Interactive Colormapping: Enabling Multiple Data Ranges and Detailed Views of Ocean Salinity

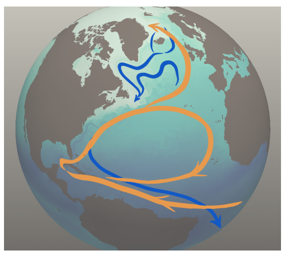

Figure 1: An illustration of the Atlantic Meridional Overturning Circulation. The surface currents (orange) move warm water northward while the deep ocean currents (blue) move cold water south.

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Abstract
Ocean salinity is a critical component to understanding climate change. Salinity concentrations and temperature drive large ocean currents which in turn drive global weather patterns. Melting ice caps lower salinity at the poles while river deltas bring fresh water into the ocean worldwide. These processes slow ocean currents, changing weather patterns and producing extreme climate events which disproportionally affect those living in poverty.

Analysis of salinity presents a unique visualization challenge. Important data are found in narrow data ranges, varying with global location. Changing values of salinity are important in understanding ocean currents, but are difficult to map to colors using traditional tools. Commonly used colormaps may not provide sufficient detail for this data. Current editing tools do not easily enable a scientist to explore the subtleties of salinity.

We present a workflow, enabled by an interactive colormap tool that allows a scientist to interactively apply sophisticated colormaps to scalar data. The intuitive and immediate interaction of the scientist with the data is a critical contribution of this work.

Author Keywords
Colormaps; colormapping tools; scientific visualization; climate science; salinity; color perception.

ACM Classification Keywords

H.1.2 [User/Machine Systems]: Human Information Processing; H.5.2 [User Interfaces]: User Centered Design; I.3.m [computer Graphics]: Misc — Color

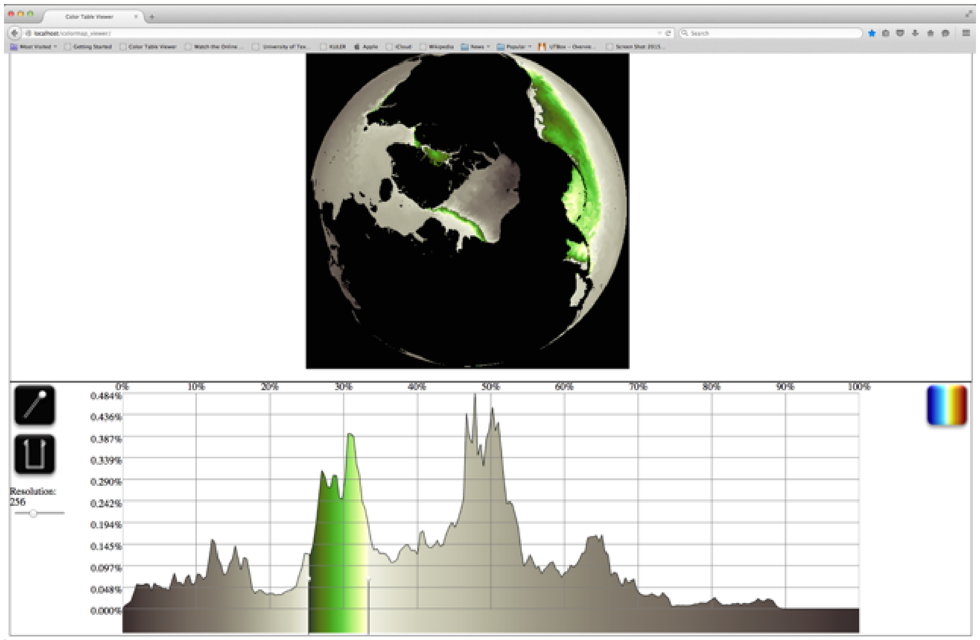


Figure 2: Screen capture of the ColorMoves tool, showing the *output* section at the top, and the *input section* at the bottom. Manipulating the colors on an interactive histogram of data values in the *input* section changes the output rendering in real time, providing a highly intuitive way to explore data values with colormaps.

