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THEMATIC ISSUE

Colormapping resources and strategies for organized intuitive environmental visualization

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Abstract

Visualizations benefit from the use of intuitive organized color application, enabling a clearer understanding and communication. In this paper, we apply the concept of semantic color association to the generation of thematic colormaps for the environmental sciences in combination with principals of artistic color theory to expand feature resolution and create visual hierarchies within a visualization. In particular, we provide sets of color scales, colormaps and color organization guidance for semantically aligned water, atmosphere, land, and vegetation visualization. Strategies for directing attention via saturation levels and saturation sets of colormaps enable deployment of these techniques. All are publicly available online and accompanied by tools and strategy guidance.

Keywords Colormaps · Visualization · Semantic color and environmental data

Introduction

Environmental data is growing in size and complexity, challenging the scientist who needs to communicate effectively at many levels: to peers, to policy makers, and to the general public. Communication is critical for fostering understanding and disseminating scientific knowledge on which decisions are based. To attend to this growing complexity, scientists are seeking means of visual dimensionality reduction and detail enhancement. Here, we focus on addressing these needs (Agrawal et al. 2015).

Color is a critical channel for communicating data in visualization Ware (2012). Our scientific understanding of color comes from research from the perceptual and cognitive sciences as well as from mathematical models of perceptual color spaces. A complementary understanding comes from the artistic community whose knowledge is based on centuries of observing and rendering nature onto a canvas. We tap that artistic knowledge to develop sets of sequential custom color scales that intuitively reflect environmental themes—water, atmosphere, land, and vegetation. These color scales draw on artistic expertise in manipulating color contrast and color interactions to construct colormaps with high discriminative power. Building on the associative color and color theory foundations used successfully in visualization by Harrower and Brewer (2003), Schloss et al. (2019), Stone (2016), Ware (1988), Zhou and Hansen (2016), our colorscales are designed to provide greater feature resolution by weaving multiple types of contrast—hue, saturation, and value—within a single color scale.

We are motivated to apply the concept of intuitive color assignment from researchers who have preceded our efforts (see Sect. 2). Norman (2013), in *The Design of Everyday Things*, summarizes that "We need to design things to be

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intuitively obvious and color representation and visual communication is no different." Robertson (1990) has pointed out: "The first step to developing a systematic approach to characterizing and choosing effective visual representations of data is to look for guidance from our interpretation of the real world." Heer and Stone (2012): "User interfaces that model human category judgments might enable more compelling forms of reference and selection." Thyng et al. (2016) states: "Intuition for the meaning of a colormap can be developed through experiencing colors in nature."

Visual communication is hardwired by nature and experience. Research in cognition and color has elucidated important points to consider in colormapping. The natural relation between content and color allows an observer to facilitate automated processes that require less conscious concentration (Bajo 1988). Additionally, nameable colors tend to be easier to remember (Berry 1991; Roberson et al. 2000).

The main contribution of this paper is to provide a diverse range of color scales, colormaps, and strategies enabling clearer, more intuitive representation and communication of data from the environmental sciences. We provide the scientific community with intuitively associated color scales, such as a series of blues for water and a series of greens for flora, as well as palettes integrated into a domain-specific colormap customization tool, *ColorMoves*, www.SciVisColor.org, enabling environmental scientists to quickly and easily select and customize colormaps and color systems to meet their observation, exploration, and communication needs. Our color scales weave multiple types of color contrast to provide greater discriminative power while staying within hue ranges, thus maintaining the associative properties of hue and natural features. Also included are divergent colormaps specifically designed for the environmental sciences needed to structure the areas of importance within a visualization. Finally, we provide a case study that outlines the process wherein an environmental scientist applies these principles, resources, and tools to better understand scientific data.

Related work

Colormap design rules

Colormapping is a very old technique with many rules and guidelines available in the literature by authors such as Zhou and Hansen (2016), Bujack et al. (2018), and Silva et al. (2011).

Common themes include *order* (Sloan and Brown 1979; Trumbo 1981; Bujack et al. 2018; Wainer and Francolini 1980), *uniformity* (Pizer 1981; Robertson and O'Callaghan 1986; Tajima 1983; Ware et al. 2018), *smoothness* (Levkowitz 1996; Robertson and O'Callaghan 1986; Rogowitz and Treinish 1998), *monotonicity in luminance* (Bergman et al. 1995; Pham 1990; Rogowitz et al. 1996), and a *high discriminative power* (Levkowitz and Herman 1992; Pizer et al. 1982; Tajima 1983). While most of these rules can theoretically be satisfied using the shortest path through a perceptually uniform color space, high discriminative power requires a long path through a color space, which is in direct conflict with the other design rules. Additionally, individual perception is highly nonlinear and not fully understood; optimization of this space is impractical at present. It is likely that multiple solutions exist but cannot fully address the heuristic experience of peoples' color perception as that is strongly influenced by the interaction with adjacent hues (Albers 2009; Lotto and Purves 2000) and the relative proportion of the surrounding hue properties. Artists are able to control these relationships and are trained to do so but in scientific visualization the data drives the hue selection and coverage. Color interaction is strongest in the presence of highly saturated values (Itten 1961), thus in "Employing saturation to direct attention" we discuss means of allocating saturated palettes to areas of importance, contrasting contextual data using low-saturation color scales. For a comprehensive treatment of colormap design rules, we refer the reader to Ware (2012), Bujack et al. (2018) and Zhou and Hansen (2016).

Intuitive colors in visualization

Robertson (1990), in introducing his *natural scene paradigm*, states that for the display of multiple variables in complex scenes (such as those which occur predominantly in the environmental sciences (Bujack and Middel 2016)), intuitive representations of the data are very important.

