True Colors of Oceanography: Guidelines for Effective and Accurate Colormap Selection

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True Colors of Oceanography
Guidelines for Effective and Accurate Colormap Selection

By Kristen M. Thyng, Chad A. Greene, Robert D. Hetland, Heather M. Zimmerle, and Steven F. DiMarco

Data graphics shape the way science is communicated, and the color schemes we employ can either faithfully represent or tacitly obscure the data a figure is intended to convey (Tufte, 1983). Tasteful use of color can make data graphics visually appealing and can draw viewers in, engaging the audience and encouraging further inspection of a figure. But wherever color is used to represent numerical values, its role transitions from a mere aesthetic nicety to carrying the responsibility of conveying data honestly and accurately. Yet, biases introduced by some common colormaps have gone widely unrecognized within the oceanographic community. Here, we describe the pitfalls of some commonly used colormaps, provide guidelines on effective, accurate colormap selection, and present a suite of perceptually uniform cmocean colormaps that have been designed for oceanographic data display. The cmocean package is available across multiple software programs, including MATLAB, Python, R, Generic Mapping Tools, and Ocean Data Viewer.

RAINBOW DECEPTION

When color is employed to show numerical data, viewers expect the overall distribution of color they perceive to match the distribution of the underlying data. However, perception of color is often overlooked in oceanography as we continue to rely on colormaps that have complex transfer functions between what is visually perceived and the underlying

data being represented. One common colormap that is perceived in false relation to the data it represents is the rainbow-colored *jet* colormap, whose popularity stems largely from its decades-long residence as the default setting in MATLAB and similar programs (Eddins, 2014). The *jet* colormap visually distorts information through two primary mechanisms. First, *jet* places emphasis at arbitrary locations along the color scale corresponding to local maxima and minima in colormap lightness (Rappaport, 2002; Stauffer et al., 2015). This effect leads to higher rates of error in identifying regions of maximum and minimum data values, even among experts who are familiar with the data type under evaluation and who have experience with *jet* colormap (Spence et al., 1999; Borkin et al., 2011; Bryant et al., 2014).

The second mechanism by which *jet* deceives viewers is through false gradients introduced by a non-monotonic lightness profile, which accelerates at a different rate than the data it represents (Light and Bartlein, 2004; Borland and Taylor II, 2007). For oceanographers, the danger of *jet's* false gradient profile is its ability to covertly exaggerate fronts in some regions of the color scale while minimizing the presence of fronts elsewhere (Ware, 1988; Mersey, 1990). Figure 1e shows *jet's* misbehavior, where a cone with linear sloping sides viewed from the top appears smoothly varying when plotted with a simple, unbiased, perceptually uniform, grayscale colormap, yet the same smooth

data appear to have sharp edges and broad plateaus when plotted with *jet*. A common argument in favor of *jet* is that its sharp gradients allow proximal colors to be distinguished by a meticulous viewer, and indeed, Figure 1c shows that in some subranges within the color scale, *jet* offers superior point-to-point discrimination. However, the high-performing regions of *jet* are offset by regions elsewhere in the spectrum where changes of the same size are nearly imperceptible.

HOW TO SELECT AN HONEST, EFFECTIVE COLORMAP

To avoid the pitfalls of *jet* and other perceptually nonuniform colormaps, we offer the following guidelines for selecting data-appropriate colormaps that show numerical values effectively, intuitively, and in proper proportion.

Reflect the Nature of the Data

The first step in selecting an appropriate colormap relates to the nature of the data being displayed. Numerical data represented by pseudocolor can typically be categorized as sequential, diverging, or cyclic.

1. Sequential. There is a regular interval relationship in sequential data, such as a range of salinity values. Sequential data should be represented with a monotonically increasing range of lightness values (Stevens and Marks, 1965; Rheingans, 2000), such as in a grayscale colormap, but can also have variations in hue. The

gray and haline colormaps in Figure 1 are sequential, with lightness values that increase in lockstep with the underlying data. Sequential, perceptually uniform colormaps maintain value order when printed in grayscale, a common need for papers.