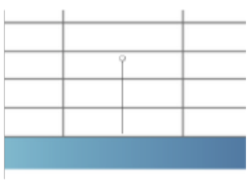
Background

As our understanding of the physical impacts of climate change have grown, there is greater focus on the human impacts associated with climate change. Human issues can include food security, energy needs and production in a warming world. People living in poverty can face greater impacts from extreme weather events such as drought or flooding. People living in near poverty can fall into poverty as a result of such events. The developing world is much more susceptible to these negative impacts.

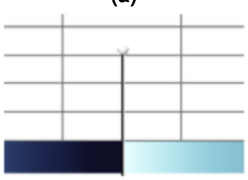
In response to the issues of human impacts due to climate change, the Department of Energy's Office of Biological and Environmental Research is funding and facilitating a new initiative in climate modeling, the Accelerated Climate Modeling for Energy project [6]. ACME brings together the leadership computing resources of the national labs to build state-of-the-science climate models covering all aspects of earth system modeling necessary for century-long climate change predictions. The ocean component of ACME is MPAS-Ocean, Model for Prediction Across Scales, developed at Los Alamos National Laboratory [13]. MPAS-Ocean employs a variable-resolution mesh that allows multi resolution modeling of critical physical processes and the ability to explore important geographical regions at high resolution.

Ocean currents, which transport heat and nutrients throughout the global oceans, are a key component in understanding climate change and its effects. Ocean currents are driven by changes in both salinity concentration and temperature. Decreases in salinity occur as the polar ice caps melt and due to the influx of fresh water in river deltas throughout the world. The Gulf Stream is part of a larger circulation pattern called the Atlantic Meridional Overturning Circulation, where warm waters move northward at the surface, sink near the Arctic (Figure 1). Salinity, released during ice formation, increases Arctic water density causing it to sink and thus driving the AMOC. Arctic warming and increased precipitation makes the waters of the North Atlantic warmer and less salty, which will likely weaken the Gulf Stream and impact global weather patterns. Based on the assessment of models, observations, and our understanding of physical mechanisms, it is very likely that the Atlantic Meridional Overturning Circulation will weaken over the 21st century (where "very likely" is defined as a probability of 90% or greater) [10].

Analysis of salinity presents a unique exploratory and visualization challenge for the climate scientist as the interesting data are found in narrow ranges of the data that vary in different geographical regions. Changes in salinity are important in understanding the behavior of the ocean due to the linkage between changes in salinity associated with climate change and changes in ocean currents.



(a)



(b)

Figure 3: Split operation - Clicking the splitter button changes the cursor, then clicking in the histogram (top) splits the colormap, as shown in (bottom).

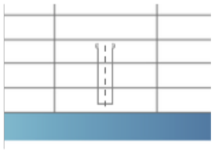
Because of the narrow and geographically varying data ranges, salinity is difficult to map to colors using traditional tools. Default or commonly used colormaps may not have the capacity to expose important detail in the data. Our experience has shown that most data sets require a customized colormap to optimize the perceptual reach into the data. Domain conventions, scientific goals of the visualization, statistical distribution and focal points must all be considered in creating a colormap specific to the data. Extracting salinity detail from current editing tools normally used by the climate scientist is difficult and time consuming, hindering the scientist's ability to explore the data. We are constantly left wondering what important information and scientific insights we are missing in the huge datasets resulting from these large scale simulations.

Building on our previous work in nested colormaps and our ongoing collaboration with the climate modeling team at LANL, we present a workflow, enabled by a novel interactive colormap building tool that allows a scientist to interactively apply sophisticated colormaps to scalar data. The workflow puts sophisticated colormaps - created by an artist to maximize the expression of detail in the data - under the control of a scientist. This enables the scientist to apply dense colormaps where detail is needed, and muted color where data need not be emphasized. The intuitive, interactive and immediate interplay of the scientist with the data is a critical contribution of this work. The scientist can explore data through color so quickly and intuitively that a whole new type of interaction with data results. Through our ongoing collaboration with Dr. Mark Petersen of the LANL COSIM team, we are able to focus on the specific exploratory aspects of data visualization needed by the domain scientist that must be addressed during the development of a colormapping tool.

