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DIVA - Data Imaging and Visualization Analysis
Thesis Proposal

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We pledge that we have not given or received any unauthorized assistance on this assignment.

Abstract

Over the last few decades, satellites have collected vast quantities of climate and weather data, providing a better picture of Earth's global and regional climates (Dasgupta et al., 2016). Interest in understanding Earth's climate has risen in light of human-fueled climate change, which poses an existential threat to the human population in the form of extreme droughts, floods, and other natural disasters (Kelley et al., 2015; Madsen et al., 2014; Ruane et al., 2013). However, little effort has been spent to develop effective visualization tools that allow researchers or the general public to understand climate data thoroughly (Dasgupta et al., 2016). Today, climate scientists are still using software with basic plotting capabilities and limited interactivity and comprehensibility (Alder et al., 2013; Potter et al., 2009; Teuling et al., 2011; Wickham et al., 2012). Team DIVA proposes a new visualization tool utilizing Virtual Reality (VR) to fully immerse a user into an interactive and intuitive data analysis environment. With such technology, climate data will become more understandable and accessible, allowing a larger audience of both technical and non-technical individuals to be educated about certain climate issues facing the Earth.

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SECTION 1 - INTRODUCTION

Due to a series of missions commissioned by NASA, NOAA, and other governmental organizations, climate scientists today have access to very large amounts climate data (Skytland, 2012). For instance, it is projected that by 2030, NASA alone will have collected 350 petabytes of climate data, more information than the contents of all the letters sent by the US Postal Service in one year (Skytland, 2012). And as climate change has begun to escalate in the form of droughts, floods, and storms, it has become more and more important for climate scientists to be able to understand these data (Cai et al., 2014; Kelley et al., 2015; Madsen et al., 2014; Ruane et al., 2013).

However, climate data suffer from what researchers refer to as an 'analytical bottleneck' because data are collected at a rate faster than humans can analyze and understand them using the data visualization and analysis techniques of today (Dasgupta et al., 2016). The two major current methods of climate data visualization are two-dimensional maps and three-dimensional globes. Although these provide some insight into the values and trends of spatial variables, these visualizations lack interactivity, do not display more than a few variables at a time, and do not demonstrate the relationships between variables and geographical location (Alder et al. 2013; Du et al. 2015; Liu et al. 2015; Potter et al. 2009; Teuling et al. 2011; Wickham et al. 2012; Zhang et al. 2016). These methods typically display data statically and place much of the burden of forming conclusions on the expert viewing the data, instead of helping these experts visualize relationships between discrete data sets. These problems prevent both technical audiences and non-technical audiences from easily understanding climate data and drawing valuable insights.

Team DIVA's research project seeks to ameliorate these glaring shortcomings in climate data visualization.

Team DIVA proposes developing an interactive virtual reality (VR) tool to help both experts and the general public to better understand the copious amounts of underexplored existing climate data. The three research questions that will guide Team DIVA to reach its goal are as follows:

1. In terms of computation time, feature selection, and storage, how can the team most effectively design and create a Virtual Reality climate data visualization tool?
2. What are the most user-friendly, aesthetically pleasing and informative ways for scientists and the general public to visualize climate data through VR?
3. How can Team DIVA's novel tool help scientists gain insights they would not have been able to gain otherwise?

The first research question describes the actual development process and the objective quantitative metrics the team will use to benchmark the visualization tool's performance. The second research question is more related to the experience of using the tool which is subjective and will differ from user to user. The last question touches upon the ultimate goal of Team DIVA's project: to move beyond simply visualizing data with aesthetically pleasing figures and colors and develop analytical methods that mirror an expert's cognitive process to help them gain more valuable insights into climate data. Team DIVA hypothesizes that a newer climate data visualization tool can be developed which is as fast and efficient as existing tools, while allowing users to gain new insights through its interactivity, intuitive interface and easy-to-understand visualizations which could not be gained from older tools.

To answer the three research questions, Team DIVA will follow a methodology that can be divided into three main phases: (1) product development, (2) product improvement, and (3) product evaluation. Product development entails constructing a Graphical User Interface (GUI), integrating VR to visualize climate data, and comparing methods of visualization. During this process, the team will design a preliminary user interface, develop control mechanisms for the user and implement optimal climate data visualization methods into VR. Next, the team will proceed to the product improvement stage. During this phase the team will hold focus groups to receive constructive feedback on the prototypes as the team develops the product through an iterative process. Once Team DIVA develops the final product, the team will enter the product evaluation phase, which entails administering individual surveys to both the general public and the climate experts in order to evaluate the visualization tool. These data collected will help the team compare performance of the VR tool to the performance of current visualization tools.

Team DIVA hopes that the results from this investigation will help society by allowing researchers to supplement conventional 2D visualizations on a computer screen with advanced VR visualizations. VR is a field with a lot of unexplored scientific potential since there have been many recent technological improvements such as reduced delay times, hand controllers, and higher resolution displays. These developments have made VR a more viable option for displaying scientific information. The team hopes to be able to develop a product that will not only be used by experts at climate research labs and universities, but also serve as the basis for further developments in VR data visualization.

This thesis proposal paper will begin by highlighting current visualization techniques and describing the current state of VR in the literature review section. Next, the methodology for completing the investigation will be outlined, detailing every phase of the project. Finally, a proposed budget and timeline will be presented in the appendices section.

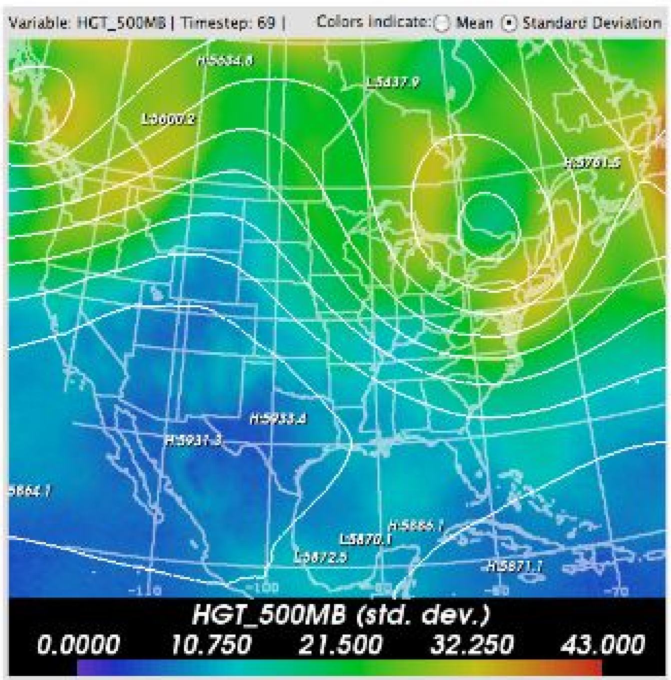
SECTION 2 - LITERATURE REVIEW

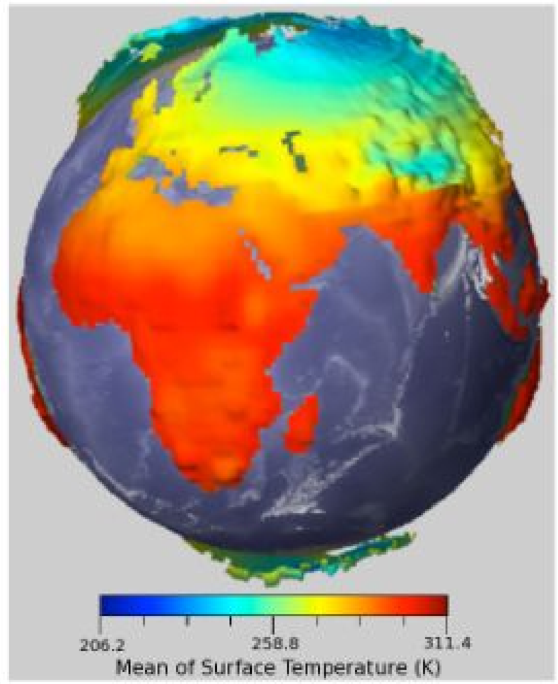
Section 2.1 - Current Climate Data Visualization Methods

Current methods of visualizing large sets of climate data can be divided into two broad categories: two-dimensional renderings, which utilize colors or glyphs to display climate data across latitudes and longitudes; and three-dimensional renderings, which visualize data which vary with respect to longitude, latitude and elevation using programs such as Google Maps and World Wind (Liu et al., 2015; Zhang et al., 2016). Both approaches have their strengths and weaknesses. For instance, two-dimensional renderings require a relatively small amount of processing power, but can only display a limited number of parameters (Alder et al. 2013; Potter et al. 2009; Wickham et al. 2012). Conversely, three-dimensional renderings require very powerful processors, but can display 3D-vectors, volume renderings of three-dimensional data, and useful trends in the data which cannot be visualized on a flat plane (Liu et al., 2015; Zhang et al., 2016). However, neither type of visualization has been tested to determine how effectively it can convey climate information to human factors. This is an area of concern, since more general studies of data visualizations indicate a correlation between aesthetic appeal and comprehensibility (Filonik and Baur, 2009).

