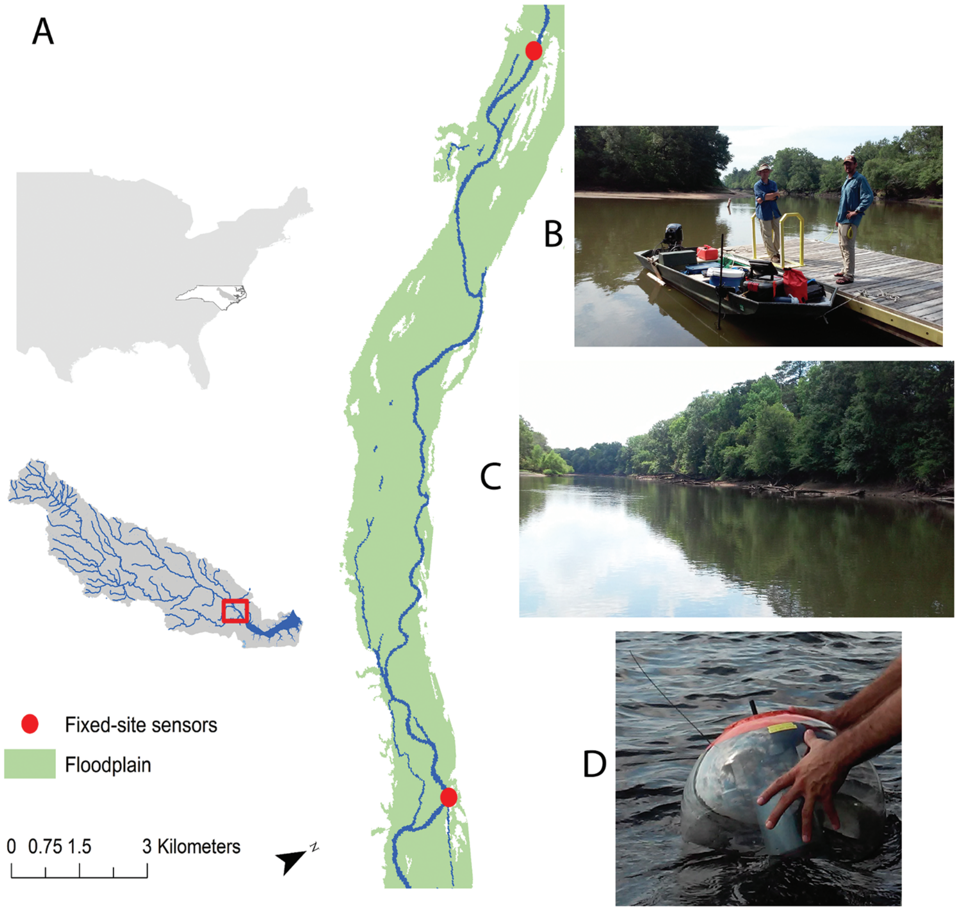

Figure 2. Location of Neuse River watershed in the eastern USA (North Carolina) and the planform of the river channel and floodplain (A), vessel used for snapshot survey of study reach (B), Neuse River at low river stage (C), and HydroSphere at the water surface after preprogrammed, automated surfacing at the end of the study reach (D).

say techniques available and physical access to the ecosystem. Theoretically, choice of a measurement approach also depends on which pattern in a variable, spatial or temporal, a limnologist expects to provide the most information about the rate of a process. If the process rate of interest varies little spatially but varies greatly temporally, then a fixed-site time series would provide the most information. In contrast, if spatial variability is much greater than temporal variability, then the snapshot approach would provide the most information. If spatial and temporal variability are comparable, then the flow path approach provides a compromise that captures both sources of variability. In practice, a limnologist may not know both sources of variability before making measurements and may not have a choice in the measurement approach used. However, a diagnostic tool would be useful for evaluating the suitability of the chosen measurement approach for evaluating spatial and temporal patterns and the subsequent rate of a process.

To compare how a given combination of spatial and temporal variability is represented by each measurement approach, spatial and temporal variability must be considered in the context of the time it takes water masses to mix and the time it takes a process to change the concentration of a variable. We will define what is meant here by mixing time and process time using the example of rivers. In rivers, the time required for water masses to mix fully across the cross-section can be translated into a distance downstream (mixing length) resulting from dispersion (Fig. 4). For example, a storm sewer could introduce a plume of runoff into a river that cannot be measured on the opposite river bank until 100 m downstream (mixing length is 100 m). At a flow velocity of 1 m/s, water moving past the storm sewer would require 100 s to mix across the river. This example illustrates how space and time are related in moving water ecosystems and, thus, how mixing time can be converted to mixing length.