Prior Work

Color is a critical component of a good visualization, particularly with data that is complex, or data with nuanced ranges. Research shows that tasks and color usage are closely intertwined [17], and that the proper use of color is critical to optimizing analysis. It is also well understood that rule-based systems that account for this dependency between data and task can assist in the selection and application of color scales [7] [20]. Naturally, then, researchers have long studied color choice in visualization, with the result that rules for color use [7], ways of choosing optimal color scales [12, 16] and the impact of color spaces [14, 23] are widely understood. Principles of perception are a central theme of this area of research [8], as is an understanding of how attention is allocated [24]. Research has also been done in algorithmically determining colormaps based on specific characteristics of the data, as in [22].

Additionally, useful tools exist to help users create color palettes appropriate for an array of visualization tasks, and a good survey of current tools is found in [21]. These include ColorBrewer [11], the NASA color tool [2], and Gregor



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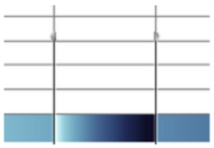
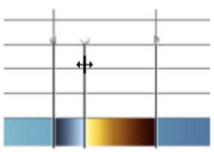


(b)

Figure 4: Nest operation. Clicking the nesting button changes the cursor, then clicking in the histogram (a) adds a nested colormap, as shown in (b).



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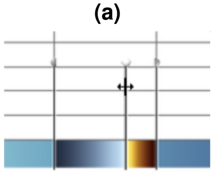

(b)

Figure 5: Moving pins. Pins can be dragged by mouse, as in draggin from position (a) to position (b). Dragging the pin onto the trash removes it. Removing a nested colormap also removes any pins within that colormap.

Aisch's `chroma.js` [1], a javascript library for working with colors. These tools provide highly specialized color palette design capabilities, but are not tied to a specific application. [11] is highly integrated with a sample map visualization, but the tool is used to design colormaps for a variety of application domains. Importantly, visualization software used by this community's scientists, (for example, ParaView) necessarily includes user interface components for designing or importing colormaps. Relevant details of the tools available in ParaView are discussed in relation to ColorMoves in the **User Studies** section. It is this type of combined colormap/scientific data visualization tool that is most useful to our collaborators, and which is the topic of this paper.

The Tool

A colormap editing tool should be a lightweight, cross-platform application that can be easily used across devices by users familiar with standard image viewers. Towards that end, we have developed ColorMoves, an application that fulfills these requirements. ColorMoves is described in detail in this section.

Tool Structure

Figure 2 shows a screen capture of ColorMoves. There are three physically separate sections of the tool: (1) the input section, (2) the output section, and (3) the colormap picker section. The lower section of the interface is the input section and is the workspace for colormap assembly. The upper section of the interface is the output section; it shows the visualization with the current colormap applied. The colormap picker section acts as a toolbox for the input section, and scrolls into view as needed by the user. Each section is described in detail below.

Output Section

The output section looks and feels like a standard image viewer. The visualization changes in real-time as the map is adjusted in the input section. The image can be moved and zoomed by dragging and scrolling with the mouse.

Input Section

The input section is an editable graph that shows the current colormap along the horizontal axis. A histogram of values for the current image is integrated into the colormap. Histogram resolution can be changed with a slider. Similar to the image in the output section, the assembled colormap and histogram can be magnified and scrolled through using the mouse. This allows for easy fine tuning of narrow colormap sections. The histogram is surrounded by controls for colormap editing (see **Workflow** section), one of which opens up the colormap picker.

Colormap Picker Section

The colormap picker works similarly to a traditional color picker control. It contains colormaps horizontally grouped into different linear and divergent colormaps, as well as a range of solid colors. Colormaps are introduced into the input section by dragging them with the left mouse button. Optionally each colormap can also be flipped before use. New colormaps can be imported by dropping colormap files in XML format onto the colormap picker.