Two-dimensional Renderings

Two-dimensional renderings, such as colored maps or glyph-maps, use colors and symbols, respectively, to demonstrate variation in one or more variables over a large geographic area. Numerous methods and apps have been developed to illustrate data in this way. Many two-dimensional climate maps use colors, typically varying from red to blue to indicate high to low levels of a parameter. One such map, developed by Potter et al. (2009) from the University of Oregon, displays the mean of a parameter through color on a graph, and allows the user to display the standard deviation of the parameter as contour lines or a height field line (Fig. 1).





(a) (b)

Fig. 1: *These maps, developed by researchers from the University of Oregon, allow users to display means by color and standard deviations by either contour lines (a) or height fields (b) (Potter et al., 2009).*

However, this approach displays a single variable at a time, so users can gather a limited amount of information from the maps. Other maps have been developed that can display multiple variables through a two-color gradient. For instance, researchers from the Institute for Atmospheric and Climate Science in Switzerland developed one such bivariate color map to display temperature and relative humidity (Fig. 2) (Teuling et al., 2011).

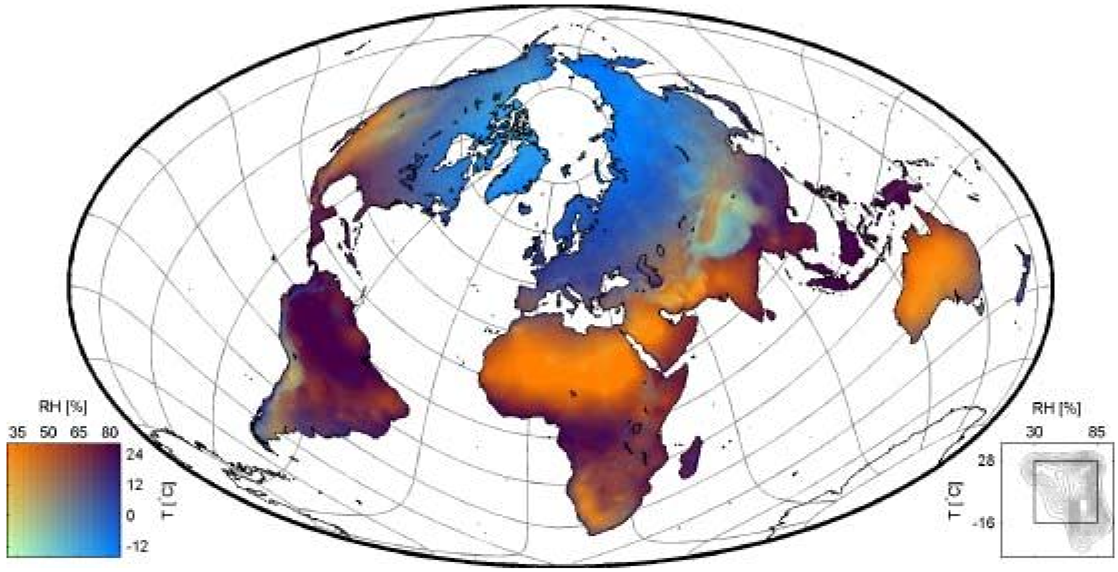
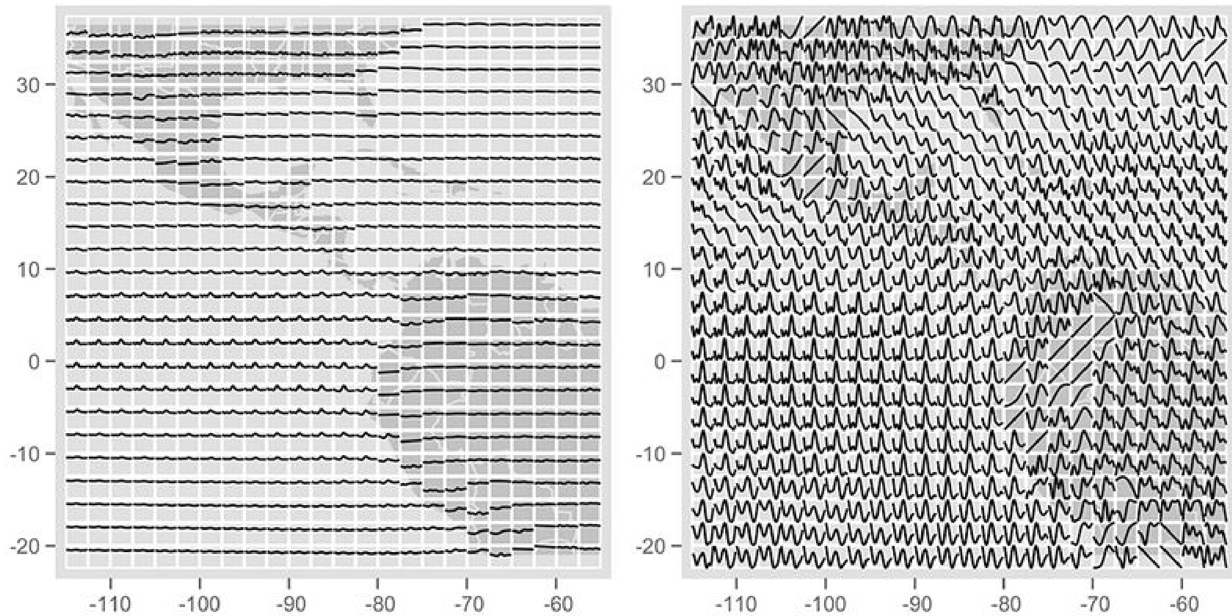


Fig. 2: *Researchers from the Institute for Atmospheric and Climate Science in Switzerland developed this bivariate color scheme, which indicates temperature and relative humidity by mixing colors to varying degrees. The results are intuitive: the Sahara desert has a sandy color that indicates hot and dry, the Arctic has a deep blue that indicates cold with high relative humidity, the tropical regions are clearly distinguishable, etc. (Teuling et al., 2011)*

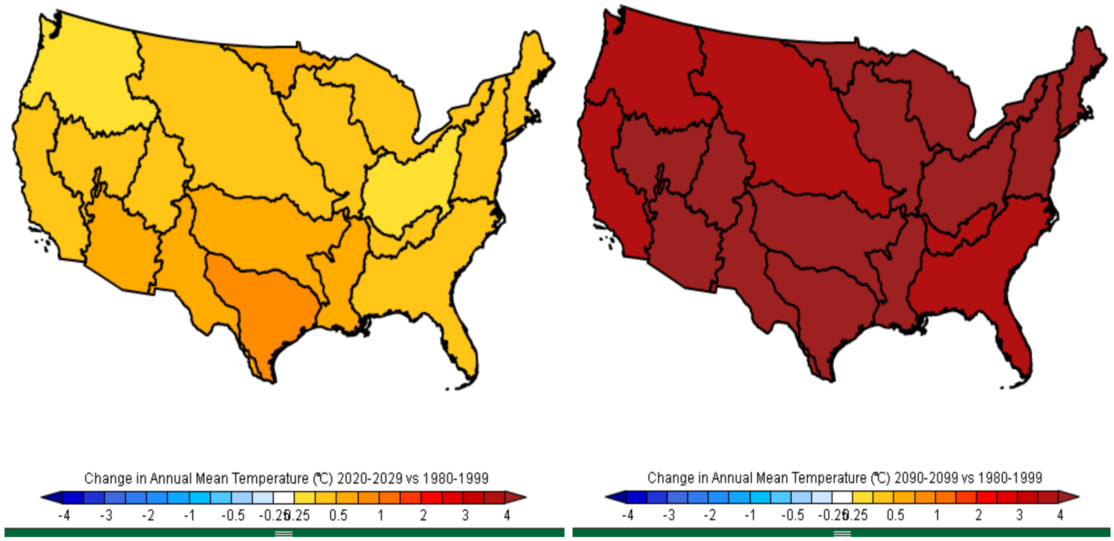
Currently, few existing two-dimensional maps in the literature can handle more than two parameters at a time, and often require contour lines or other unintuitive approaches to do so (Potter et al., 2009; Teuling et al., 2011). Furthermore, very few strategies have been developed for two-dimensional maps that can demonstrate changes in a parameter over time. One approach to displaying changes in parameters over time is the glyph-map. This type of map was developed by Wickham et al. (2012) from Rice University to display changes in a single variable over space and time by placing tiny graphs all across a world map, with each graph using the same scale (Fig. 3). While glyph-maps allow users to view changes in a parameter over time and help highlight aberrations in the data, they may be slightly unintuitive for some meteorologists, technical experts from another field, and the majority of the public.