2. Diverging. Data can also be plotted relative to a critical value; for example, anomalies or changes over time may be presented as deviations about some nominal value. A diverging colormap should reflect the relative nature of the data it represents by combining two sequential colormaps, but with mirrored lightness values. The *balance* colormap in Figure 1 is diverging where positive and negative data of the same absolute value are given equal weight. When printed in grayscale, diverging colormaps maintain monotonic lightness for each half of the colormap, but are ambiguous because the

halves have mirrored lightness. To allow grayscale printing, contours with distinct line styles for each half of the colormap can be overlaid.

3. Cyclic. In the special circumstance of periodic data that steps through a cycle, such as tidal phase, the colormap should have fixed lightness and span several hues, starting and ending with the same hue. This allows a plot of tidal phase to smoothly transition from 360° to 0° without a jump in the colormap. The *phase* colormap prints to a single grayscale value, as seen in Figure 1b, so overlaid contours are important when printing to grayscale.

Consider Perceptual Uniformity
In a perceptually uniform colormap, any step in the map is perceived by the viewer to be the same size as any equally sized step elsewhere in the colormap (Newhall, 1940; Meyer and Greenberg,

1980). Perceptual uniformity is essential for displaying numerical data without artificial weighting. Human perception of color value is primarily a function of lightness, but is secondarily related to hue (Spence et al., 1999). A perceptually uniform colormap can be easily generated in the CAM02-UCS colorspace, where equal changes in Euclidean distance correspond to equal perceptual changes (Li et al., 2012). Such a colormap can be created using **viscm**[1], in which the minimum and maximum lightness values are set, and the points in between can be stretched through different hues and saturation with linearly increasing lightness values, while always maintaining a uniform stepping distance between points (Smith and van der Walt, 2015).

Perceptual uniformity aligns rate of change through the colormap with that of the data. However, sometimes we may want to purposefully emphasize a meaningful critical value in the data. Diverging colormaps do this with a perceptual jump at the middle of the colormap around white. The *oxy* colormap discussed later employs both a divergence and a perceptual change in hue for emphasis.

Appeal to Intuition and Be Consistent
Effective data graphics can often be understood without any verbal explanation. One trick for creating intuitive figures is to take advantage of cultural implications we associate with many oceanographic data types (Robertson, 1990). For example, the terms "warm color" and "cold color" imply appropriate colors for use in temperature profiles. Similarly, sea ice concentration might best be displayed by a colormap that increases from dark ocean blue to white, and chlorophyll might best be displayed in a palette of greens.

Intuition for the meaning of a colormap can be developed through experiencing colors in nature, or through repeated exposure to a unique colormap
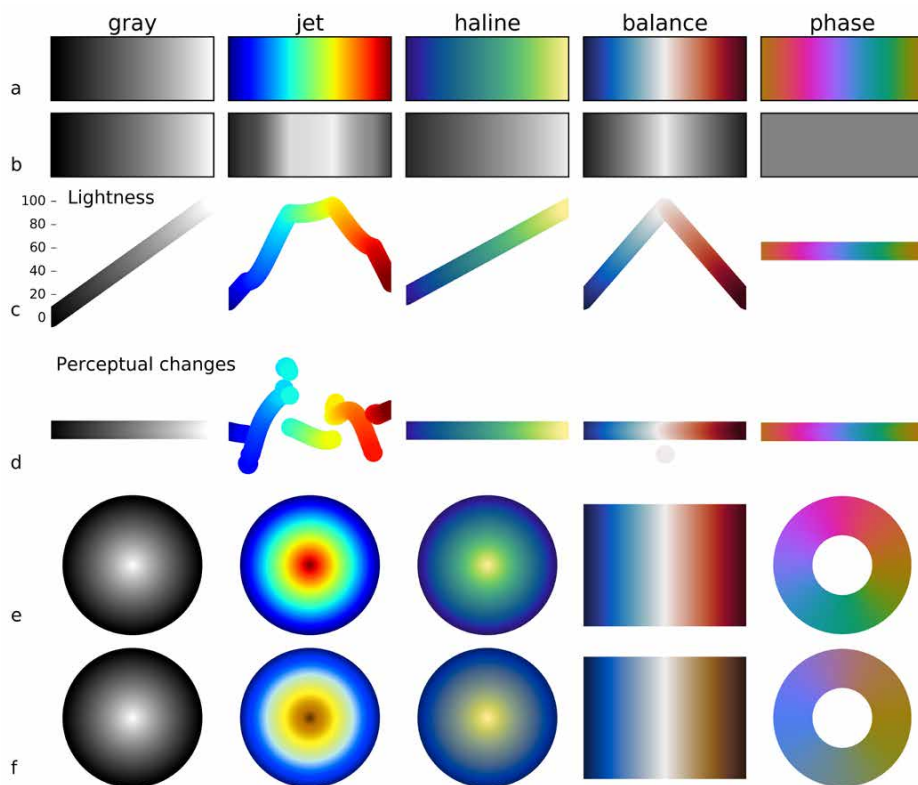
FIGURE 1. Rows a and b show five example colormaps in color and grayscale, respectively. Row c shows the lightness across each colormap. Row d shows the perceptual changes across the colormap (Smith and van der Walt, 2015). Row e shows a plot using each of the colormaps: a plan view of a cone with a uniform slope, a tent for *balance*, and values rotating in a circle for the *phase* colormap. The same plots from row e are shown in row f as they look with moderate (50%) deuteranomaly color deficiency (Smith, 2015).