Individual Operations

To build a colormap, users have the ability to *flip*, *split* and *nest* colorscales. Flipping a colormap is implemented using the *flip* button next to the corresponding colormap in the colormap picker. Splitting and nesting are utilized by dragging a splitter pin (I-shaped pin) or a nesting pin (U-shaped pin) from the respective button onto the colormap in the input section (Figures 3, 4, 5, & 7).

Figure 7: Buttons used to control the ColorMoves tool.

Figure 8: Examples of colormaps available in the colormap selection area. There are a wide selection of colormaps arranged by color, which can be dragged and dropped into the histogram.

Tool Workflow

A typical workflow for creating a tailor-made colormap from scratch with ColorMoves consists of the following. The user starts with a default colormap over the whole data range. To create a new colormap, a different colorscale is dragged from the colormap picker. A user can then insert a pin and drop in a second colormap (Figure 6 top).

The user can change histogram resolution or zoom into the histogram or image to help identify regions of interest in the data. By dropping a nested colormap (U-shaped pin) and choosing a contrasting color for it, a reference between a part of the value range and the corresponding area of the visualization can be established. The inverse problem of identifying a value range corresponding to certain areas (pixels) in the image is easily done by moving the boundaries of the nested colormap until it surrounds those pixels (Figure 5). Once the value range for the area of interest has been determined, the solid color of this nested section can be replaced by a suitable colormap (Figures 6 middle and bottom).

A suite of divergent colormaps is available or can be built by combining two linear colorscales. When the user is satisfied with the created colormap, it can be exported in XML format using the save-colormap button (button with disk icon).

User Studies

The climate scientist's workflow to render and view the simulation data takes place using the standard visualization package, ParaView [3]. For many domain scientists, the primary tools available to improve the perceptual reach into the data within ParaView include (1) changing the colormap applied; (2) varying the data range to put most of the detail in a narrow data range of interest. Additionally, while ParaView does provide the capability for a user to change

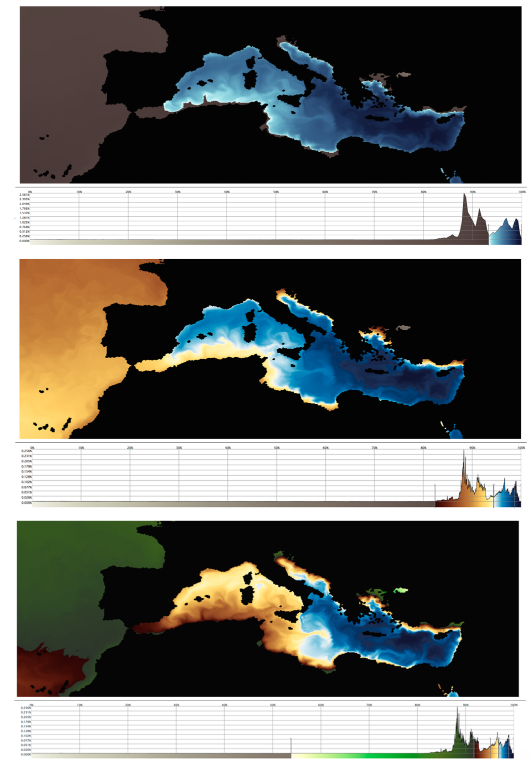

Figure 6: A typical workflow in ColorMoves starting with a neutral grayscale and adding a pin to drop in a linear blue colorscale for the high data ranges (top), adding a pin to split the colormap and insert a linear green colormap (middle) and finally zooming in and nesting a linear yellow/orange colormap (bottom).

and define control points along a colormap, it is not an easy process. While this feature may be used by visualization experts, the domain scientist commented that he seldom takes the time necessary to create a colormap with that feature: perhaps *"a few times a year"* to create something for

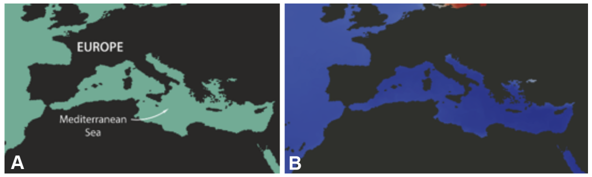

Figure 9: The user study example (left) and validation (right) panels.

a publication but not for everyday exploratory work into the data.