(a) (b)

Fig. 3: *Two glyph-maps representing the same set of temperature data for one year. Graph (a) utilizes a global temperature scale, while graph (b) utilizes a local temperature scale (Wickham et al., 2012).*

Alternative examples of 2D map applications that account for time are the Global and Regional Climate Science Viewers, which were developed by Alder et al. (2013) from the U.S. Geographic Survey and the Lawrence Livermore National Laboratory in 2012. They allow users to view predicted changes in parameters such as temperature, soil moisture, and precipitation, with reds indicating significant increases and blues indicating significant decreases (Alder et al., 2013).



(a) (b)

Fig. 4: *The Regional Climate Science Viewer visualizes predicted temperature changes over two time spans: (a) A comparison between the 2040s (predicted) and 1980s. (b) A comparison between the 2090s (predicted) and the 1980s (Alder et al., 2013).*

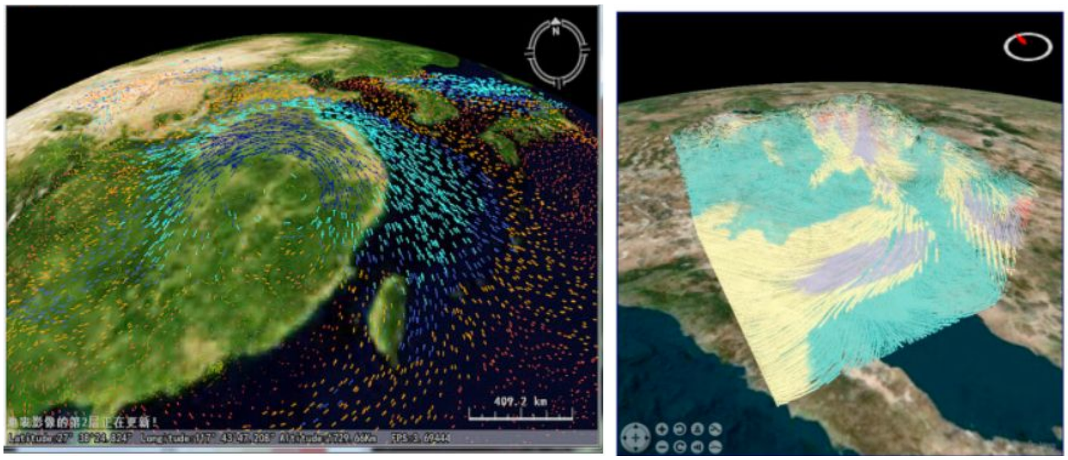
Both the global and regional tools allow users to compare predicted changes against expected changes over one or more decades. For instance, users can compare the predicted temperature increase from 1980 to 2040 against the expected increase from 1980 to 2090 (Fig. 4). The Regional Viewer also allows users to view predicted changes for specific regions in the U.S. down to the county level. However, while the Climate Science Viewers do convey changes in severity and values of parameters over time, the physical or environmental effects that such changes might have are not apparent from these and other univariate methods of climate data visualization (Liu, Gong, and Yu 2015; Zhang et al., 2015).

All 2-D data visualization maps discussed have strengths and weaknesses. It is valuable for users to see the changes in the data over time, as with the two Climate Science Viewers, but it may be difficult for users to grasp climate patterns when only one parameter is displayed.

Conversely, bivariate color graphs are useful for users to see aridity, relative humidity, and temperature, but make it difficult to grasp the changes when no time context is given. Since there are limitations on what static maps can display, none of these maps was used to visualize intricate multivariate phenomena. Moreover, these maps were never tested for effectiveness or reviewed by human factors to determine which characteristics would be most useful to researchers or the public. Without such reviews, objectively quantifying the usefulness of these maps is difficult.

Three-Dimensional Renderings

As the computational capabilities of machines have increased, it has become possible to project models and large sets of climate data using online simulations and virtual globes, such as Google Earth and NASA's open-source World Wind API (Liu, Gong, and Yu 2015). These interfaces support vectors to show the paths of particles, and volume rendering to add textures and colors to various sections of 3D-space. Furthermore, these renderings may change in real time, allowing users to observe the fluctuations of climate phenomena interactively. Researchers from the Chinese Academy of Sciences utilized these features to model the behavior of a cyclone (Fig. 5) (Liu, Gong, and Yu 2015). Their findings suggest that World Wind may be helpful for conceptualizing data sets. For instance, the researchers used vector simulation to determine the wind speeds and directions in general areas that would be affected by a storm (Liu, Gong, and Yu 2015). Similar applications have been developed by other researchers to visualize wind currents and dust storms in real-time (Fig. 5) (Zhang et al., 2015).



(a) (b)

Fig. 5: *(a) Vector simulation of a cyclone in World Wind (Liu, Gong, and Yu 2015). (b) Wind currents simulated in World Wind using volume rendering (Zhang et al., 2015). Note that the wind currents depend not only on latitude and longitude, but also on elevation.*

These three-dimensional APIs can also be used to render data not related to wind patterns or vectors. For instance, Du et al. (2015) at Zhejiang University developed an API to display CO_2 fluxes over the oceans (Fig. 6). Flux levels were displayed using colors, ranging from blue (downward flux), to red (upward flux), with elevation indicating the carbon content of a region of the ocean.

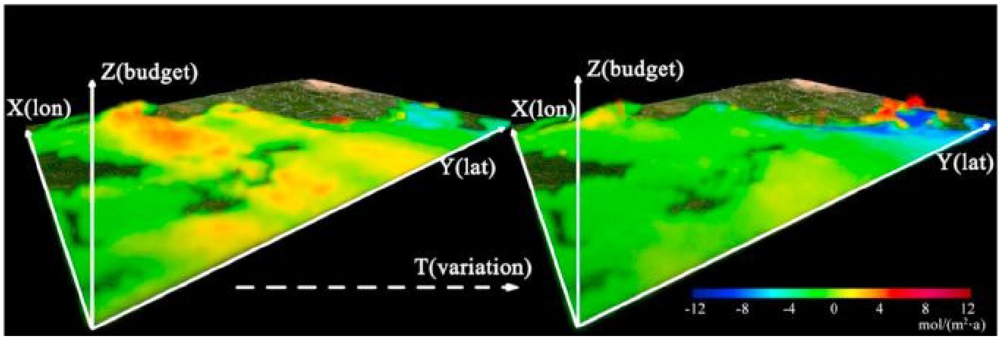


Fig. 6: *Simulation of CO_2 flux levels of the ocean, with positive values indicating an upwards flux (CO_2 leaving ocean) and negative values indicating a downwards flux (CO_2 entering ocean) (Du et al., 2015).*

In this visualization (Fig. 6), the color scheme allows the user to see that there is increased acidification (negative flux) over much of the ocean surface surveyed, which also increases in severity over time (Zhang et al., 2015; Du et al., 2015). Combined with the height field attribute and the World Wind Globe API, this visualization would be able to display carbon levels and fluxes across the entire globe over time (Du et al., 2015). This provides a viable, perhaps more intuitive, alternative to two-dimensional charts, which are rarely configured to display changes over time and typically require contour lines to display multiple variables (Du et al., 2015; Potter et al., 2009).