or any given type of data. For fields without strong natural color associations such as salinity or wave height, intuition is developed by consistently associating each variable with its own colormap. This principle can hold true within a single manuscript or may be developed over time as a convention, much like the Greek letters we tend to associate with specific oceanographic variables. Just as we do not use σ to represent temperature, density, and salinity within the same manuscript, each variable plotted in a manuscript should be represented by its own colormap.

Consider Colorblind Viewers

Rates of colorblindness are low among women, but among men, approximately 7% of Northern European descendants, 4% of Asian descendants, and 3% of African descendants have some form of red-green colorblindness (Sharpe et al., 1999). For colorblind viewers, reds and greens of similar lightness values can be difficult to discern. Figure 1f shows example colormaps as perceived with a moderate (50%) deuteranomaly, which is the most common form of color deficiency. The *gray*, *haline*, and *balance* colormaps maintain distinct colors with moderate deuteranomaly so that figures plotted with these colormaps will be readable to color-deficient viewers, though the *balance* colormap has changes in red and green values and a shift in the luminance and saturation. The *phase* colormap appears duller without green and red hue variation, but the colors in the colormap still vary smoothly. Note that the severity of the colorblindness will change how these colormaps appear because the changes are nonlinear with severity.

cmocean: AN OCEANOGRAPHIC COLORMAP PACKAGE

Following the guidelines presented above, we have developed a set of perceptually uniform colormaps tailored for use in oceanography. Figure 2 shows the cmocean collection, which is composed of several sequential colormaps meant to

elicit intuitive understanding of common oceanographic variables; three divergent colormaps; one cyclic colormap; and one hybrid colormap designed for the special case of displaying oxygen saturation. The package combines original colormaps developed specifically for this work with several preexisting colormaps (Moreland, 2009; Niccoli, 2012; Brewer, 2013; Samsel et al., 2015; see Acknowledgments); we have altered these maps for perceptual uniformity using viscm. Single-hue and multi-hue colormaps are included, and each of the sequential and diverging colormaps span a wide range of lightness to maximize dynamic range in data display. The cmocean colormaps have been given names such as *thermal*, *haline*, and *ice* to help guide users to intuitive colormaps for common oceanographic variables; however, our nomenclature is not intended to restrict usage to any particular variable.