A flexible tool for building colormaps must be able to achieve similar or better perceptual depth into the data than that available to the scientist through ParaView. It must also provide the scientist with an intuitive, user-friendly interface that allows the scientist to explore the data. To assess these properties, we used a multi-faceted approach to user studies. The perceptual properties of colormaps developed through ColorMoves were tested through an online study that compared "best-case" renderings of the data using ParaView with colormaps developed through ColorMoves. Ease of use questions were tested through a qualitative in-person or Skype interview study that asked computer scientists familiar with ParaView to create a colormap in ParaView and repeat the process using ColorMoves. Lastly, in a case study approach, two LANL climate scientists did in-depth feedback interviews to assess the capability of ColorMoves for exploratory scientific tasks.

Perceptual Depth User Study

In order to compare the perceptual quality of ColorMoves and ParaView colormaps, we created an online study that compared two colormaps created in ParaView with two colormaps created in ColorMoves. The hypothesis of the study was that the colormaps derived from ColorMoves would be at least as perceptually detailed as colormaps derived from ParaView.

In ParaView, we chose two colormaps: the standard cool/warm divergent and a new blue/orange divergent. Stemming from our team's previous work [19], this blue/orange divergent is one of a range of colorscales recently accepted into ParaView [18, 3]. The Mediterranean Sea is an interesting area to the climate scientists as the Nile river and other fresh water sources empty into it causing rapid changes over a narrow range of salinity. In ParaView, the Mediterranean was rendered using a range of sanity from 35.0 to 39.0. This data range optimized the perceptual detail available over the narrow data range of interest in this area. These represented the "best-case" ParaView colormaps. Using Colormoves, the authors converged on two best-case colormaps, one a mix of blue/green, another a mix of blue/orange. These colormaps were exported from ColorMoves and imported into ParaView to create the study images. In addition to the above four images, a validation image was created using the standard cool/warm colorscale in ParaView over the full salinity data range, 5.79 to 40.43. An example image was also created, identifying the Mediterranean so participants could orient themselves. The four study images are shown in Figure 10 while the example and validation panel are shown in Figure 9. The study images are listed in Table 1 along with a naming convention for future reference (PV=ParaView; CM=ColorMoves).

The online study was coded in Qualtrics, an online survey site [5]. After consent and colorblind exclusion questions, the survey began by showing the example image of the Mediterranean. A brief passage helped participants orient themselves geographically and explained the study task: to compare two images in different color schemes and choose the image showing the most detail in salinity.