As a whole, real-time globe environments like World Wind illustrate complex time series more realistically than do two-dimensional maps (Liu et al., 2015; Zhang at al., 2015; Du et al., 2015). However, like two-dimensional maps, these globes have only been used to visualize the effects of a single variable on the system, rather than multivariate interactions. This means that users can draw only incomplete conclusions from these visualization methods. For instance, while the methodology of Du et al. (2015) and his colleagues can display CO_2 flux, it is unclear what the effects of this would be on atmospheric or oceanic conditions. Likewise, while the methodology of Liu et al. (2015) effectively displays the path of a cyclone, it is difficult to gather details of the storm, such as the cyclone's effects on the upper ocean or changes in the cyclone's intensity, from their method of visualization. This presents a gap in literature, which could possibly be resolved by introducing a visualization method that displays multiple variables and their interactions with their surroundings. Such a method could also have an interactive component allowing users to focus on areas of interest, where different variables may appear to have a correlation, and this could be included as an analytical feature in its interface.

There is also a significant gap in literature in that no method of data visualization has been tested for its effectiveness in conveying the effects of climate data to technical and non-technical audiences, which means that improvements to these visualization methods are merely based on speculation and a general sense of inadequacy. It would be useful to test this new interactive method, as well as the older methods, to determine which visualization method is the most effective for communicating these climate data to interested audiences.

Storing and Processing Data

When designing a data visualization platform to reveal trends and interactions between data sets, it is also important to consider how these data will be stored and processed effectively to create a smoother user experience. Some issues presented by large data sets, such as climate data, include interpreting numerous different file types, efficiently processing large quantities of data, and rendering the corresponding graphics onto a user's machine (Zhang et al., 2015). Researchers have addressed these problems by developing improved database management techniques, compressing data when possible, and outsourcing computations (Zhang et al., 2015).

Climate data are recorded all over the world from a large variety of sources and in heterogeneous formats. Idreos et al. (2015) highlight the need for systems built for “data exploration,” (p. 277) where users may not be familiar with the details of how a certain data set is stored, but wish to query the system for data in an exploratory manner. This can be accomplished with “middleware,” a layer between the user interface and the database that improves the efficiency of searching for interactions between data sets. According to Idreos et al. (2015), techniques such as predictive analysis to search for interesting correlations, or data caching to store data likely to be used, can streamline this process. An exploratory system such as this could therefore help users visualize and examine data from multiple unfamiliar sources more easily.

Users may also wish to have a more comprehensive visualization by compiling many different data sets from separate sources. However, these might be stored in different formats, making them more difficult to compare. To address this issue in one of its applications, Szlam et al. (1997) developed a system for call centers to automatically consolidate data about consumers from heterogeneous sources into a single presentation, allowing agents to quickly glean information from one source. A similar technique could be implemented to compile climate data into one format for ease of use in generating visualizations. Additionally, Sun et al. (2011) developed a PHP program called KML Generator to extract data fields from database sources so that a single file could be used to generate the final visualization, prior to rendering. Employing a combination of these strategies to compile requested data sources into a single format would save time when accessing data during the visualization rendering process.

Another component of animated data visualization is the efficiency with which frames are generated. Data scheduling tasks must be established to ensure that visualizations can be generated in time for the user to view them. A technique developed by Du et al. (2015) allows for external data to be read asynchronously, so that an entire data set does not need to be loaded at once. This technique employs a node-based strategy where frames are simultaneously generated and displayed so that the next frame is prepared as the current one plays, and ensures that loading data does not interfere with the process of rendering images since only two GPU buffers are in use at any given time (Du et al., 2015). When testing this model, Du et al. (2015) concluded that frame rate is not significantly affected by data set size, demonstrating that this is an efficient method for generating and displaying animated visualizations in real time

No matter how efficient the rendering process may be, however, generating images from data still takes time and requires significant computational power. Two ways that researchers have tried to reduce computation times are by simplifying the data or by outsourcing processing power. One method for simplifying data was developed by researchers from the National Center for Atmospheric Research (NCAR) during the development of their Visualization and Analysis Platform for Ocean, Atmosphere, and Solar Researchers (VAPOR) (Norton and Clyne, 2012). In order to render large data on normal desktop computers, VAPOR utilizes progressive data access, which means that it sacrifices accuracy to speed up computations (Norton and Clyne, 2012). Norton and Clyne (2012) found that for some data sets, especially those used for volume rendering, the progressive data access approximation is adequate for visualization purposes (Fig. 7), meaning that users can visualize this sort of data on regular desktop computers.

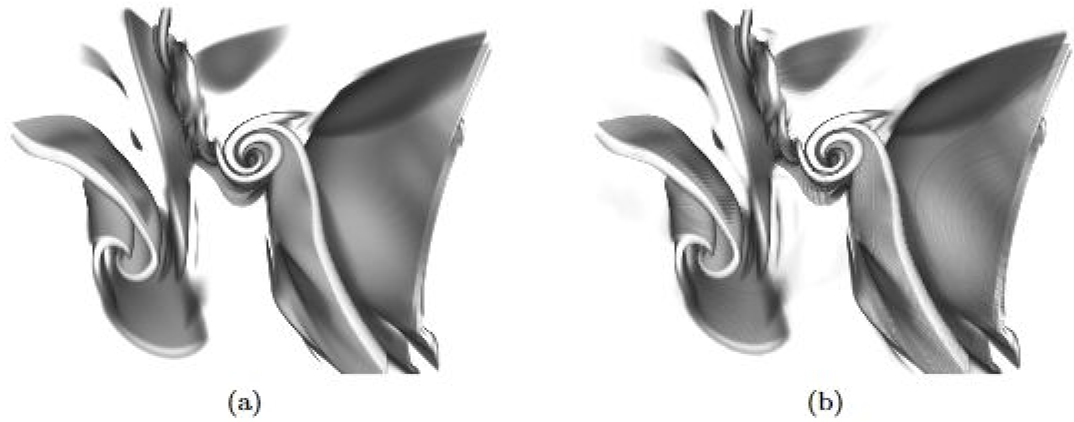


Fig. 7: *Close-up of VAPOR's volume rendering of a region reveals little difference between (a) the original, uncompressed data and (b) the compressed data (Norton and Clyne, 2012).*

In cases where data fidelity is very important, rather than relying on users to have sufficient resources, it is beneficial to outsource major computations to the cloud and simply serve clients the final product. Cloud platforms such as Amazon Web Services (AWS) can be used to gain access to remote computing power such as GPU clusters that share resources to quickly accomplish tasks (Zheng et al., 2015). This system, developed by Zheng et al., (2015), allows for customizability of visualization algorithms and takes advantage of AWS's auto scaling features so that the platform can be scaled up to include more remote GPUs if more computation power is needed. Employing a system like this would allow climate data visualization platforms to operate independently of client resources so that rendering images can be done in minimal time.

Section 2.2 - Virtual Reality

Previously discussed methods of climate data visualization suffer from a lack of interactivity. These methods can display variation in few variables at a time, but in general, it is difficult to gauge the combined effects on the surrounding environment, the oceans, and the atmosphere due to changes in one or more variables. Current methods also make it difficult to visualize the interaction between various climate variables, limiting the predictions they can make and the trends they can observe. One potential solution to this lack of interactivity would be to use VR. This would allow users to more easily visualize the effects on the atmosphere and oceans previously mentioned. It could also allow users to choose specific areas of interest in a multivariate visualization, and focus on and analyze those areas for trends or correlations. Literature suggests that VR already has analogous technical applications in the military, medicine, and engineering, so it is plausible that the benefits of VR could be expanded to climate data visualization as well (Desai et al., 2014; Goldman Sachs, 2016; Mathur, 2016; Winoto et al., 2016).

The concept of VR has existed since the mid-1990's. Over these two decades, the available technology has grown immensely, yet many challenges still remain for the developers. Even today there are no standardized tools to use or procedures to follow when working with VR (Ray, 2015). Beginning in the 1990's, developers attempted to create Virtual Environments (VEs) with various VR toolkits (Ray, 2015). Unfortunately, researchers and developers have had numerous issues when working with these toolkits. Existing toolkits are rarely reused when developing VEs, as they are often device- and use-specific. As a result, developers will often create their own toolkit from scratch (Ray, 2015). However, time is an issue when developing a new toolkit, because one often takes years to create, as seen by the large gap between the creation of CAVELib and those from the toolkit wave of the early 2000's (Ray, 2015).

Ray (2015) blames the lack of publications about VR studies as the root cause of having no standard toolkit or procedure. He suggests that researchers publish their findings, so that a standard can be developed over time. Ray also provides guidelines for those attempting to create such a standard. A toolkit should be able to work by default, stay out of the developer's way, and be easy to use. Working by default entails having interoperability between different pieces of hardware. In addition, the architecture should consist of a modular design, looking to augment instead of replace existing work.

