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ESSAY

Clarifying water clarity: A call to use metrics best suited to corresponding research and management goals in aquatic ecosystems

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Scientific Significance Statement

Water clarity is a subjective term and can be measured multiple ways. Different metrics such as light attenuation and Secchi depth vary in effectiveness depending on the research or management application. In this essay, we argue that different questions merit different water clarity metrics. In coastal and inland waters, empirical relationships to estimate light attenuation can yield clarity estimates that either under- or overestimate the underwater light climate for restoration goals, such as potential habitat available for submerged aquatic vegetation. Best practices in reporting water clarity measurements include regionally specific, temporally representative calibrations and communicating the metric that was actually measured. An intentional choice of the water clarity metric best suited to the research or management question yields the most useful results.

The term "water clarity" is inherently ambiguous. Water clarity generally refers to the distance that light penetrates through water, as well as the visibility of objects through water. In lakes, rivers, estuaries, coastal zones, and the open ocean, water clarity is an essential measurement for monitoring programs and a wide variety of research applications. For example, water clarity is used to assess habitat quality for submerged aquatic vegetation (SAV), to study visual predation, and to model primary production. Water clarity is measured using multiple methods, some focused on the depth of light penetration, some based on the depth of object visibility, and others based on the amounts of components present (Fig. 1). General metrics presented here include: Secchi disk depth (Z_{SD}) (Secchi and Cialdi 1866; Tyler 1968; Preisendorfer 1986), the downwelling and scalar light attenuation coefficients of photosynthetically active radiation (K_d (PAR) and K_o (PAR)) (Kirk 1994), turbidity (Zaneveld et al. 1980; Davies-Colley and Smith 2001; Sampedro and Salgueiro 2015; Eidam et al. 2022), and beam attenuation (Bishop 1999). In this paper, the terms K_d and K_o will refer to K_d (PAR) and K_o (PAR). Z_{SD} , K_o , and K_d are apparent optical properties, descriptors of water bodies that depend on both the substances present and the light field (Mobley 2022). Component-based metrics include colored dissolved organic matter (CDOM) commonly measured by its light absorption (aCDOM; m⁻¹) (Green and Blough 1994) or

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Author Contribution Statement: KF and CF designed the research. KF performed field work and collected data. KF and CF performed the data analysis. JT conceptualized the paper. CF and JT created the figures (data visualization). JT wrote the manuscript (original draft). JT, KF, and CF edited and revised the manuscript.

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Fig. 1. Common metrics used to monitor water clarity. General metrics presented here include Secchi depth (Z_{SD}), light attenuation of photosynthetically active radiation (K_d (PAR); referred to in this paper as K_d), turbidity, and beam attenuation. Metrics identified with specific components of the water column include colored dissolved organic matter (CDOM), total suspended solids concentration (TSS) (also known as suspended particulate matter, or SPM), and chlorophyll *a* concentration (Chl *a*). Some symbols are adapted from IAN UMCES media library.

its fluorescence (Stedmon et al. 2003), chlorophyll *a* pigment concentration (Chl *a*; mg m⁻³) commonly measured by its fluorescence (Holm-Hansen et al. 1965; Welschmeyer 1994), and total suspended solids concentration (TSS; mg L⁻¹) also known as suspended particulate matter, total suspended matter, or suspended sediment concentration (Ball 1964). For CDOM and Chl *a*, conversions from fluorescence to aCDOM and Chl *a* pigment concentration may need to account for confounding factors, such as non-fluorescing components, Chl *a* daytime nonphotochemical quenching, and high-scattering environments that can affect the strength of the signal (Oestreich et al. 2016; Cremella et al. 2018; Carberry et al. 2019).

In this essay, we share a case study from the York River estuary (henceforth referred to as the York), a subestuary of the Chesapeake Bay. This location illustrates a clarity measurement puzzle, the likes of which occurs in many other water bodies globally. The dataset includes coincident measurements of Chl *a*, turbidity, K_o , and Z_{SD} from Fall (2020); coincident measurements of Chl *a*, turbidity, and K_d from the Chesapeake Bay National Estuarine Research Reserve in Virginia (CBNERR-VA); and coincident measurements of K_d and

 Z_{SD} from the Chesapeake Bay Program (CBP) Water Quality monitoring program, all from 2014 to 2016 (Turner et al. 2022). Fall (2020) data were collected irregularly in time at eight stations within the York (Fig. 2A). CBNERR-VA and CBP data were collected once or twice per month at the Goodwin Islands and WE4.2 long-term monitoring sites, respectively (Fig. 2A).