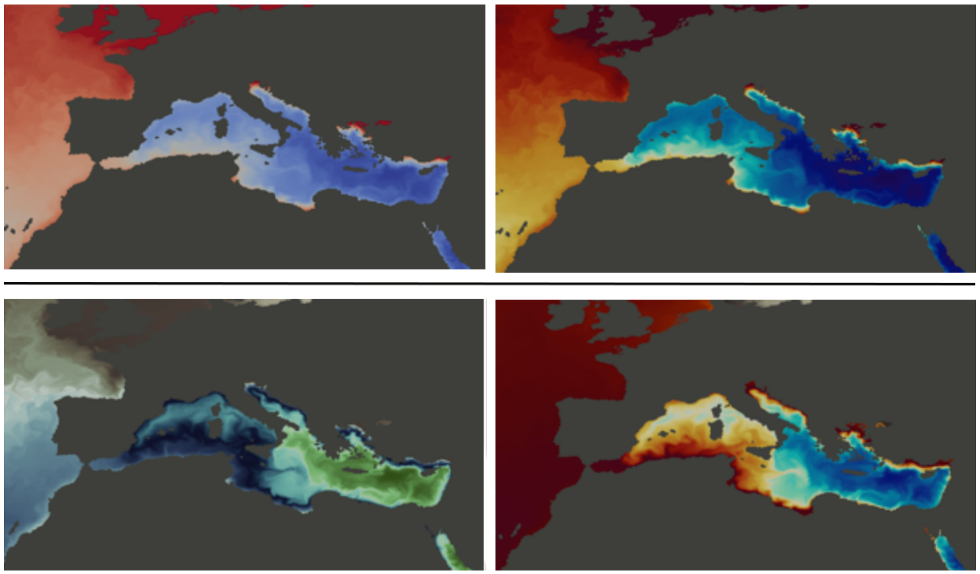

Figure 10: The user study images; top row: PVCW (left) and PVBO (right); bottom row: CMBG (left) and CMBO (right)

Table 1: List of images used for user study along with their attributes.

Name	Visualization Tool	Colorscale	Range
PVVal	ParaView	Cool/Warm	5.79-40.43
PVCW	ParaView	Cool/Warm	35.00-39.00
PVBO	ParaView	Blue/Orange	35.00-39.00
CMBG	ColorMoves	BlueGreen	5.79-40.43
CMBO	ColorMoves	BlueOrange	5.79-40.43

For the study, PVMCW, PVBO, CMBO and CMBG were each pairwise compared. The comparison questions were randomly presented and within each comparison, randomly presented as A versus B or B versus A. As a validation question, participants were asked to compare PVCW with PVVal. Basic demographic information was collected. A total of 85 participants were recruited via Amazon Mechanical Turk, an online crowdsourcing site commonly used by behavioral science researchers [4, 9, 15]. Only two participants failed the validation question. The comparison results of the study are summarized in Table 2.
As can be seen, comparing the ParaView colormaps, participants found that the ParaView blue/orange had more perceptual depth than the standard ParaView cool/warm ($p<0.000001$). Likewise, participants found the ColorMoves colormaps, both in blue/green and blue/orange, to provide more perceptual detail than the standard ParaView cool/warm ($p<0.000001$). The ColorMoves blue/green was comparable to the ParaView blue/orange ($p=0.094$) while the ColorMoves blue/orange was an improvement over the ParaView blue/orange ($p<0.01$).

Table 2: Results of online user study.

Colormap A	Colormap B	N_A	N_B	p-value
PVBO	PVCW	79	4	p<0.000001
CMBG	PVCW	73	10	p<0.000001
PVBO	CMBG	47	36	p=0.094
CMBO	PVCW	76	7	p<0.000001
CMBO	PVBO	52	30	p<0.01
CMBO	CMBG	49	34	p<0.05

In-Person Qualitative Feedback on Usability

Four computer scientists/engineers were recruited for a qualitative study to assess the usability and learning curve of the ColorMoves Tool. Each participant was asked to rank their ParaView expertise on a scale from one (least familiar) to seven (most familiar). Participants included two Ph.D. participants rating their expertise at a level of seven, a CS

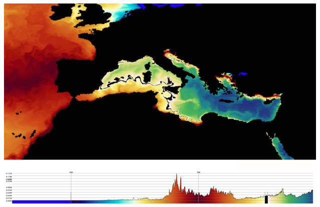

Figure 11: In the above colormap, the scientist opened up a very narrow range in the data (in dusty blue) to highlight a specific contour in salinity concentration.