The importance of color names for the design of color palettes is stressed and applied by Brewer (1994) and Harrower and Brewer (2003). Havasi et al. (2010) provide an algorithm that associates a color to a word. They make use of known associations from databases and interpolate between the colors and related concepts for unknown words. Heer and Stone (2012) and Stone (2016) stress that the naming of colors strongly influences an observer's capacity to categorize and judge the physical world. They provide a framework for probabilistic color naming.

Lin et al. (2013) demonstrate how colors that semantically correspond to the displayed content increase the speed of bar chart reading and develop an algorithm to correlate a set of colors to words.

Extensive research has been done on the study of color and visualization. Many disciplines have applied their expertise to the task—computer science, information visualization, cognition, perception, and color theory. Despite concerted efforts by all of these communities and in spite of the rainbow colormap being recognized as sub-optimal, it maintains prevalence, sometimes for historical reasons but mostly because of its default "ease of use" (Borland and

Taylor 2007; Light and Bartlein 2004; Rogowitz and Treinish 1998; Zhou and Hansen 2016; Dietrich et al. 2010; Middel et al. 2014; Windyty 2016). The recent work of Thyng et al. (2016), Schloss et al. (2019), and Samsel et al. (2015) are notable exceptions.

Schloss and Heck (2017), and Spence and Wong (2006) specifically address complexities and variation of color association in environmental visualization. Schloss et al. (2019) describe how internal expectations such as the *dark-is-more* or the *opaque-is-more* biases influence how observers interpret colormaps.

Thyng et al. (2016) suggest a set of colormaps, *cmocean*, for the visualization of ocean data. They agree with general colormap theory in that uniformity is important and that sequential, diverging, or cyclic colormaps need to be chosen to match the data type. But they also suggest two new rules. One is consistency, by which they mean that within one context two variables should not be represented by the same colormap, just as two variables would also not be assigned the same Greek symbol. The other one is intuition, meaning that cultural implications and the nature of matter and variables can enhance understanding; for example, sea ice should be visualized using blues and whites.

Samsel et al. (2015) worked with the Climate, Ocean, Sea-Ice Modeling team at Los Alamos National Laboratory to identify how artistic color knowledge may provide greater insight into ocean models via more complex colormapping.

Colormap design tools

Many common visualization tools, such as ParaView (Ahrens et al. 2005) or VisIt (Childs et al. 2012), come with an integrated colormap editor and a set of suggested default colormaps but no guidance or analysis.

The visualization community has provided several tools for the guided generation of colormaps. Bergman et al. (1995) introduced PRAVDA Color and suggested colormaps based on the visualization task, data types, and spatial frequency. ColorBrewer (Harrower and Brewer 2003) provides carefully designed discrete color palettes and recommendations based on different data types and goals. ColorCAT (Mittelstdt et al. 2015) extends the task-based concept of PRAVDA Color to combinations of visualization tasks. The matplotlib (Hunter 2007) extension VisCM (http://github.com/matplotlib/viscm) lets the user design uniform colormaps that increase linearly in luminance through adjusting the control points of a spline in the chromaticity plane. The platform *I want Hue* (http://tools.medialab.sciences-po.fr/iwanthue/index.php) generates discrete color palettes with custom restrictions of hue, chroma, and luminance.

Our color scales are grounded in the detailed analysis of color interaction research and artistic color theory which draws on 500 years of painting traditions. As with many researchers in colormap design, (e.g. Brewer 1994), we build on the work or Albers and Itten (Albers 2009; Itten 1961) as well as more contemporary sources (Bujack et al. 2018; Ware 2012). The subtle manipulation of types and degrees of contrast articulated by Itten and further studied by Albers enable the subtle shifts within the color scales to provide the discriminative power within the narrower hue range. The flexible tool ColorMoves (Samsel et al. 2016, 2018) allows users to build customized colormaps by combining pre-designed colormaps at specific value ranges via drag and drop in real time on their own data.

Color scales for associative palettes

Environmental scientists face many challenges when it comes to the visualization of their data Boulton (2018). They often need to display several variables (temperature, salinity, wind speed, etc.) at once to see and analyze multivariable correlations. Since the spatial embedding often plays an important role, they must include topographic features (e.g., geopolitical borders, rivers, or terrain information) that require both space and colors in a visualization. The ability to see perceptual depth (discriminative power) in the data is usually a key goal. Communication to a broad audience with a mixed background of knowledge must be considered.

The sets of color scales that we provide address these challenges while striving to follow some of the more important colormap design rules. They are designed to respect intuitive order and uniformity. These requirements are balanced against the need to create a longer line in color space so as not to sacrifice the discriminative power available in the color scales despite the narrow hue range.

Using semantic colors, the non-scientific audience is invited to participate in the visualization because we know from the cognitive sciences that intuitive color choices help scientists and non-scientists alike to more quickly understand the content of a visualization (Lin et al. 2013; Shinomori 2018; Schloss and Heck 2017; Spence and Wong 2006).

These colormaps also help to remedy the other common problems faced by the environmental scientist. When displaying many variables, each can be shown in a different intuitive color scale, emphasizing the contrast between variables. When spatial contextual information is crucial for the interpretation of their findings, these color scales provide the visual distinction when employing multiple color scales. A color scale that goes through too broad a spectrum creates issues when insufficient color channels are left for encoding all variables or auxiliary information.