Light attenuation is often estimated from other water clarity metrics

Estimating light attenuation from Secchi depth is problematic

The simple hyperbolic relationship between K_d and Z_{SD} is widely represented as $K_d = \alpha/Z_{SD}$ such that the product of $K_d \times Z_{SD} = \alpha$ (Holmes 1970). However, often K_d and Z_{SD} do not adhere to a consistent relationship described by a constant α . The value of α has been found to vary widely in estuaries, lakes, and other aquatic environments across many latitudes, hydrologies, and climatic conditions (Lee et al. 2018; Bowers et al. 2020). Consequently, in turbid environments it is often disadvantageous to calibrate α (Preisendorfer 1986). In the present study, the York serves as an extreme example of this variability (Fig. 2B).

Instead, what information can be gained from the decoupling of K_d and Z_{SD} ? First, if the goal is to understand light penetration, measuring K_d directly will be most useful (Table 1). Second, if the goal is instead to understand transparency or visibility, measuring Z_{SD} alone may suffice. Finally, simultaneous measurement of K_d and Z_{SD} can be used to gain insight into how dissolved and particulate constituents interact with light, since the mismatch between K_d and Z_{SD} yields more information about light-blocking substances in the water.

This mismatch between K_d and Z_{SD} provides useful information about the constituents that limit light penetration. In moderately turbid waters, K_d often has a smaller value (i.e., indicates clearer water) than that predicted based on a simple relationship with Z_{SD} ($\alpha < 1.45$). Smaller K_d values than expected based on Z_{SD} are often attributed to the properties of the suspended particles (Hou et al. 2007), such as reduced visibility of the disk due to increased forward scattering by small organic particles (Hernández and Gocke 1988; Armengol et al. 2003; Effler and Peng 2012). For example, changes in particle scattering may contribute to the long-term shallowing of Z_{SD} in the Chesapeake Bay while K_d indicates minimal change or even an improvement in clarity (Gallegos et al. 2011; Harding et al. 2016; Testa et al. 2019; Turner et al. 2021). In the other direction, high quantities of CDOM can cause deeper Z_{SD} compared to what K_d would predict, due to high visibility yet rapid light absorption ($\alpha > 1.45$) (Pedersen et al. 2014).

Water clarity is critical for SAV, which requires light penetration to depth for photosynthesis. During SAV restoration



Fig. 2. York River estuary case study location and water clarity data. Blue circles indicate cruise measurements from Fall (2020). Red squares indicate Chesapeake Bay National Estuarine Research Reserve in Virginia measurements at the Goodwin Islands station. Black triangles indicate Chesapeake bay Program cruise measurements at station WE4.2. (**A**) Map of data collection locations in southwestern Chesapeake Bay. (**B**) Relationship between directly measured light attenuation coefficient (K_d) and observed α (the product K_d × Secchi depth (Z_{SD})), black line indicates commonly used $\alpha = 1.45$. (**C**) Directly measured K_d vs. predicted K_d estimated from $1.45/Z_{SD}$. (**D**) Directly measured K_d vs. predicted K_d estimated using the York River (Virginia Group 2) attainment criteria in USEPA (2008), where S = salinity, T = turbidity (NTU), and Chl = chlorophyll α concentration (mg m⁻³). Black lines in (**C**) and (**D**) indicate a 1 : 1 relationship between observed K_d and predicted K_d. In all subplots, Fall (2020) blue circles indicate scalar light attenuation (K_o) measurements in place of downwelling light attenuation (K_d). Values for K_d and K_o differ minimally in turbid, optically deep waters (Kirk 1994; Tilzer et al. 1995).

work, the use of one water clarity metric to estimate another can over- or under-estimate depth limits of habitats. For example, in a fjord in Denmark, Z_{SD} deepened over time, but K_d remained relatively high due to large CDOM concentrations, causing Z_{SD} to overestimate the potential habitat for SAV (Pedersen et al. 2014). Consequently, K_d should be used rather than Z_{SD} as a proxy for light penetration depths to infer SAV habitat quality, since the plants collect plane irradiance (Zimmerman 2003, 2006).

Estimating K_d from multiple metrics

Researchers and monitoring programs frequently estimate K_d from a subset of other metrics. In oligotrophic waters,

these relationships are based on the contributions to K_d mainly from phytoplankton; thus, K_d is most commonly derived from Chl *a* (Smith and Baker 1978; Baker and Smith 1982; Kim et al. 2015). In coastal waters, estuaries, and many lakes and rivers, K_d is estimated from not only Chl *a*, but also CDOM (or salinity) and TSS (Woodruff 1996; Gallegos 2001; Fear et al. 2004; Xu et al. 2005; USEPA 2008; Feng et al. 2015; Cerco and Noel 2017; Turner et al. 2021). Other estimations of K_d from multiple metrics employ semi-analytical relationships (e.g., Gallegos 2001; Lee et al. 2005, 2007; Zimmerman et al. 2015), enabling the use of satellite remote sensing to estimate water clarity at high spatial resolutions relevant to lakes and estuaries (Lee et al. 2015, 2016).