Process time is the time necessary for a rate of a process to produce a measurable change in a variable. Process time is a function of the rate of a process, the volume of water in which the change in concentration is being measured, and the resolution and accuracy of the variable measurement (Fig. 4). For example, consider the time required to mea-

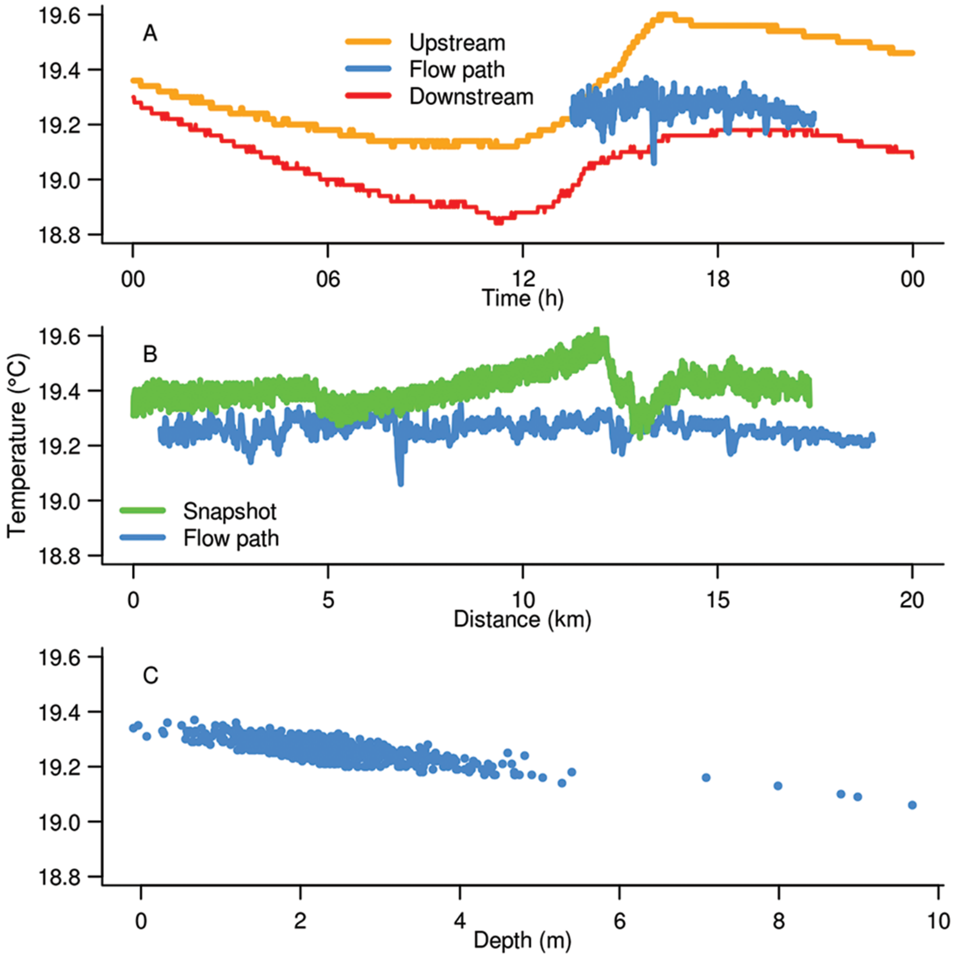

Figure 3. Temperature in the study reach shown in Fig. 2 based on fixed-site sensors and flow path measurements (A), flow path and snapshot measurements (B), and variability in temperature over depth in the water column in flow path measurements (C).

sure a change in temperature at the surface of a river for a given intensity of sunlight (i.e., the process of converting solar radiation into heat energy as measured by the variable, water temperature). Measuring a change in temperature of a large, deep river will take longer when using a thermometer with 1.0°C resolution than in a small, shallow stream when using a thermometer with 0.1°C resolution. The time required to observe a temperature change in ei-