Figure 3 compares four oceanographic fields plotted with *jet* alongside the same data plotted with cmocean colormaps. At the top of the figure, sea surface anomalies are represented by the divergent *balance* colormap to highlight deviations from a zero reference level. In this context, the *balance* colormap makes it immediately clear to the viewer which values are above the reference level, which values are below, and by how much each location deviates from nominal sea level. Temperature and salinity profiles are shown with *jet* in Figure 3c–f, illustrating the brief confusion that can result from using the same colormap to represent multiple variables within a manuscript. Temperature and salinity have an inverse relationship in these profiles, and as a result, when the same colormap is used to represent both fields, the first impression may be that the ocean has inverted itself. Confusion is cleared up upon inspection of the color bar labels, but comparison to the same data plotted with cmocean colormaps shows artifacts introduced by *jet*. Namely, while *jet* captures most of the features present in the underlying data, it also gives the

impression of a series of fronts located near *jet's* band of yellow, where the perceptually uniform cmocean thermal colormap shows that in reality, temperature is smoothly varying and no strong gradients exist.

Figure 3g–h shows a special case of the hybrid *oxy* colormap developed to represent river plume regions that may include both low and supersaturated oxygen conditions. The *oxy* colormap is an example of a specialized colormap designed for a very particular application—highlighting both a critical value that defines hypoxic conditions, with associated water-quality management implications, as well as identifying supersaturated oxygen conditions—while still following the general guidelines for designing good colormaps. Although its inflection point is not centered, *oxy* is a divergent colormap designed to emphasize the critical

**FIGURE 2.** Colormaps available in the cmocean package.

100% saturation point of oxygen. By limiting the colormap to a simple grayscale to represent normal oxygen conditions, red remains available to bring attention to the low-oxygen finger visible in Figure 3h while yellow highlights the supersaturated Mississippi River plume.

CONCLUSIONS

We have offered guidelines to consider when selecting or creating colormaps for oceanographic data display. Our guidelines are aimed at increasing the effectiveness and accuracy of scientific communication by considering human intuition, the science of visual perception, and the benefits of consistent association of unique colormaps with unique variables. Although appearance of any colormap will vary by computer monitor or printer, an accurate colormap slightly distorted will, in most cases, outperform an inaccurate
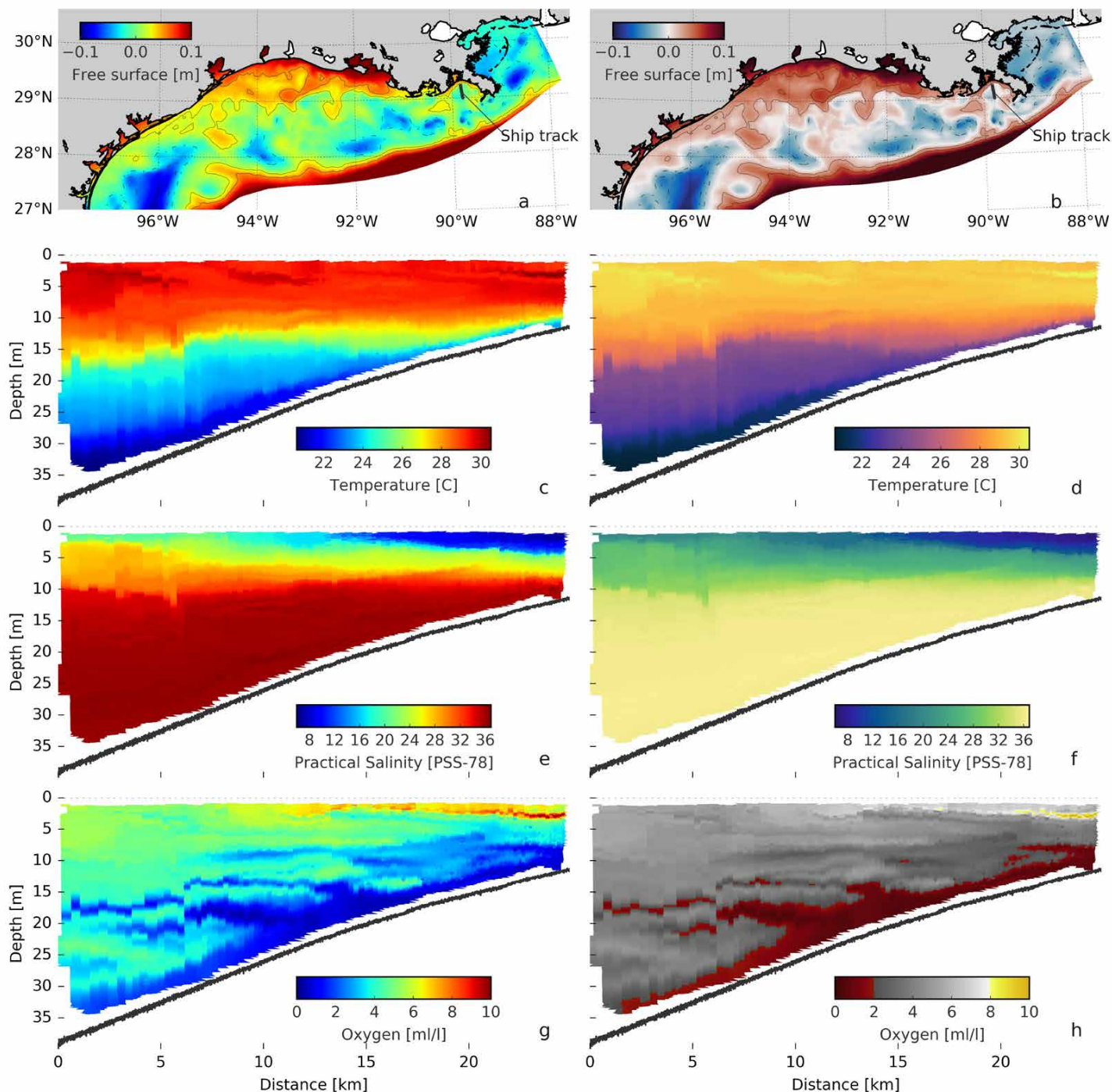
FIGURE 3. Examples of colormap use. The free surface in the northwestern Gulf of Mexico is shown (subplots a and b, where solid line/red are positive values, dash-dot/blue are negative values, and gray solid lines are bathymetric contours) with a ship track indicated. Data collected from an undulating towed vehicle along the ship track are shown are shown in the following rows. Depth vs. distance plots along the track are temperature (c–d), salinity (e–f), and oxygen (g–h). Each property is shown at left in jet and at right in a colormap from cmocean. *Data are recent work of authors DiMarco and Zimmerle for an atlas of oceanographic observations of the mechanisms controlling hypoxia*