Modern Day Applications

VR technology has a variety of applications ranging from everyday uses in home entertainment to more technical uses in medicine and engineering. For instance, in the video game industry, consumers are eager to have a more immersive experience that puts them right in the center of all the action (Goldman Sachs, 2016). VR also has military uses; the United States military currently utilizes advanced simulation to provide soldiers with combat and flight training (Goldman Sachs, 2016). VR is also commonly used by engineers for Computer Assisted Design (CAD) and has become a popular method for prototyping new designs, and viewing them from different perspectives (Goldman Sachs, 2016). Finally, VR technology is currently widely used in the area of medicine. For example, VR medical training was used to substitute traditional surgical training in the field in one study done by Mathur (2015).

Just as VR technology presents new possibilities for engineers, doctors, and the military to visualize their designs better, it also presents new ways for people to visualize data. Effective data visualization is especially useful for scientists trying to analyze their data as well as to present their results and findings. New methods of data visualization can be developed to capitalize on VR platform to help increase understanding of certain data set, which is what the team aims to accomplish with its research.

Current State and Limitations of Virtual Reality

In order to better understand the potential of visualizing climate data with VR, it is important to evaluate the device that Team DIVA plans to use for its strengths and weaknesses. Currently, the most popular and widely used VR device is the Oculus Rift by Oculus VR. The team plans to use the newest model, the Oculus Rift DK2, to develop its data visualization environment. It has a very high display resolution of 960 pixels by 1080 pixels, 100 degrees' field of view, and a refresh rate of up to 75 Hz, making Oculus Rift a truly immersive and life-like experience for the users (Desai et al., 2014). With regards to the sensor system, the Oculus Rift has a gyroscope to measure angular velocity, an accelerometer to measure acceleration, and a magnetometer to measure direction which transfers data at 1000 Hz, making the headset ultra-responsive to head movements and improving the overall user experience (Desai et al., 2014). Other capabilities of the Oculus Rift that the team can take advantage of are head and positional tracking, which can be used as controls for the visualization tool (Developer, 2016). This emphasis on immersion is an important consideration in the selection of Oculus as the team's visualization platform.

Despite the Oculus Rift's many strengths, it shares many of the same drawbacks with other VR devices. One weakness is the screen door effect, the empty black spaces that a user sees between each pixel on the screen (LaValle, 2014). The screen door effect can distract users and make the visuals seem less life-like. Another limitation of Oculus Rift is ghosting, the trailing image left behind any moving object on the screen caused by low pixel switching frequencies (Desai et al., 2014). This ghosting produces a blurring effect and decreases the apparent resolution of the images. This means that objects on the screen have a maximum speed at which they can move without producing the ghosting effect. Another disadvantage of the Oculus Rift is that some subjects in VR studies have reported motion sickness. This was so pertinent of an issue that a question on motion sickness appeared on a survey to participants involved in a study using VR to help autistic children learn words (Winoto et al., 2016).

Future of Virtual Reality

According to a Goldman Sachs research report, the development and growth of VR technology will likely be comparable to the growth of PC, smartphones, and tablets (Goldman Sachs, 2016). Following the trend that PCs have taken over the past three decades, VR will surely benefit from the economy of scale, driving the price of VR product down. Goldman Sachs (2016) also describes the VR platform as a new potential computing platform that offers a new level of interaction with computers; just as the tablet introduced the concept of touchscreen interaction. In that sense, VR can be seen as an extension to existing general purpose computing technologies. This huge potential VR technology presents has not gone unnoticed by tech companies as over $3.5 billion of investment have been poured into VR and Augmented Reality technologies in just the past two years (Goldman Sachs, 2016). Given the massive potential growth for VR in the future, the team believes that VR is the best platform on which to develop its new and modern climate data visualization tool.

Section 2.3 - Human Factors

Emotional appeal and user perceptions of models and visualizations are becoming increasingly important, especially for communicating data to technical audiences outside of the field and to the general public. Currently, data models tend to be extremely complex and pay little attention to human perception, but studies on emotional aspects of data visualization suggest that human perception plays an important role in how audiences understand data (Grinstein and Levkowitz, 2013).

Data sets tend to be influential when presented emotionally, as they make the data more relatable to users (Herring et al., 2015). Two important factors that appeal to emotions are spatial and temporal proximity. Spatial proximity refers to how close the user is to the data being described, while temporal proximity refers to how immediate the data are, i.e., how close the data set is to the user in terms of space and time. Studies have found data that are modeling the near past or near future are far more impactful to the user than data that are too far into the future or too far into the past (Kostelnick, 2016). Also, people find models that are changing with time more interesting than multiple snapshots (Kostelnick, 2016). This is known as temporal fluidity, which can help enhance temporal proximity by making the user feel closer to the data (Kostelnick, 2016). Through the use of VR, the users' spatial and temporal proximity could be heightened much further by bringing them closer to the time and location of the data presented.

Another factor in appealing to the emotions of the user is making the method of data visualization more user-friendly and interactive. One simple technique is the manipulation of color. Color creates visual stimuli that physiologically, aesthetically, and culturally arouse the user's emotion (Elliot et al., 2014). Colors have been proven to enhance both user engagement and excitement when used in data models. Since data are so content specific, colors become far more important (Elliot et al., 2014). For example, when a user wants to model a specific data set, he or she may want to add emphasis on an aspect through colors to evoke an emotional or physical reaction.

Visualization techniques such as dense pixel displays and iconic displays improve visual designs for climate data. Dense pixel displays use single pixels to represent each data value with color, which allows the user to see mass data (Keim, 2002). This allows the users to see detailed information on local correlations, dependencies, and hot spots and compare data trends (Keim, 2002). Iconic display allows the user to see data more clearly and can vary depending on the data being shown. Often times, combining aesthetically pleasing visuals with other techniques can further enhance the user experience. An example of a technique that can be combined with visual aspects is the use of haptic icons (HI). HI are brief signals conveying an object's or event's state, function or content which are often combined with haptic feedback, which is the feedback received to the user through the sense of touch on a graphical interface. This allows the user to use hand gestures to interact with a system (MacLean and Enriquez, 2003). Utilizing haptic techniques in conjunction with aesthetically pleasing visual design may improve emotional appeal and understanding of the data more than using any one of the technique by itself.

Section 2.4 - Conclusion

While current methods of climate data visualization and analysis can effectively display a single variable, they are generally not able to represent interactions in data (Alder et al. 2013; Liu et al. 2015; Potter et al. 2009; Wickham et al. 2012; Zhang et al., 2015). This prevents researchers and other interested individuals from grasping the full effects of variations in the data, since these interactions are what allow researchers to understand climate phenomena in the first place. For instance, global temperature distributions are connected to wind patterns in the atmosphere and the surface temperature of the ocean, which are in turn connected to global precipitation patterns, but current methods do not allow users to see this sort of relationship

(Alder et al. 2013; Liu et al. 2015; Potter et al. 2009; Wickham et al. 2012; Zhang et al., 2015). Current two-dimensional maps are almost completely restricted to univariate or bivariate data visualization, while three-dimensional globe interfaces have not yet been implemented to allow users this sort of control or interactivity (Teuling et al., 2011; Zhang et al., 2015).

A potential means of improving this lack of interactivity between the user and variables with the display would be to integrate VR technology with these methods. VR has already been used in medical, military, engineering and educational applications in order to give users a better understanding of important tasks. In the area of climate data visualization, VR could allow users to visualize multiple data sets simultaneously,focus on the trends of interest, and depict the effects of changes of these variables on oceans and the atmosphere, a key component missing in current methods. Furthermore, psychological studies suggest that spatial proximity and suitable color schemes help users better perceive the significance of data; VR would help incorporate both of those features. Together, these features would create an experience in which climate researchers and other interested individuals can view how large sets of climate data interact to produce many of the oceanic and atmospheric patterns observed today. In the following section, the plan to develop and evaluate such a tool to visualize climate data will be described in great detail.

SECTION 3 - METHODOLOGY

Current climate data visualization tools show static visualizations; they typically display only a few variables and do not make it easy for users to see correlations or other interesting trends in the data (Alder et al. 2013; Du et al. 2015; Liu et al. 2015; Potter et al. 2009; Teuling et al. 2011; Wickham et al. 2012; Zhang et al. 2016). To address these issues, the team will first develop a virtual reality (VR) tool to visualize climate data using techniques derived from previous research. Once the team completes a prototype of the tool, the team will collect some initial data to guide the design and inform the team of areas that could be improved. Lastly, once the final product is complete, the team will collect data on the performance of its tool. Thus, the team's research can be broken up into three main phases: product development, product improvement, and product evaluation.