The colormap design approach draws on the concepts of color contrast theory. Figure 2 illustrates the construction of colormaps that employ multiple types of color contrast within a single color scale, a colormap with one luminance range. Green Pond goes beyond a simple dark to light contrast by employing both cool and warm greens as primary control points. Moving through two types of contrast increases the discriminatory power of the colormap. Figure 2 shows the development of Green Pond, which combines these additional shifts of cool/warm greens stepping through the linear value distribution. These complementary shifts of multiple types and distributions of contrast create greater discriminative power, as was found in Samsel et al. (2015), an early example of color evaluation work.

The full set of color scales, shown in Fig. 1, is designed to provide a variety of color scales that address specific color themes in environmental science. Blues are used for water, ice, and sky/air. Greens can be used for land or water. The browns, reds, and yellows cover earth and air. Within these color families are many varieties of contrast types. Color scales have different value ranges. Some span only a section of the value scale such as YellowFields. Others move from black to white within the family, useful for a general overview of data. Color scales within one hue family also vary in saturation level and distribution.

Color scales with a wider range of hues (BlueSpectrum, RedSky, GreenFields) can be used to get an overview of data, taking a longer arc through color space. Color scales that span a greater luminance range with similar intensities (e.g., BlueIce, GreenPond, YellowFields) work well together in a blended colormap. To create distinct breaks along a dividing line between environments (e.g., water vs. land), colormaps that extend to the darkest values (BlueWater, BrownEarth) are used. Continuity can be emphasized by

Fig. 2 This figure shows the construction of a green color scale that moves from a *warm* dark yellow-green through a mid-range *cool* blue-green and back to a *warm* light yellow-green. This allows the color scale to maintain intuitive order while moving between warm and cool greens, shifts that create greater contrast

combining a series of colormaps, light end to light end and dark end to dark end.

Artistic color contrast theory speaks of contrast of hue, contrast of saturation, and contrast of value (Itten 1961). Contrast is what enables us to see the data. Here, we are using hue as an intuitive association for the subject matter. For example, the ocean is blue, foliage is green, and dry areas are brown. In addition to communicating intuitive subject matter properties, hue also denotes physical properties. Examples include that red is associated with higher temperatures, higher kinetic energy, as well as danger.

Color contrast theory can also help to inform user choices as color scales are combined (Albers 2009; Ware 2012). Types of contrast such as warm–cool are useful starting points. If two similar hues are needed, choosing one warm and one cool will highlight the differences. e.g., mixing the warm GreenPond and the cool GreenSeas. Across color

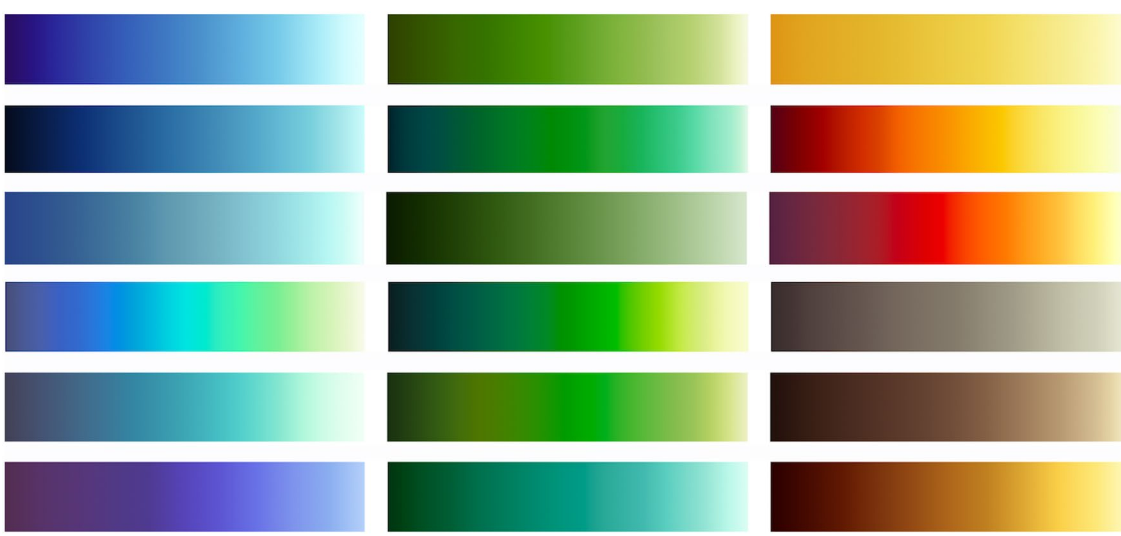

Fig. 1 Blue color scales for water and sky, from top to bottom: BlueClear, BlueWater, BlueSky, BlueDeep, BlueIce, BlueSpectrum. Green color scales for vegetation and water, from top to bottom: GreenPond, GreenLagoon, GreenPines, GreenSeas, GreenFoliage, GreenFields. Brown, red, and yellow color scales for earth and air, from top to bottom: YellowFields, YellowFire, RedSky, BrownYellow, BrownEarth, BrownGray. XML files for these color scales are available on the SciVisColor website, sciviscolor.org/colormaps

ranges, a warm green (GreenLagoon) with a cool blue (BlueDeep) will maximize contrast. The yellows can also provide a warm contrast to mix with the cooler greens or blues.

Figure 3 provides a set of ready-made divergent colormaps aligned with environmental themes. Users can choose from divergent colormaps with blue, green, or yellow hues based on subject matter.

In Fig. 3, the grid of divergent colormaps is organized by saturation level and types of hue combinations. Columns, from left to right, represent the primary hue tones associated with: water, flora, and earth, soil, and air in the third column. The rows from, top to bottom, are: similar divergent hues; saturated divergent hues; alternative medium saturation divergent colormaps; and muted hues. Usage application guidance can be found in Sect. 4.2. All .xml files can be downloaded at https://sciviscolor.org/home/environmental-palettes.