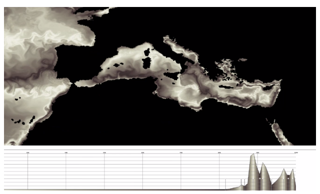

Figure 12: In the above colormap, the scientist exposed maximum detail in salinity by using the histogram to define local minima and maxima points.

graduate student with an expertise rating of 3 and an expert in visualization design, illustration and scientific animation (B.S.) with an expertise rating of 2 for ParaView. All were familiar with the basic ParaView colormap editor functions and the ability to change color control points in the ParaView colormap editor. The interviewer used the temperature variable in the North Atlantic to demonstrate the concept of perceptual depth. Participants were then asked to input a specific set of input files for ParaView which rendered the salinity variable in a neutral colormap over its full range for the full globe (flat projection). Participants were given a maximum of 20 minutes to create an effective colormap where "effective" was defined as showing the most perceptual depth and detail in the salinity variable in the Mediterranean Sea. Participants variously changed the data range and colormap. All four participants manipulated the control points in an attempt to add additional perceptual depth. Most participants expressed some level of frustration at how difficult it is to place color exactly where needed through the standard ParaView colormap. Participants took anywhere from 7 minutes to 20 minutes to achieve a colormap in ParaView that they felt sufficiently showed detail in the Mediterranean.

After exploring the data in ParaView, the interviewer demonstrated the use of ColorMoves and its features, again using temperature data in the North Atlantic. The version of ColorMoves used was locked prior to the beginning of the study and included all of the above described features. Participants were given a data file showing the full range of salinity in the Mediterranean and asked to use ColorMoves to produce a colormap designed to show detail. Varying in time from 5 minutes to 13 minutes, participants were quickly able to come up the learning curve and produce what they considered an effective colormap for the described task using ColorMoves.

Participants were also asked for subjective feedback. A comment repeated by each subject was the intuitive nature of the tool: *"super-intuitive"*. Participants also commented positively on ease of interactively exploring the data: *"I was able to hone in on data of interest very quickly and immediately started making good decisions based on the data.*"; *"It changed how I was thinking about the problem because of all the tools that I had."*; and *"Fascinating to see the break points in the data and how a change in colormap captured those details."*

Participant suggestions for improvements included: modifying the histogram range to include the actual data values; adding additional colorscales; and adding the ability to change the endpoints of the colormaps. Several subjects missed the ability in ParaView to change the control points within a colorscale. Overall, all participants agreed that they were able to quickly create an effective colormap for the task.

Domain Scientist Feedback

A final interview was conducted with Mark Petersen and with another LANL scientist, Dr. Phillip Wolfram, who was not involved at any stage of the development process of ColorMoves. Given the salinity data in ColorMoves, both scientists spent time determining the ways in which he could explore the data with the new tool. Both scientists appreciated the intuitive nature of the tool: *"It is incredible how extremely intuitive [the tool] is."*

Each scientist chose a different exploratory task. Petersen focused on identifying individual narrow ranges in the data, exposing contours of salinity, while Wolfram delved into the data, tying to expose as much detail possible. The ease with which he could explore the data and, using the histogram, highlight and follow a contour in ColorMoves was critical to Petersen: *The tool allows you to explore on the fly* *with a great deal of precision since you can zoom in on the histogram. It is easy to follow a contour of interest in real time.* Figure 11 is example of how the scientist placed and moved the pins to open up a small range and highlight a specific contour in salinity. By placing pins at the local minima and maxima of the histogram and applying the same colorscale in alternating (flipped) directions, Wolfram was able to maximize the perceptual depth into the data. His result is shown in Figure 12 and his impression is summed up in: *"I have never been exposed to a tool this capable before."*. Both agreed that trying to achieve the same results using the ParaView colormapping tools would not have been possible on a practical level.

As for additional features, both agreed that the ability to crop the colorscales to decrease the amount of white space would be a useful feature. An extended palette of linear colorscales and in-depth statistical analyses would also be very useful.

Conclusions and Future Work

Our experience has shown that more detail can be gleaned from data if colormaps are customized to the data distribution and to the goals of the scientist. Work to implement the suggestions from the qualitative study and from the domain scientists is underway. A cropping tool, in-depth statistical analysis of the data and additional colorscales are all features to be implemented. The next phase is to extend beyond climate science to other big data domains. Another major pathway is to move into discrete color combinations as a means of representing categorical data, resulting in the ability to address both categorical and scalar data representation within a single interactive interface.

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