Section 3.1 - Product Development Plan

Current methods of climate data visualization, such as 2D and 3D renderings, are generally restricted to univariate data sets, and options to view multivariate data sets are quite limited (Liu et al. 2015; Teuling et al. 2011). This causes difficulties for climate scientists to identify areas of interest where there may be meaningful correlations that are hidden between multiple variables. The older methods of data visualization are also typically not interactive via an intuitive interface (Alder et al. 2013; Liu et al. 2015; Potter et al. 2009; Wickham et al. 2012; Zhang et al., 2015). For two-dimensional maps, users cannot zoom in, change their location, or adjust elevation on the map to focus on different parts of the data without coding significant control scripts. Due to the lack of interactivity and sometimes complicated nature of current maps and globes, years of experience are often required for users to use these tools proficiently. Team DIVA plans to address some of these shortcomings by integrating NASA's open source World Wind Globe API (Application Programming Interface) with Oculus Rift VR technology so that technical users can observe multiple climate data sets simultaneously, focus in on areas of interest, and exercise greater control over the display of their data.

World Wind Globe API

Currently, the most advanced climate data visualization methods involve 3D renderings displayed on virtual globes. The most prominent of this type of visualization is NASA's open source World Wind Globe API (Liu et al. 2015; Zhang et al., 2015). Researchers from the Chinese Academy of Sciences and Wuhan University have used World Wind to display vectors representing cyclones and dust storms, respectively (Liu et al. 2015; Zhang et al., 2015). However, these tools are neither versatile nor interactive. Team DIVA's goal is to generalize World Wind's applications to encompass multiple kinds of data so that climate scientists can observe correlations among multiple variables and domains. For example, the team would like to display not only wind direction but also other variables, such as temperature, atmospheric humidity, and oceanic salinity. Although World Wind has only been used to display a few climate patterns, it is well suited to multivariate visualization as it can display both vectors and volume rendering (Zhang et al., 2015). Since the World Wind API is written in Java, it supports any rendering from the Java Open Graphics Library (JOGL), which is Java's versatile standard 3D graphics library (Zhang et al., 2015). With this framework, the tool could display, for instance, land and ocean temperature with a color gradient, wind speed and direction with vectors, and precipitation with height fields. Climatologists will then be able to observe these values change over time, thereby determining if there are any consistent relationships between the variables or any anomalies which may indicate a significant regional change in climate. This visualization process can then be generalized to any variable of interest and add customizability for color and texture, giving researchers the opportunity to simultaneously view as many data sets as needed and choose how they would like to view them.

Integration of Oculus Rift

As literature has indicated, existing forms of climate data visualization are often non-immersive and provide limited options for visualizing different types of data (Alder et al. 2013; Liu et al. 2015; Potter et al. 2009; Wickham et al. 2012; Zhang et al., 2015). This makes climate data visualization a non-intuitive experience and may limit climate scientists' understanding of the data (Filonik and Baur, 2009). For instance, the temperature variation with altitude may affect climate patterns, but this is essentially impossible to visualize on a two-dimensional map. Another example of how an interactive display may be helpful is if a researcher observes a localized trend in the data and would like to zoom in on that particular region for further investigation.

The implementation of a climate data visualization system within a VR framework will allow for greater interactivity between the user and the data. This provides users with the control to choose which parts of data sets to focus on in order to observe important relationships.

Specifically, Team DIVA will use the Oculus Rift to develop its visualization system. The Oculus Rift headset has an accelerometer, gyroscope, and magnetometer, from which head orientation (yaw, pitch, roll) can be inferred. In addition, the Oculus Rift comes with an infrared camera, which tracks the position of an array of infrared micro-LEDs on the headset, allowing developers to track head position (x, y, z) of the user (Desai et al. 2014). The Oculus Rift software development kit (SDK) includes a head model code, which the team will use to access the position and orientation measurements (Desai et al. 2014). The team will take advantage of head orientation tracking to allow the data display to rotate with the user's head, creating a truly immersive experience.

Furthermore, the team will utilize head position tracking to allow users to zoom in on and zoom out of fields of interest by leaning in and leaning out, making the product even more user friendly and intuitive. To reduce latency, the time between head movements and updated display, the team will use the predictive tracking code included in the Oculus SDK. Oculus will soon release the Oculus Touch, which are two controllers, one for each hand, that allow users to interact with the VR environment. Oculus Rift can track wrist movement using these controllers in addition to tracking conventional button pressing (Oculus n.d.). Using the Oculus Touch, the user will be able to interface with select menus and other aspects of the GUI. Overall, the team will take advantage of these systems to allow users to control their movements throughout the World Wind environment, observe changes in multiple sets of data, and focus in on areas where correlations exist.

The team plans to use Oculus Rift in conjunction with a web-based application. Hosting the application remotely and serving users through a web interface has two main benefits: being able to reach a wider audience and developing on a more consistent architecture. Not everyone has an Oculus-ready PC since running Oculus Rift requires certain minimum specifications for the processor, graphics card, and operating system. By developing a web-based application, the team will allow users without the required hardware to use its visualization tool, eliminating one boundary between product and user base. This format will also allow for taxing calculations and rendering tasks to be performed on a remote server with a known computing power, so that the speed and efficiency of the application is consistent from user to user. The Oculus Rift’s ability to interface with the web allows the team to ensure that the VR application will not need to rely on any users’ hardware and can deliver consistent, reliable results (Developer, 2016).

Data Processing and Computational Efficiency

Oculus Rift's web compatibility allows the team to outsource large computations and graphical visualizations to the cloud, reducing the load on client machines. Climate data are typically stored in large files on the order of gigabytes as either Network Common Data Form (NetCDF) or Gridded Binary (GRIB) and GRIB2 files. NetCDF is a self-describing data format, which means the file includes metadata and a description of how the data is formatted throughout the file. This description allows NetCDF parsers to access meaningful values from millions of lines of binary data. GRIB is an older, less flexible type of climate data file which simply attributes values to a series of grid squares, and can be converted to NetCDF. However, due to the sheer magnitude of global data, these files can take substantial amounts of time to process on an ordinary desktop computer (Zhang et al. 2016). This is why Team DIVA plans to use Oculus's cloud connectivity to outsource computations to Graphical Processing Units (GPUs). The team will then utilize a cloud-based application to send the rendered frames directly to the Oculus Rift display. In this way, the client machine hosting the Oculus Rift hardware will only need to display the visualization and not process huge sets of data on a local machine (Fig. 1). Therefore, the team will be able to display very smooth renderings of its visualization for the user.

Example Application of Product: El Niño

In order to gather survey and focus group information regarding the project, Team DIVA plans to display and analyze a climate phenomenon to showcase the potential of its tool's ability to render multivariate interactions in full 3D over a time domain. The team believes that El Niño is an ideal choice to display the potential of its visualization system. El Niño is a climate pattern during which warmer ocean water from the western Pacific flows eastward, affecting global weather patterns by increasing rainfall in the eastern Pacific and causing drought in countries bordering the western Pacific (NOAA n.d.). This is a great example of ocean conditions influencing atmospheric conditions, and vice versa, which will allow the visualization to demonstrate its ability to highlight the correlations among these data sets.

Since El Niño is such a complex phenomenon, researchers in the fields of both visualization and analysis have used this phenomenon to evaluate the success of their software. Marwan and Kurths (2002) modified a method of analyzing nonlinear data through cross recurrence plots and chose to apply this technique to El Niño data in order to test their ability to identify relations in multivariate data. By comparing the results of their new method and the traditional linear method, they deemed their method a success because it could identify a trend of increased local rainfall in Argentina better than the traditional model could (Marwan and Kurths 2002). In another study, McCormick et al. (2004) chose El Niño as a case study to test the effectiveness of multivariate visualization rendering on GPUs as opposed to CPUs (Central Processing Units). The team believes that displaying a visualization of El Niño to focus group and survey participants will adequately exhibit the capabilities of the software and allow the participants to evaluate the VR tool against traditional visualization methods.

Section 3.2 - Data Collection

In the following section, the process of collecting data and which types of methods will be used to analyze the data will be described. The team has taken into account the limitations of its methods as well as other factors that may affect the data collection. The team will have three focus groups during the development phase: graphics experts, general public, and climate researchers. Once the team completes the development phase, the team will conduct surveys in order to evaluate the tool. All of these focus groups and surveys will require approval from the Institutional Review Board (IRB).