Custom colormapping

No single colormap is optimal for all domains, statistical distributions, or tasks (Zhou and Hansen 2016). Here, we illustrate how clarity and communication can be improved via semantic color usage aligned with physical features within a visualization and how attention can be directed via hierarchical contrast application.

Environmental semantics

The previously released tool, ColorMoves (Samsel et al. 2018), allows the scientist to build custom colormaps, delineating regions of interest with *pins* and *nests*. These defined regions in the data can be given their own color scales. The ability to interactively adjust the endpoints of these regions in real time enables the scientist to craft very data-specific colormaps. Full details on its use can be found on the ColorMoves site: http://sciviscolor.org/home/colormoves. The environmental colormaps are included in the ColorMoves interface and shown, as organized here, on the Environmental Color Sets page https://sciviscolor.org/home/environmental-palettes.

Arctic scientists are studying how subtle changes in the tundra topography can lead to significant changes in vegetation type and distribution. The visualizations in Fig. 4 illustrates topographical LIDAR data collected representing the Arctic tundra studied to understand the relationship between topological shifts, hydrology, and foliage distribution.

Figure 4 compares standard colormaps to semantically intuitive colormaps with data and luminance aligned representations of LIDAR data measuring topographic changes in the Arctic tundra. This figure illustrates the value of intuitive hues aligned with the specific science content illustrating the science while also providing greater detail. The visualizations in the top row, rendered in the standard Viridis and cool–warm colormaps, lack the intuitive representation of the subject matter—the link between changes in topography and hydrology that are driving significant changes in the ecosystems of the Arctic.

Employing saturation to direct attention

In addition to guiding intuitive associations between hue and subject matter, color contrast theory also speaks of saturation as an attentive property that organizes data based on importance. Here, we provide a guide for choosing color scales that enable the easy creation of visual hierarchies within a visualization.

Saturation is the primary channel for directing attention visually. Areas of high saturation draw the most attention visually and those of least saturation draw the least attention. Figure 5 presents color scales in three hues—blue, green, and red at three levels of saturation, increasing from the left column of muted color scales to the right column

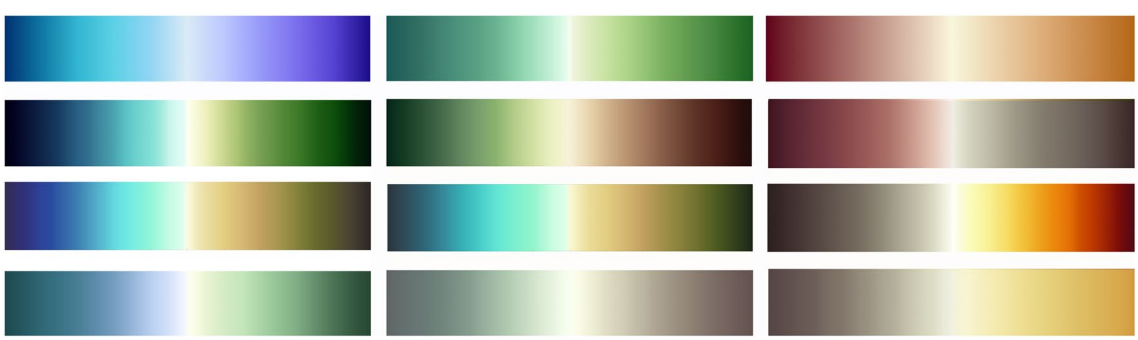

Fig. 3 Divergent environmental hue colormaps from the left: Column 1—BlueFlorals, BlueGreenJewel, BlueGreenSeaCoast, BlueGreenMist; Column 2—GreenAquatics, GreenBrownForest, TurqoiseCoast, GreenBrownMist; Row 3—RedPumpkins, RedGrayStrata, GrayDustFire, GraySun. The top rows, from the top, contain divergent maps with similar hues, saturated color scales, mixed color scales and muted color scales. The columns, left to right, contain the same three categories shown in the color scales of Fig. 1