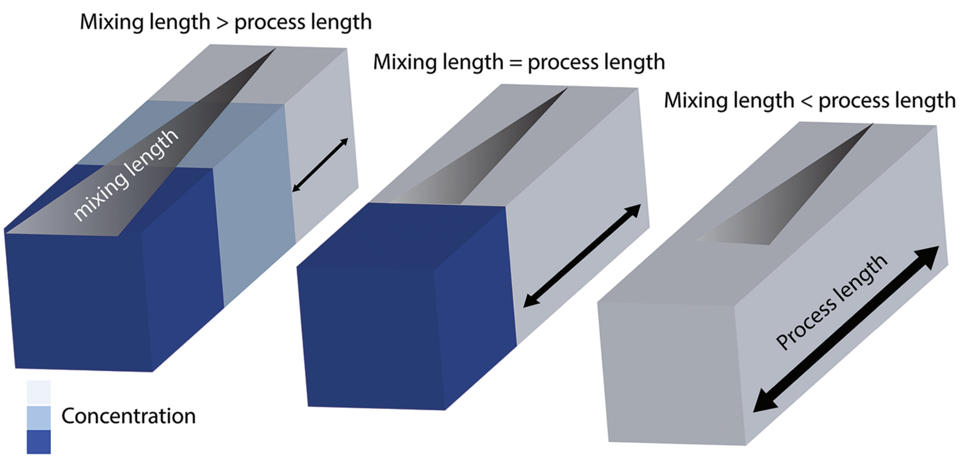

Figure 4. Conceptual depiction of 3 relationships between longitudinal mixing length and process length in a river.

ther situation is the process time, and the distance water moves downstream over that period of time is the process length.

Knowledge of mixing time and process time enables us to sort any combination of spatial and temporal variability into a variable space for diagnostic analysis (suitability) of fixed-site, snapshot, and flow path suitability for characterizing a process rate. If no spatial variation in a process rate occurred across the fully mixed length of a river but temporal variation occurred in the process rate during the time it took mixing to occur, then fixed-site measurements would allow the best characterization of that change in process rate. A snapshot would not show any spatial pattern in the variable being measured. This scenario would be represented as a point in the lower right corner of Fig. 5A. In contrast, if the process rate varied spatially over the length of river required for mixing but no temporal variation occurred, then the only way to detect a pattern and measure a process rate would be to use the snapshot approach. Fixed-site measurement would not show any difference in the variable over the time and spatial scale at which the process rate varied. This scenario would be represented as a point in the upper left corner of Fig. 5A.

The 2 examples above represent extreme conditions in spatial and temporal variability in which one or the other is negligible. A 3rd example, in which spatial and temporal variability in a process rate are similar, would result in a point falling near the 1:1 line in Fig. 5A (green portion). In this case, the flow path approach provides a compromise between the fixed-site and snapshot approaches that allows simultaneous characterization of both spatial and temporal variability. In other words, flow path measurement conjoins spatial variability in process rate with temporal variability in process rate, and neither source of variability is measured in isolation from the other. The flow path measurement enables one to measure changes in a process rate that occur more rapidly and over a shorter distance than physical mixing, an advantage over the fixed-site and snapshot measurements, which cannot detect changes in a process rate at less than the mixing time. This advantage of the flow path approach spreads over a wider range of variability when process length and time are shorter and more rapid than mixing (Fig. 5B). Shorter process length and faster process time potentially increase the heterogeneity of conditions for individual flow paths, and this variation in conditions can change process rates that can be detected only with flow path measurements.

A STRATEGY OF MULTI-APPROACH MEASUREMENTS

Rather than thinking of the different measurement approaches in isolation, we now consider how the 3 measurement approaches, their corresponding reference frames, and resultant analytical frameworks can provide complementary data to interpret process rates over space and time. Even the most optimized measurement approach provides only a portion of the information about a process rate, so it may be more effective to use multiple measurement approaches simultaneously, thereby using information derived from each approach to fill the gap in knowledge about process rate left by the other approaches. Limnologists have developed almost intuitive strategies that combine multiple approaches, such as nutrient spiraling and stream metabo-