Focus Groups

The first focus group will consist of about five graphics experts from the University of Maryland and will last about an hour. The purpose of this focus group is to refine the aesthetics and user interface of the visualization. This will be a facilitated discussion guided by questions concerning the current state of visualization techniques and headed by two teammates. These questions will not directly concern climate data, but instead will concern the aesthetics of the visualization. The team will give a demographic survey to each of the graphics experts before the discussion. The team will inform them that the discussion will be recorded for research purposes. Based on the feedback from these experts, the team will make improvements to the graphics and user interface.

Next, the second focus group will consist of members of the general public. This focus group will have the same structure as the group of graphics experts, except the questions will focus more on the general feel and usability of the tool. To obtain participants, the team will advertise throughout the University of Maryland, targeting a diverse group of students not only majoring in STEM fields, but also in the arts. This is because the team wants to make the user control scheme as intuitive as possible. In addition, the team does not want poor aesthetics to hamper the later focus group of climate researchers from giving feedback on the visualization techniques. To do this, the team will advertise at the Computer Science Instructional Center, Tawes Hall, William E. Kirwan Hall, and the Clarice Smith Performing Arts Center. The team will obtain approximately 30 students and plan to separate them into five subgroups of six students. The team can then make further improvements to the usability and aesthetics of its VR tool based on the general comments of the public.

Lastly, the team will hold a climate researcher focus group, which will consist of 10 climate data experts from NOAA, NASA, and/or within the University of Maryland. This focus group will have the same structure as the previous two focus groups. However, the main subject of this focus group will be what the experts can interpret and learn from the visualization such as making general comments about correlations and viewing specific data.

Individual Surveys

After the focus group data have been obtained and consequent improvements have been made to the VR tool, the team will test its prototype against earlier visualization tools, such as older implementations using World Wind, by administering an extensive survey to the general public and experts.

The variables the team will measure are usability, aesthetic appeal, comprehensibility, motion sickness caused by the visualization tool, and the time to complete given tasks. For this data, the team will ask users to rate these variables on a scale from 1-5 and will time how long it will take to complete the tasks assigned. This data will help the team focus on where the product shines and fails compared to current visualization tools. Usability can be measured by both the time spent and accuracy of the tasks as well as the participant’s direct rating on a scale of 1-5. Aesthetic appeal is also an important data set to consider. Not only does it increase user interest and engagement for the data, but it also improves effectiveness of the tool (Lau and Moere 2007). The comprehensibility of the data is also important, especially for the public, because it defines how much information the data visualization is able to convey to the user (McCormick et al. 2004). Measuring motion sickness is important because ideally the visualization tool should not cause any motion sickness for the user.

To account for confounding variables, the team will collect demographic information of the participants including age, ethnicity, gender, and profession/major. For the general public, it will be important to measure the user's familiarity with both technology and climate data as these are potential confounding variables. For the climate experts, the team will collect data on familiarity and experience with technology, place of work, position in the research community (such as seniority and authority level), and research interests (theoretical or applied). For both groups, the team will run correlation analyses, such as multiple logistic regression, between test results and demographic information to determine if there is any relationship between them. This way, the team can determine whether or not its results are statistically significant.

Due to convenience and proximity, Team DIVA only plans to conduct the general public surveys on students from the University of Maryland. To gather participants, the team will post advertisements and flyers across campus at the most popular locations such as McKeldin Library, Adele H. Stamp Student Union, the Computer Science Instructional Center, and Glenn L. Martin Hall. The team will obtain approximately 50 participants for these surveys. Since the team expects its participants to have little prior experience dealing with climate data, the team will set up a pre-made data visualization on both its platform and an existing visualization tool for all participants. The team will allow the participants to get familiar with the visualizations for approximately five minutes. The team will begin by asking the participants to fill out a survey in which they will rate both tools on the variables mentioned previously on a scale of 1 to 10, with

1 being “Poor” and 10 being “Near perfect”. Afterwards, the team will set up questionnaires for each participant, asking them to analyze the data displayed on its visualization tool. For example, the team will ask them to zoom in on a particular region and read some data points. The participants will be given a score based on the accuracy of their answers.

The surveys for the researchers will be held at a different time but will consist mostly of the same process. The team will have a group of 10 experts to take the survey. For this group, the team will provide a bare data set, and ask them to visualize it given a set of instructions instead of giving them a pre-made data visualization. Due to their extensive knowledge of climate data visualization, these experts will be able to give more insight into how easy it is to load data into the device and visualize it. The team will measure how much time it takes for the experts to visualize the data on the tool as well as an older tool. For this older tool, the same survey will be given to the experts to complete.

Data Analysis

The surveys will supply the team with data of the participants’ evaluations of the old visualization tool and the team’s virtual reality tool. The two objective data sets the team will analyze are the accuracy of their analysis and the time taken to complete the analysis. In addition, the team will have multiple subjective data sets that gauge the participants’ attitudes towards the features of the tool. The team can tabulate the results by tool and factor. The team’s null hypothesis is that the scores and the evaluations of the features are not significantly different between the old tool and the VR tool. The team’s alternate hypothesis is the opposite - that there exists a significant difference between the scores of the old tool and the team’s VR tool. The team will use a One-Way Analysis of Variance test (ANOVA) to calculate how likely it is that the two sets of results occurred simply due to chance. The team will run this test on each feature as well as the score variable to see how much the team's VR tool improved or did not improve. A P-value will generated from the team's statistical tests. This P-value states the probability that the team's results occurred due to chance. If this value is below a certain threshold such as 0.05, then the team can reject the null hypothesis and state that there is a significant difference between the usage results of the old tool and those of the virtual reality tool. The analysis is similar for the set of experts, except that the team will also analyze how much time it takes for the experts to visualize the data. It is important to note that the team will analyze both groups separately. In addition, for the expert group, the team will have a greater degree of uncertainty because of the small sample size.

Section 3.3 - Conclusion

Overall, the team's methodology will involve three main phases: product development, product improvement and product evaluation. The product development phase will entail creating a working prototype that uses preliminary visualization techniques. Team DIVA plans to utilize the World Wind API with Oculus Rift to produce its visualizations. In order to reach a wider audience, the team will use a web-based interface and outsource the computations to a cloud computing service so that any computer connected to the web will be able to use the tool. Once the team creates a prototype, the team will transition to the product improvement phase. This will involve a series of focus groups: first, with graphics experts to improve the interface, then with the general public to assess usability, and finally with climate data experts to evaluate the final product. This process will be iterative, during which the team will improve the tool based on each focus group's feedback. This ensures that the final product will be tailored to the target audience of climate data researchers. Finally, in the product evaluation phase, the team will collect both quantitative and qualitative data to determine how users interpret the program's features and how users feel about existing visualization tools. The team will use ANOVA to compare these results to determine whether a statistically significant difference exists between the usage of the team's tool and an existing tool. This way, the team will determine whether integrating virtual reality with a globe environment is indeed superior to existing methods of climate data visualization.

Since the team is focusing heavily on interactivity, employing a multilayered iterative design, and testing the product during each phase, the team believes that its tool will demonstrate a statistically significant improvement when compared to existing tools. This is largely because existing methods of climate data visualization have not been developed based on feedback from experts and the public, but have instead been based on mere intuition and a general dissatisfaction with previous tools (Alder et al. 2013; Liu et al. 2015; Potter et al. 2009; Teuling et al. 2011; Wickham et al. 2012; Zhang et al. 2016). Furthermore, no older method has employed VR technology as a potential solution to these problems of interactivity (Alder et al. 2013; Liu et al. 2015; Potter et al. 2009; Teuling et al. 2011; Wickham et al. 2012; Zhang et al. 2016). By utilizing feedback from a series of focus groups to optimize its product, the team anticipates that VR technology can be used to improve climate data visualization methods.