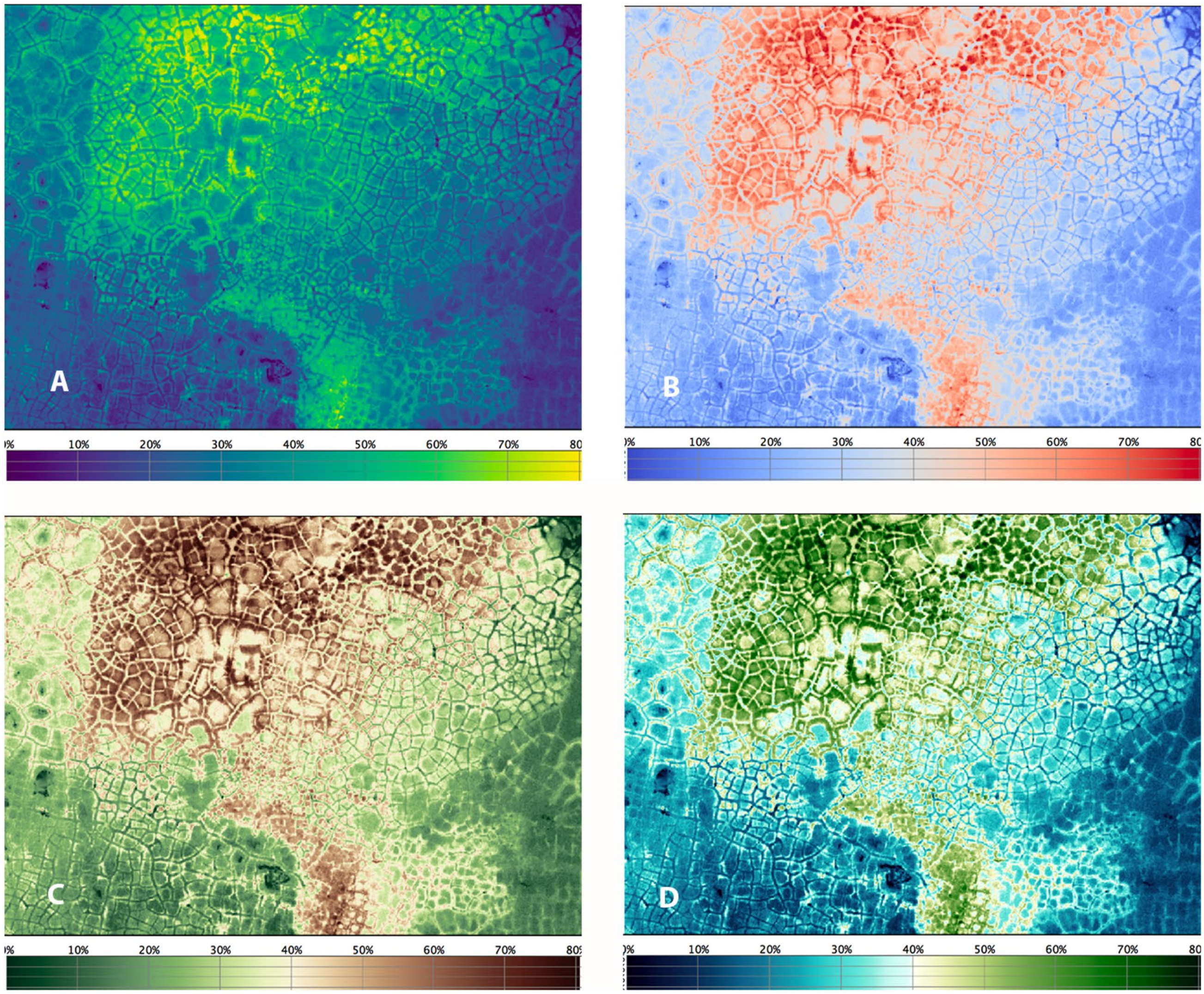

Fig. 4 Arctic tundra lidar data visualization divergent colormap comparison: A—viridis; B—cool–warm; C—green brown divergent; D—blue-green divergent. Semantically associated colormaps, such as C and D, convey topics of concern to the scientist: dry areas; foliage coverage; and wet areas

of saturated color scales. Users should select high saturation for areas with the most important data, medium saturation for areas with contextual data, and low saturation for areas with background or nonessential data.

In Fig. 6, visualizations of coastal flood data demonstrate how color theory principles pertaining to hue and saturation can be used to focus and direct attention to areas of highest interest while balancing the presentation

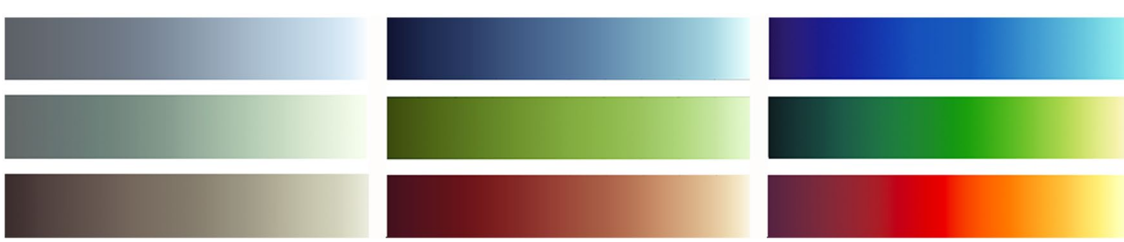

Fig. 5 Comparison of three hues of colormaps that range from low to high saturation. Aligning the saturation level, low, medium, and high, left to right, to the areas of highest interest enables one to direct the attention, sequentially, through levels of significance within the data

of the contextual areas. Figure 6a, b is commonly used colormaps—rainbow and cool–warm—generic defaults that are not aligned with intuitive associations and do not successfully focus attention on the important regions. Figure 6c, d draws on intuitive associations between hue and subject matter in using blue for water, a linear and divergent, respectively, with Fig. 6d communicating areas of important data using saturation, in which the most important areas are the most saturated blue, whereas the least important areas are low saturation. Figure 6e, f draws on physical associations of hue using red to convey danger associated with flooding. In Figure 6e, f, red areas indicate a dangerous point has been reached. Figure 6F also employs two levels of saturation, applying a high-saturation colormap *only* to the areas of danger, thus drawing attention almost entirely to those areas. One of the challenges in the visualization of environmental data is the need for providing spatial context and the comparison multiple regions within a visualization (Boulton 2018). Using different saturation levels along with hue shifts is particularly effective in such cases as these methods distinguish between regions, presents multiple scalar ranges and steers attention (Ware 2012).

Case study

Phillip Wolfram applied the principles to create custom colormaps, using the tools discussed above for higher discriminatory power in his visualization. The data are a simulation of biogeochemistry within the Model for Prediction Across Scales Ocean (MPAS-O) (Ringler et al.