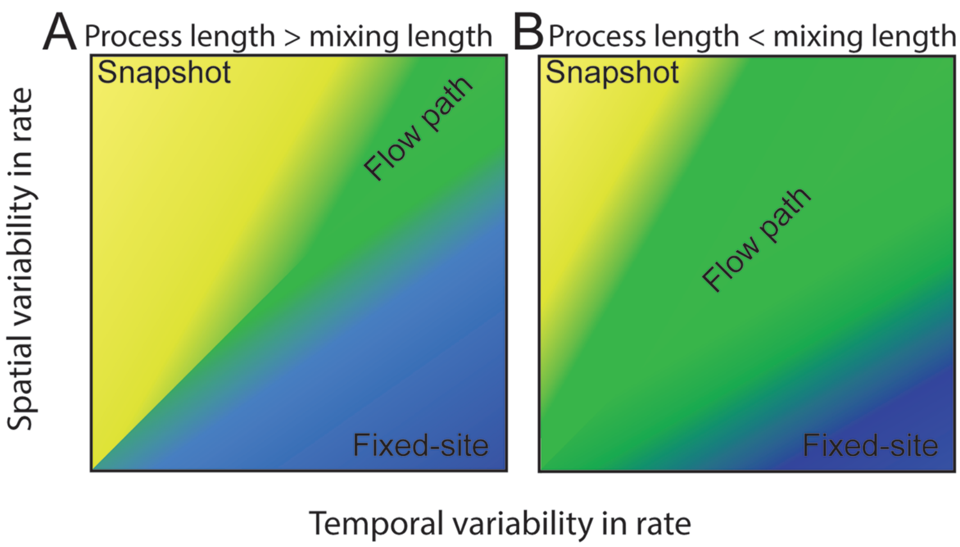

Figure 5. Match between measurement approach and relative spatiotemporal variability over mixing scales when process length and time are longer (slower) than mixing length and time (A) and when process length and time are shorter (faster) than mixing length and time (B).

lism, both of which interpret fixed-site measurements in a Lagrangian reference frame. Statistical approaches have been developed to link spatial and temporal variation in variables at different scales measured with a combination of measurement approaches (e.g., Vatland et al. 2015). However, a framework does not exist for multiple measurement approaches by which to convert spatial and temporal patterns of a variable into a process rate.

By being precise about how we derive (interpret) process rates from patterns in variables, we can more easily recognize the information gained from simultaneous measurements from the other approaches. To demonstrate this information gain, we developed a simple numerical example for visualizing the spatial and temporal patterns in a variable observed from the fixed-site, flow path, and snapshot perspectives. Our example considers a hypothetical river reach downstream from a source of constant-temperature water, such as a groundwater-fed spring. Water traveling the river reach cools at a different rate in the upper than the lower half of the reach because of differences in lateral groundwater inflow. In addition, the rate of cooling increases across the entire river reach at sunset. We simulated temperature at one fixed-site, one snapshot in time, and one flow path on this hypothetical river reach to help us discuss what these patterns reveal about the rates of a process that changes in space and time. The rate of river water temperature change is the process rate of interest.

A numerical, 1-dimensional advection–dispersion–reaction model was used to simulate temperature (T) in the river reach over time (t) and space (x), where U is the velocity (m/s), D is the dispersion coefficient (m^2/s), λ is a 0-order rate of temperature change (°C/s), λ_t is the rate of change relative to time (°C/s) and λ_x is the rate of change relative to space (°C/s).

$$\frac{\partial T}{\partial t} = -U\frac{\partial T}{\partial x} + D\frac{\partial^2 T}{\partial x^2} + \lambda \qquad \text{(Eq. 1)}$$

$$\lambda = \lambda_t + \lambda_x \qquad \text{(Eq. 2)}$$

The upstream boundary condition was 9°C, and, for simplicity of discussion, dispersion was assumed to be 0. The simulated reach was 100 m and velocity was 0.016 m/s. From 0 to 25 min, λ_t was −0.0001°C/s and from 26 to 100 min, λ_t was −0.0003°C/s. From 0 to 50 m, λ_x was −0.00005°C/s, and from 51 to 100 m, λ_x was −0.00013°C/s. The model was initialized to steady state with $\lambda = -0.00015$°C/s from 0 to 50 m, and $\lambda = -0.00023$°C/s from 51 to 100 m, then a 100-min simulation period began with λ_t changing after 25 min. The model results provide us with a synthetic data set with which to analyze process rates while assuming we had no prior knowledge of the river reach, its upstream condition, or environmental drivers affecting temperature change. Figure 6A provides a schematic of the model and rates of temperature change. Selection of a different location of fixed-site measurement or time of snapshot measurement would not change our interpretation of the process rates described next.