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Variable	Other names or related metrics	Units	Recommended applications
K _d	K_o , K_d^{-1} , PLW, light extinction coefficient	m ⁻¹	Submerged aquatic vegetation
			Benthic micro-algae
			Coral reefs
			Photosynthesis
			 Phytoplankton dynamics
			Heat transfer
Z _{SD}	Transparency, visibility	m	 Visibility and transparency
			 Property values and recreation
			 Fish predation on mesopredators and related behaviors
			 Citizen science and community engagement
			 Comparison to long-term historical data sets
Turbidity	OBS, side-scattering	FNU, FTU, NTU	 Total light scattering by particles
			 Long-term measurements with simple but resilient sensors
Beam attenuation	Light transmission, transmissometry	m^{-1}	 Proxy for particulate organic carbon in oligotrophic waters
			Long-term measurements with simple but resilient sensors
aCDOM	CDOM, gelbstoff, gilvin	m ⁻¹	 Dissolved substances from rivers and wetlands
			 Dissolved substances produced by marine plankton
			 Contribution of dissolved substances to spectral K_d
Chl a	Chl <i>a</i> fluorescence	mg m $^{-3}$	Primary production
			Contribution of algae to K _d
			 Phytoplankton dynamics
			Harmful algal blooms
			Long-term measurements with simple but resilient sensors
TSS	TSM, SPM, SSC	mg L^{-1}	Marsh accretion
			Contribution of particles to K _d
			Sediment seabed modeling
			Mass transport of sediments
			Health of oyster reefs

Table 1. Usefulness of common water clarity metrics for different applications.

In the Chesapeake Bay and its tributaries, monitoring programs map K_d spatially in shallow waters to assess habitat potential for SAV, making use of an empirical equation with turbidity, salinity (as a proxy for CDOM), and Chl *a*. These latter three metrics are collected with a flow-through method, increasing the temporal and spatial coverage. K_d is measured directly at a few validation stations, but it is also often calculated from regionally determined empirical relationships with turbidity, salinity, and Chl *a*. This approach groups multiple subregions and time periods together to generate a relationship that describes a wider distribution of conditions (Dennison et al. 1993; USEPA 2003, 2007, 2008; Moore et al. 2009; Reay 2009; Tango and Batiuk 2013).

Best practices for estimating water clarity using available resources

Report the metric that was measured

Perhaps the most important practice in measuring water clarity is to report the actual metric used. Some studies use one term when the metric analyzed does not represent what the term implies. For example, Wang et al. (2013) describe patterns in K_d when the metric measured was actually Z_{SD}, from which K_d was derived using the conventional K_d = 1.45/ Z_{SD} relationship that is inherently less useful in turbid waters (Fig. 2B,C). However, if an empirical equation between metrics is required due to cost, sampling resolution needs, or other factors, then the method should be clearly communicated (e. g., CDOM estimated from salinity), and the cross-calibration data used should be made available. In the case of light attenuation, the use of a scalar (K_o) or downwelling (K_d) coefficient should be reported explicitly.

Measure K_d with deep light profiles

In some cases, K_d may be over- or under-estimated due to measurement error when light profiles do not extend deep enough into the water column. Collecting downwelling or scalar irradiance depth profiles over varying depth ranges can result in inconsistent estimates of the best-fit K_d most relevant to the full photic zone, particularly when irradiance is not measured to a deep enough light penetration depth (Lee et al. 2018). Whenever possible, light profiles should be measured to the depth of 1% illumination to avoid measurement error.

Locally calibrated

Empirical models for K_d need to be locally calibrated because the characteristics of the water's dissolved and particulate matter vary greatly, sometimes at a fine spatial scale. In the Chesapeake Bay, a single K_d relationship applies only to some subregions, but not all. In smaller tributary rivers such as the York and Elizabeth Rivers, there is relatively more CDOM, while in larger tributary rivers such as the Potomac and Susquehanna Rivers, there is relatively less CDOM than salinity would predict (Cerco and Noel 2017). The diversity in contributions to K_d likely results from the variety of river inputs; while the largest rivers have mountainous uplands and deliver relatively more sediment, the smaller rivers drain coastal plains and wetlands and deliver relatively more CDOM (Najjar et al. 2020; Henderson and Bukaveckas 2022). In addition, the response of K_d to TSS may vary strongly with distance along a given estuary due to systematic variations in suspended sediment floc size, density, and organic content (Yard 2003; Fall et al. 2020).