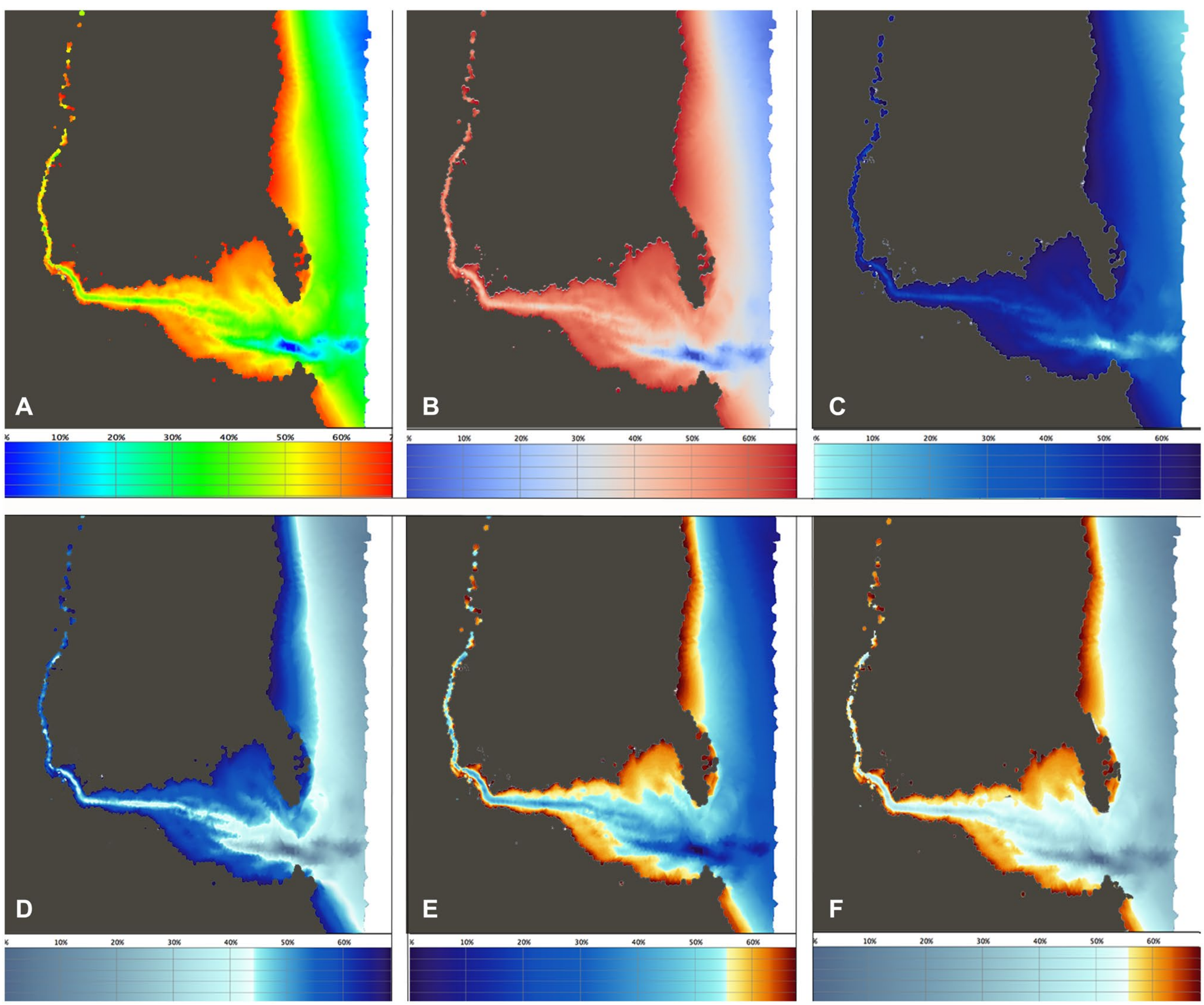

Fig. 6 This comparison of visualizations of coastal flooding data demonstrates the ability of saturation allocation to focus and direct attention to the areas of importance

2013) that is designed to represent the transport of nutrients that are needed to assess the growth of macroalgae to perform a suitability assessment of mariculture for the macroalgae production for biofuels. For simplicity, in this paper we consider surface nitrate (mmol m^{-3}). We focus on the California coast due to its rich nitrate waters, which arise from coastal upwelling along the coast. Nitrate is designated via the colormap.

Transport of nutrients from the upwelled waters occurs due to large eddies in this eddy-permitting simulation. Sea surface height, which can be used to indicate the presence of eddies, is contoured in black as it provides a simple way to visualize current rotational motions via closed circular contours, which are indicative of eddies. Thus, eddies pull filaments of nutrient-rich waters away from the coast and entrain the nutrients away from shore, which provides a potential physical process that may be leveraged to facilitate macroalgae growth production. However, identification of these eddies and the filaments they produce is challenging and improved visualization is useful to better communicate the engineering possibilities suggested by the data, clearly illustrate the physical processes responsible for the mixing, and highlight some connections between eddies and the nutrients as needed to assess viability of macroalgae production via seeding in eddies.

The colormap highlights regions of interest in the simulation: greens indicate regions of high nitrate, orange regions of medium nitrate for possible consideration for macroalgae farming, and grays and blues with low background level of nitrate unsuitable for macroalgae farming. The nested structure of the colormap allows the detail inherent in the data to be extracted.

The following steps were involved in honing the visualization to best align with the data, colormap, and message and correspond to the panels in Fig. 7:

1. Using *ColorMoves*, he began by applying a muted map to the unimportant data (the land and water far from the coast) and a highlight map for the important data (water near the coast). This is shown in the far left of Fig. 7.
2. In the second panel in Fig. 7, he changed the muted green to a muted blue. He made this decision because it allowed him to use bright green to indicate areas rich in nitrate. The muted blue also aligns more intuitively with the subject matter of the ocean.
3. He then added a bright blue as a third indicator of the area most likely to produce macroalgae, third panel in Fig. 7.
4. As the area most likely to produce macroalgae is the most important area in the visualization, he changed it from bright blue to red, the most saturated, attentive color. He then used bright blue to indicate the area where fish that produce the nutrients that help the macroalgae to grow live. The green area indicates nitrates. While these are not the most important areas of data, they both provide an important context. This iteration, shown in the far right panel of Fig. 7, emerged as the favorite. Fig. 8 is a full-size version.