Fixed-site

A change in temperature over time indicates a change in the rate of a process occurring over some distance upstream (Fig. 6B). With no prior knowledge of the study reach other than the fixed-site data, we would not know if the rate of temperature change upstream was positive, negative, or 0. Seventy minutes elapsed while the temperature changed, but without knowing flow velocity we cannot calculate the distance over which temperature changed upstream from our sensor. The stabilization of temperature after 95 min tells us that the rate of temperature change was negative over some distance upstream or that the rate of change was 0 while water temperature entering the upstream reach changed. In summary, none of the 4 distinct rates occurring in time and space were apparent from the fixed-site data, but we know that a change of −0.0002°C/s occurred in the rate over time.

Snapshot

The change in temperature over distance at a single time showed the combination of spatial and temporal changes in rate over the reach (Fig. 6C). Ninety minutes into the measurement period, the snapshot exhibits 3 segments with different slopes, and these locations (50 and 65 m) provide information on where or when the rate changed. However, we cannot estimate a rate (°C/s) from these slopes (°C/m) because we do not know flow velocity, and we cannot distinguish spatial (λ_x) from temporal (λ_t) changes in rate that created the 3 segments.

Flow path

The flow path measurement also revealed 3 segments with different slopes and an accompanying flow velocity (Fig. 6D). During the first 25 min in the upper 25 m of the river reach temperature decreased by 0.00015°C/s, from 25 to 50 min (25 to 50 m) the temperature decreased by 0.00035°C/s, from 50 to 100 min (50 to 100 m) temperature decreased by 0.00043°C/s. However, we cannot determine whether the changes in rate were caused by time-varying (λ_t) or space-varying (λ_x) rates.

Combining data from 3 approaches

By combining data from all 3 approaches we obtain perfect knowledge of not only the aggregate rates in space and time (λ), but also the specific contribution of temporal (λ_t) and spatial (λ_x) rate changes that affected the aggregate rate (Table 3). First, we convert the slopes measured by the snapshot (°C/m) to rates (°C/s) by dividing by flow velocity measured along the flow path (elapsed time required