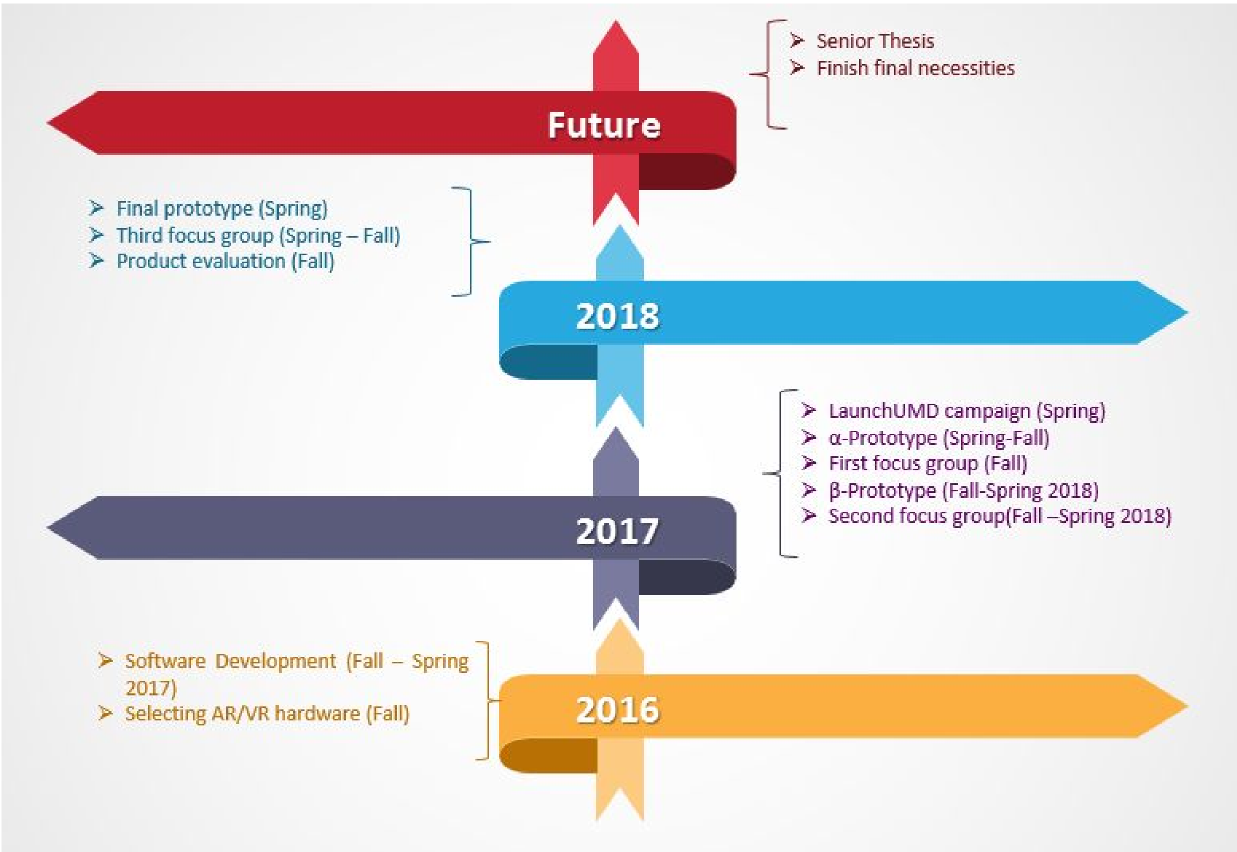
SECTION 4 - CONCLUSION

With such an abundance of climate data and rather ineffective ways to study them thoroughly, there is a need for an interactive and intuitive visualization tool. The team has proposed to utilize virtual reality to help researchers and the general public to better understand climate data. Therefore, this research will test—in terms of computation time, feature selection, and storage—how effective the team's product is compared to older methods of climate data visualization. Even if the team fails to reject the null hypothesis, the research will still be valuable. The tool created will be the first of its kind: a visualization tool using VR, capable of displaying multivariate datasets over time. Such a technique can still be extremely useful to climate researchers.

Team DIVA hopes not only to aid the climate research community, but also to assist members from other research areas. In the future, this research tool can be expanded to handle other types of datasets. Moreover, the team could implement machine learning to output meaningful graphs to researchers from other fields. The team's ultimate hope is that the tool will help to bridge the gap between experts and the public, as researchers will be able to provide more straightforward and comprehensible explanations to a variety of phenomena.

APPENDICES

Appendix A - Timeline



Appendix B - Budget

	Name	Unit Price	Quantity	Costs	Date
Expenses					
	Oculus VR Device (w/Oculus Touch)	$ 800.00	1	$ 800.00	Spring 2017
	Oculus VR Device (w/Oculus Touch)	$ 800.00	1	$ 800.00	Fall 2018
	Graphic Designer Focus Group	$ 20.00	10	$ 200.00	Fall 2017
	Student Focus Group Compensation	$ 15.00	30	$ 450.00	Fall 2017 / Spring 2018
	Climate Expert Focus Group	$ 20.00	10	$ 200.00	Spring 2018 / Fall 2018
	Student Survey Compensation	$ 5.00	50	$ 250.00	Fall 2018
	Travel Expenses / Conferences**	$ 1,200.00	3	$ 3,600.00	Spring 2019
Total				**$ 6,300.00**	
Revenue					
	Launch UMD**	$ 4,500.00	1	$ 4,500.00	Spring 2017
	Gemstone Funding*	$ 600.00	1	$ 600.00	Fall 2016
	Gemstone Funding*	$ 600.00	1	$ 600.00	Fall 2017
	Gemstone Funding*	$ 600.00	1	$ 600.00	Fall 2018
Total				**$ 6,300.00**	
	*** Goes away after every school year**				
	****Very rough estimate**				

Appendix C - Survey Questions

Age: ________________________________
Major/Profession: ___________________________
Date: __/__/______
Gender (Circle One): Male / Female / Other
Ethnicity (Place X): __ Caucasian __ Asian American / Pacific Islander
__ Native American __ Hispanic
Familiarity With Technology: 1 2 3 4 5

Please answer this before you start your experience:

What do you expect the virtual reality experience to look like?

____

____

How well are the following features implemented in virtual reality and the old visualization? (Rate 1-5)

Feature	**Virtual Reality**	**World Wind**
Color Palette		
Visualization		
Speed		
Gestures		
Motion Sickness		--
Comprehensibility		
UI		

Answer the following questions after you have experienced both programs:

How much better was the virtual reality experience than the old visualization's experience?
How much did this exceed your expectations? 1 2 3 4 5
What feature did you find most unappealing/displeasing (None also option)?

____

What features do you want to have implemented in the future?

____

What was the first thing that disrupted your VR experience?

____

How quickly were you able to adjust to the VR experience?

____

Appendix D - Glossary

Application Programming Interface (API) - The set of pre-made programming libraries, documentation, and tools used by developers to write their code.

Central Processing Unit (CPU) - A hardware component in a computer which handles basic arithmetic, input/output, and control of other components.

Elevation - How high above sea-level a point is.

General Regularly-distributed Information in Binary form (GRIB) - A self-describing data format which is often used for big weather data. The files contain a description of a grid space and the values of data points in each square of the grid space. GRIB files can be converted to NetCDF files.

Graphical User Interface (GUI) - What the user sees on the screen; an interactive visual display which the user can interact with to operate the software.

Graphics Processing Unit (GPU) - A hardware component in many computers which specifically handles generation of graphics.

Haptic Icon (HI) - Brief signals conveying an object's or event's state, function or content which are often combined with haptic feedback.

Heads-up display (HUD) - A program which displays information on the screen without requiring the user to move his or her head.

Network Common Data Form (NetCDF) - A self-describing data format which is often used for big weather data. The files contain a description of the data, followed by the data itself, allowing for greater flexibility in the actual data format.

Java Open Graphics Library (JOGL) - An API which allows the user to interact with GPUs of computers to produce computer graphics. It is cross-platform, which means that it can be used on different operating systems, like Windows and macOS, and with different programming languages, like Java and C.

Latitude - A geographic coordinate which describes how far north or south a point is. It is the angle measurement of the point above the equator.

Longitude - A geographic coordinate which describes how far east or west a point is. It is the angle measurement of the point with respect to the Prime Meridian, which passes through Greenwich, England.

Three-dimensional data - Data which vary depending on latitude, longitude and elevation.

Three-dimensional (3D) data visualizations - Globe APIs which render three-dimensional data, usually represented as vectors or color gradients, in such a way that users are able to move throughout the 3D environment to see the data at different points.

Two-dimensional data - Data which vary depending on latitude and longitude, but not on elevation. Usually, all points in the data set are collected at a specific altitude to avoid variation resulting from elevation.

Two-dimensional (2D) data visualizations - Two-dimensional maps which use colors and/or symbols distributed across a geographic area to indicate values of variables at different points in space. Use to represent two-dimensional data.

Virtual Reality (VR) - Technology utilizing goggles equipped with LEDs and motion detection to make users feel as though they are in a different environment than their actual surroundings.

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