Colormap construction via *ColorMoves*

ColorMoves, the interactive interface for the construction of colormaps tuned to data can be seen in Fig. 8. *ColorMoves* enables interactive colormap construction from a series of color scales. This enables alignment of color and contrast with the structure of the data and goals of the visualization. Watching the changes on data in real time provides the ability to precisely place color scales within specific data ranges. It enables the movement of color scales across areas of the data, facilitating exploration. Providing the means to highlight multiple areas of interest using different color scales facilitates presentation and communication. By loading multiple time steps into the viewer area you can create colormaps effective across time-varying data. Once created the colormap is exportable in .xml or .json. All resources are openly available at www.SciVisColor.org.

Using these color scales within *ColorMoves*, Phillip Wolfram of the COSIM group at LANL notes, “Separation of the ocean and land boundary in the coastal zone, allowing key detail to be manifest, is particularly important because it allows key gradients in the terrestrial aquatic interface to be found. Having these abilities will enable me to more quickly share this information.”

In this paper, we have introduced sets of intuitive environmental color scales that have been incorporated into an online tool, providing environmental scientists with a means of specifying the placement, hue, saturation level, and order of color within their visualizations to enable clearer, more intuitive results.

These colormaps, and their suggested use, address the most important challenges that environmental scientists understanding and conveying their data. The association of the challenges with the specific characteristic of the colormaps are summarized in Table 1.

Conclusions

The value of semantic color association has been well documented Shinomori (2018); however, given its power to assist in intuitive understanding of environmental visualization

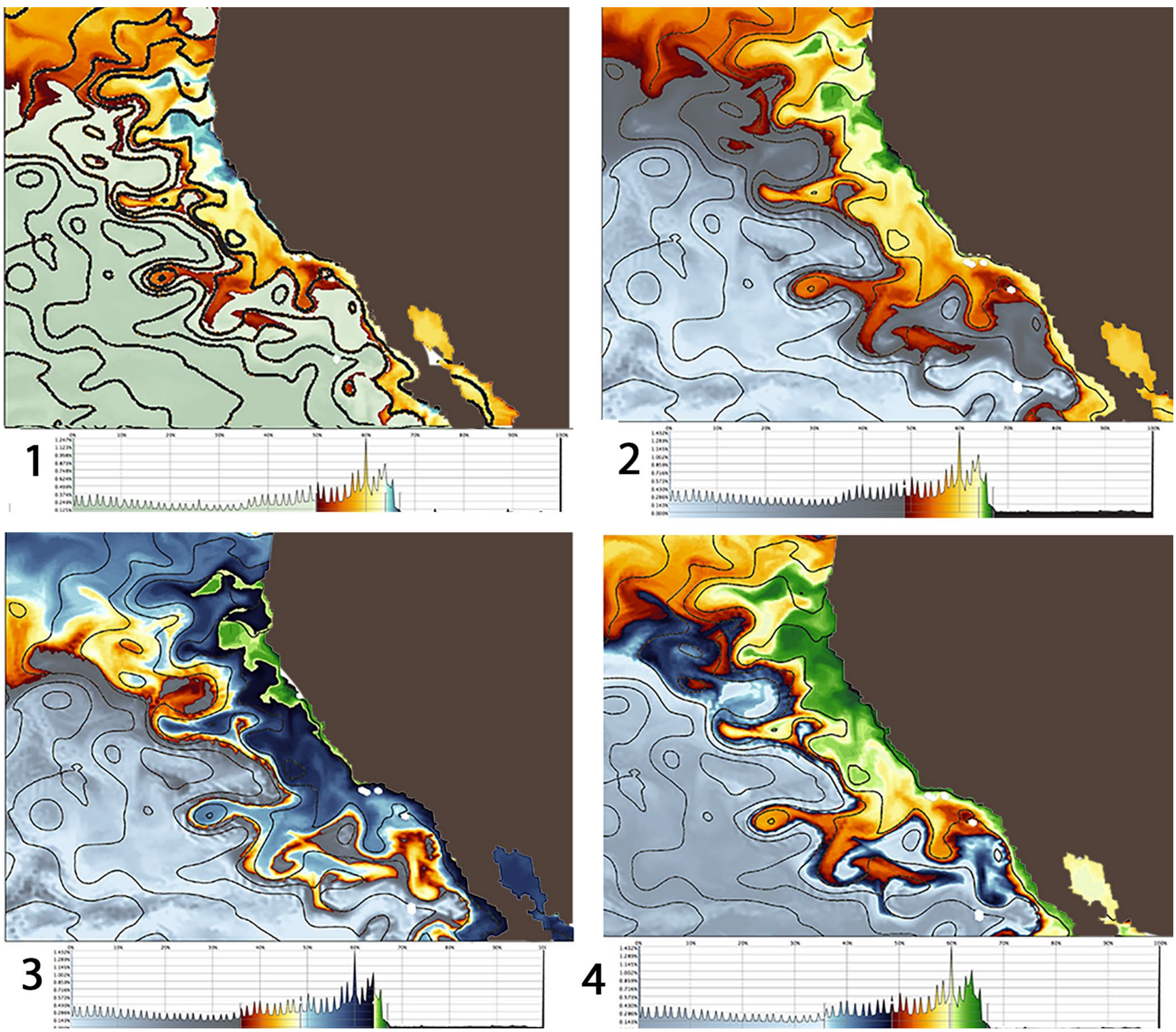

Fig. 7 Wolfram built the colormap for the visualization to align the hues with subject matter and to use saturation to organize the data by importance. Muted blue came to indicate background data and the ocean; bright blues and greens indicated areas of contextual data; highly saturated reds indicated the areas of most importance that were most likely to produce macroalgae