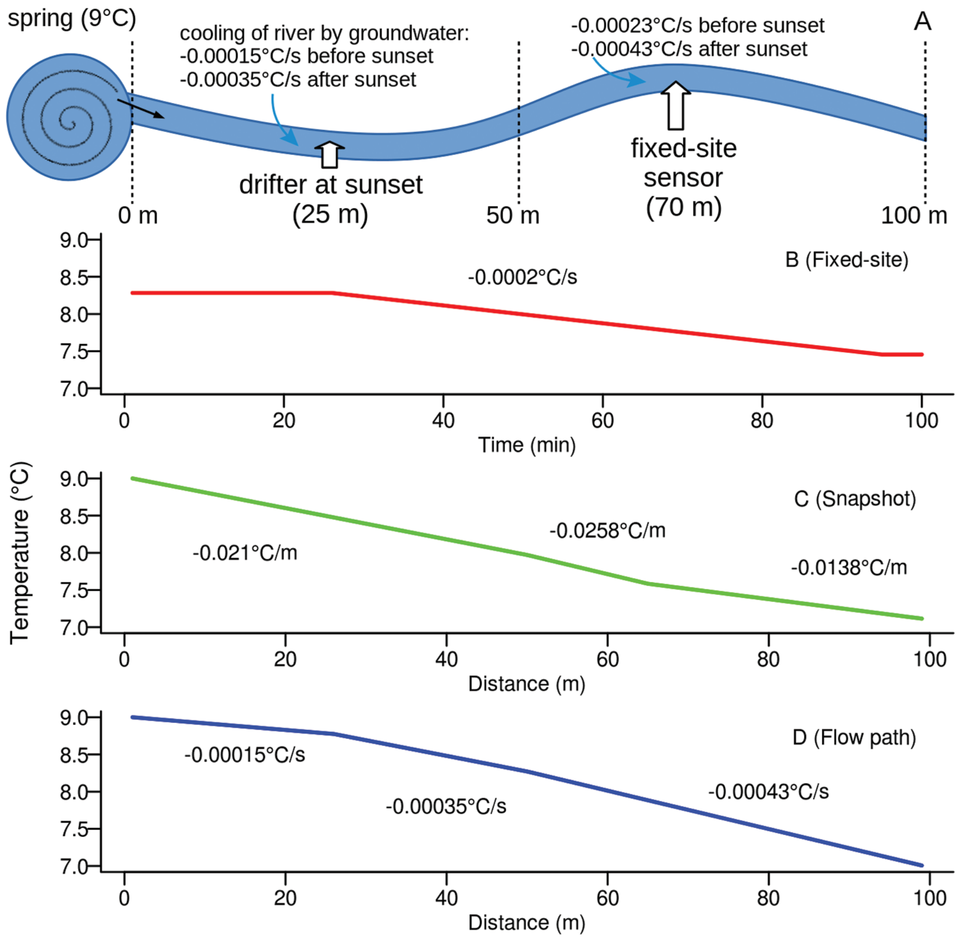

Figure 6. Schematic of a numerical model simulating spatially and temporally variable rates of temperature change in a river reach (A), temperature at a fixed-site 70 m downstream from the spring (B), temperature during a snapshot 90 min after measurement began (C), and temperature measured by a drifter along a flow path (D).

for measurement divided by reach length). The snapshot data revealed rates of −0.00035°C/s, −0.00043°C/s, and −0.00023°C/s. Combining rates at their respective locations and times with rates measured from flow path data (Table 4), we have 4 distinct aggregate rates that apply over the complete time and space of the river reach. A change in slope occurred at the same location in both the snapshot and flow path data, indicating that a change in rate occurred in space at this location (−0.00008°C/s). The fixed-site data confirms that the change in slope at 25 m was a result of a

Table 3. Derivation of process rates in time and space from combinations of measurement approaches. U = velocity, λ = rate of temperature change, $t(\Delta\lambda_t)$ = time at which a rate change occurred across the reach, and $x(\Delta\lambda_x)$ = location at which a rate change occurred, i = time or location between beginning (t_0, x_0) and end (t_n, x_n) of a sequence.

Approach	Fixed-site at x_i	Snapshot at t_i	Flow path from x_0 to x_n and t_0 to t_n
–	$\Delta\lambda_t$	λ/U for all x when $t_i < t(\Delta\lambda_t)$ $(\lambda/U) + \Delta\lambda_t$ for all x when $t_i > t(\Delta\lambda_t)$	λ for all (x_i, t_i) when $t_i = x_i/U$
Fixed-site at x_i	–	λ/U for all x when $t_i > t(\Delta\lambda_t)$	$\Delta\lambda_x$ from x_0 to x_i and t_0 to $t_i < x_i/U$
Snapshot at t_i	–	–	λ for all x and t
Fixed-site at x_i and snapshot at t_i	–	–	Distinguish all $\Delta\lambda_x$ from $\Delta\lambda_t$ for all x if snapshot occurs before $\Delta\lambda_t$

Table 4. Process rates, changes in spatial and temporal process rates, and additional information derived from simultaneous measurements demonstrated in Fig. 6 and formulae in Table 3. Bold values indicate the rates and changes in rate we sought to calculate. λ is the rate of temperature change.

Approach	Fixed-site at 70 m	Snapshot at 90 min	Flow path from 0–100 m, 0–100 min
–	At 25 min: $\Delta\lambda_t = -\mathbf{0.0002°C/s}$	0–50 m: −0.021°C/m	0–25 m (min): $\lambda = -\mathbf{0.00015°C/s}$
		50–65 m: −0.0258°C/m	25–50 m (min): $\lambda = -\mathbf{0.00035°C/s}$
		65–100 m: −0.0138°C/m	50–100 m (min): $\lambda = -\mathbf{0.00043°C/s}$
Fixed-site	–	Confirmation that no change in rate occurred during snapshot	50 m: $\Delta\lambda_x = -0.00043 + 0.00035 = -\mathbf{0.00008°C/s}$
Snapshot	–	–	25 min: $\Delta\lambda_t = -0.00035°C/s + 0.00015°C/s = -\mathbf{0.0002°C/s}$
			50 m: $\Delta\lambda_x = -0.00043°C/s + 0.00035°C/s = -\mathbf{0.00008\ °C/s}$
			50–100 m, 0–25 min: $\lambda = -0.0138°C/m \times 0.0167$ m/s $= -\mathbf{0.00023°C/s}$
Fixed-site and snapshot	–	–	Confirmation that a temporal change in rate did not coincide with spatial change in rate along flow path after the snapshot

change in rate in time (−0.0002°C/s). In summary, we successfully derived all rates of temperature change and partitioned changes in rate over time from changes in rate over space with one set of fixed-site, snapshot, and flow path measurements. No prior knowledge of boundary conditions, flow velocities, or process drivers was required to derive these process rates from these synthetic data.