Temporally representative

Ideally, a relationship used to estimate K_d should incorporate measurements representative of different times and conditions, so that the variability over the targeted dataset is captured. A calibration performed during one season or tidal stage will likely not apply to the entire dataset of interest. In the York, an empirical relationship developed during a certain set of years (pre-2008) underestimates clarity compared to observations collected years later (Fig. 2D). The disagreement may be in part because 2014–2016 were hydrologically dry

years in the Chesapeake Bay with lower nutrient and TSS concentrations, and generally clearer water than the early 2000s. These types of discrepancies have implications for management and restoration of important habitats. In the York example (Fig. 2D), directly measured K_d would predict a greater spatial area suitable for SAV, while the empirical relationship from USEPA (2008) underestimates light availability. It could be argued that this somewhat conservative underestimation of habitat is a minor problem. However, overestimating light availability would result in negative ecological implications such as overpredicting the amount of suitable habitat for SAV (e.g., Pedersen et al. 2014).

Choose wisely: Select a water clarity metric targeting the research or management goal

When planning water clarity measurements, it is recommended to select the most useful metric or metrics according to the specific application (Table 1). For example, if K_d can be measured directly, it should be measured using a light sensor rather than estimated from other metrics. If an empirical relationship or a simple sensor is needed due to cost or other factors, use of best practices is recommended. When relevant to the goal, even the simplest water clarity measurements are valuable for environmental monitoring and restoration, whether by citizen scientists, non-profit organizations, or local sampling programs.

K_d is the most relevant measure of water clarity for most research in aquatic ecosystems. K_d is well-suited to research involving benthic autotrophs such as SAV in estuaries (Zimmerman 2003; Moore 2004) and lakes (Schwarz et al. 1996; Borowiak et al. 2017), benthic microalgae (Newell et al. 2002), kelp forests (Graham et al. 2007; Tait et al. 2021), and coral reef habitats (Baird et al. 2016; Jones et al. 2016). Scalar or downwelling light attenuation (Ko or Kd) may be more appropriate for different applications. For phytoplankton photosynthesis, Ko better represents the amount of total light energy available to cells from all directions. For benthic macrophytes, K_d is more suitable because plants' flat leaves collect downwelling light (Zimmerman 2003, 2006). For citizen scientists or non-profit organizations wishing to measure K_d directly, low cost light intensity loggers are available as an alternative to expensive traditional sensors (Long et al. 2012).

 Z_{SD} is a representative measurement of visibility. Z_{SD} applies to human perception of water clarity (Keeler et al. 2015; West et al. 2016) and water clarity's effect on property values (Klemick et al. 2018). Z_{SD} is also relevant for sighted animals and their trophic interactions, such as visual foraging efficiency of zooplankton and fish (Aksnes 2007; Aksnes et al. 2004; Goździejewska and Kruk 2022) and interactions between predators and mesopredators (Benfield and Minello 1996; Baptist and Leopold 2010; Lunt and Smee 2014; Reustle and Smee 2020). Z_{SD} also serves an important role in citizen science and community engagement (Crooke

et al. 2017; Pitarch 2020) and in maintaining especially long time-series (Jassby et al. 2003; Opdal et al. 2019).

TSS is a representative measurement of particles that block light, directly affecting water clarity. However, TSS is truly a measurement of the mass of suspended particles rather than light penetration. Therefore, TSS may be most useful for research applications that benefit from quantifying the mass of sediments present in the water column, such as questions involving sediment resuspension, shoreline erosion, or river inputs (Fall et al. 2014; Palinkas et al. 2019; Tarpley et al. 2019; Moriarty et al. 2020). TSS can be a useful metric for shellfish research, since high concentrations of sediments can clog oyster gills and can blanket oyster reefs via deposition (Luckenbach et al. 1999; Beck et al. 2011; Gernez et al. 2014).

Chl *a*, turbidity, and beam attenuation are useful in that recent technologies allow sensors to be deployed at relatively low cost for long periods of time. Platforms like buoys, moorings, and floats are well suited for optical in situ sensors, thus many programs use these sensors for continuous long-term monitoring (Boss et al. 2018). Chl *a* and turbidity are often used in the field as stand-alone metrics. Chl *a* provides more information about the effects of phytoplankton on the underwater light climate, while turbidity provides more information about light scattering by suspended particles (Boss et al. 2009).

Looking to the future, the ability to collect data at high spatial and temporal resolution by a wider diversity of researchers is critical. While these measurements may be less directly representative of K_d in dynamic systems, their importance should not be diminished. Provided that calibrations are well-performed, these simple longer-term measurements represent a fruitful way forward in water clarity research and monitoring. When factors contributing to light attenuation are not well understood, multiple measurements are needed to evaluate the relative magnitude and importance of the factors affecting light reduction. Use of multiple metrics is especially important in management of the causes of changes in water clarity.

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