beyond the widely used standards—rainbow, viridis, and cool–warm—we have extended its availability by creating color scales and palettes specifically designed for the environmental community. Combined with the tools and workflows developed by Samsel et al. (2018), scientists now have a practical means to apply semantic hues and to direct the viewer's attention to the areas of highest importance. The value of these combined principals is demonstrated in Fig. 6 and reasoning outlined in Table 1. All of the resources presented here along with more in-depth research and guidance are freely available at www.SciVisColor.org.

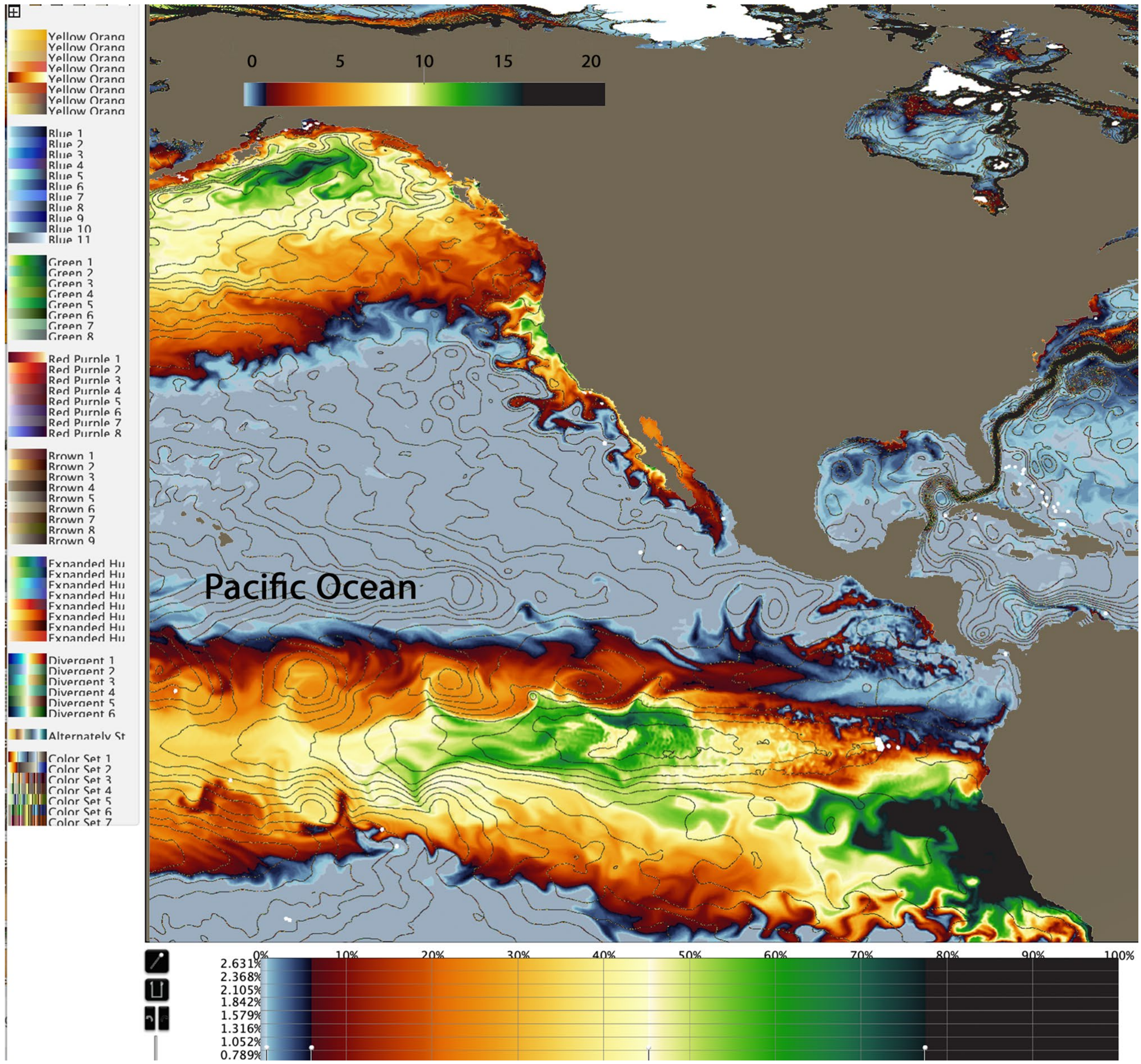

Fig. 8 Biogeochemistry MPAS simulation using hue and saturation to communicate the five categories of locations with roles in marcoalgae production

Table 1 Summary of how the suggested color scales, tool, and workflow help the environmental scientists face typical visualization challenges Zhou and Hansen (2016)

Challenge	Solution
Broad audience with varying scientific backgrounds	Intuitive colormaps work on many levels
Visualizations need to leave colors for the display of other parameters, spatial context, highlights, or glyphs	Narrow hue range and distinct saturation levels of intuitive color scales enables clear thematic distinction from other visualization items
Not enough perceptual depth, or detail in the data	Artist-designed color scales provide high discriminative power despite narrow hue range
The colormaps do not reflect the complicated structure of the data or do not sufficiently emphasize the central statement	The provided tool: *ColorMoves* allows simple and precise fitting of the colormap to data and tasks while saturation levels guide attention

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