Translation of this theory to practice requires consideration of the effects of mixing time and process time on spatiotemporal patterns and how we measure them. First, measuring more frequently than the process time (or length) does not provide additional information in multi-approach measurements. Second, measuring more frequently than the mixing time (or length) will introduce variability and uncertainty in rate measurements proportional to the spatial heterogeneity in the parameter. Third, only changes in process rate lasting longer than the mixing time can be determined.

Our simulation of snapshot data assumes high-resolution spatial data (1 m). In practice, snapshot data often integrate conditions over a larger spatial scale. This situation can be an advantage for the application of multi-approach measurements because when measurement resolution ≥ mixing length, the spatial variation between measurements is equal and does not affect patterns in the variable. Unlike the fixed-site approach, snapshot measurements can remove spatial variability if the measurement resolution ≥ mixing time, but the cost is a reduction in the ability to detect spatial differences in process rates occurring over distances less than the mixing length.

In practice, flow path measurements are not constrained by the same mixing time limitations as fixed-site and snapshot approaches because the reference frame is a matrix of mixing water with different biogeochemical 'histories'. Measurements made over time (or space) reflect the history of biogeochemical influences that are contingent on flow path. The magnitude of this contingency may increase as mixing length increases. For example, it takes >100 km for the Purús River to mix across the Solimões River (upstream end member of the Amazon River; Bouchez et al. 2010). Thus, a flow path measured along one side of the confluence could be very different than the other side, and this effect will continue for many km downstream. Likewise, highly variable process rates will increase contingency effects because particles, solutes, and organisms are exposed to a broader set of possible conditions depending on the particular path (and subsequent process rates) to which they are exposed. Similar to the fixed-site approach, the ability to discern a change in a variable over time (a process rate) depends on the magnitude of the process rate relative to the variability in rates between flow paths.

SUMMARY AND CONCLUSIONS

Application of 3 approaches to measure spatial and temporal patterns simultaneously reduces the need for extrapolation and assumptions for estimating process rates. Limnologists have leveraged mixed-approaches in the past to understand processes in moving water, including ecosystem metabolism, although never with all 3 approaches simultaneously. For example, the diel O_2 method can be used to calculate ecosystem metabolism by interpreting fixed-site time-series data through a pseudo-Lagrangian reference frame based on reach-scale flow velocity (Odum 1956). An-other example of hybridizing measurement approaches (interpreting data from 1 reference frame with a 2nd reference frame) to derive process rates is nutrient-spiraling theory (Webster and Patten 1979). We cite these examples as evidence that limnologists already use multiple measurement approaches to measure process rates, although they do so by combining the underlying reference frames with analytical tools and assumptions instead of making simultaneous measurements. We contend that simultaneous measurements based on multiple approaches may alleviate many of the assumptions and subsequent uncertainties involved with existing process-rate measurement techniques.

In any aquatic environment and for any process rate, spatial patterns exist that are caused by environmental heterogeneity, temporal patterns exist that are caused by cyclical drivers (e.g., discharge, sunlight, temperature, population cycles), and a convolution of both exists that is driven by water mixing. With the increasing availability of more accurate, precise, inexpensive, and miniaturized sensors, one is tempted to imagine that limnologists may overcome current technological limitations of environmental process-rate measurement. However, new tools also require limnologists to reconsider measurement approaches and how to analyze the data derived from different approaches. Theoretical frameworks and associated statistical processing must keep pace with this increasing flow of data (see Reichert et al. 2009 and Hall et al. 2015 for examples of statistical and Bayesian methods applied to ecosystem metabolism), lest the signals we seek become obscured by variability created by a convolution of poorly understood spatiotemporal patterns. Our intention was to show that use of multiple measurement approaches simultaneously provides a strategy for deriving rates of environmental processes in situ, while enabling characterization of overlapping spatiotemporal patterns in process rates, and thus, how to make use of these new streams of data.

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