colormap slightly distorted. Our intent is to maximize the overall accuracy of communication in oceanography by providing evidence-based guidelines along with a collection of colormaps that have been developed with these guidelines in mind. The cmocean colormaps are freely available online for Python[2], MATLAB[3], R[4], Ocean Data Viewer[5], and Generic Mapping Tools[6], and the *ice* colormap has been absorbed into Antarctic Mapping Tools for MATLAB (Greene et al., in press). The cmocean colormaps are provided to add to the pool of options available to oceanographers. Our intent is not to make these the standard colormaps of oceanography; rather, our intent is to help oceanographers make deliberate and informed choices when choosing a colormap to communicate their data. ⊚

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AUTHORS

Kristen M. Thyng (kthyng@tamu.edu) is Assistant Research Professor, Department of Oceanography, Texas A&M University, College Station, TX, USA. **Chad A. Greene** is Research Science Associate, The University of Texas at Austin Institute for Geophysics, Austin, TX, USA. **Robert D. Hetland** is Professor, Department of Oceanography, Texas A&M University, College Station, TX, USA. **Heather M. Zimmerle** is Research Assistant, Department of Oceanography, Texas A&M University, College Station, TX, USA. **Steven F. DiMarco** is Professor, Department of Oceanography, and Geochemical and Environmental Research Group, Texas A&M University, College Station, TX, USA.

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[2] http://matplotlib.org/cmocean
[3] http://www.mathworks.com/matlabcentral/fileexchange/57773
[4] http://dankelley.github.io/oce
[5] https://github.com/kthyng/cmocean-odv
[6] http://soliton.vm.bytemark.co.uk/pub/cpt-city/cmocean/index.html