6. Geographic Visualization

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Geographic visualizations always played an important role in human history, especially in the earth sciences, long before computer visualizations became popular. The earliest examples of geographic visualization even date back to the stone age with map-like wall paintings depicting the surroundings of our ancestors. Since then cartography, the art and science of map-making, has evolved continuously until today. This is why computer-based geographic visualization can build upon a large base of established cartographic knowledge. Well-known examples of static visualizations beyond geographic maps are thematic maps that display the spatial pattern of a theme such as climate characteristics or population density. Moreover, the use of modern visualization technology offers many new possibilities for geographical visualization tasks. These visualizations may help to explore, understand, and communicate spatial phenomena.

Many readers will have a vague idea of what geographic visualization is about. Nonetheless, to avoid misconceptions, the most common definitions of the term *geovisualization* (short for geographic visualization) will be given. The following notion according to the 2001 research agenda of the International Cartographic Association (ICA) Commission on Visualization and Virtual Environments is most widely accepted today: *"Geovisualization integrates approaches from visualization in scientific computing (ViSC), cartography, image analysis, information visualization, exploratory data analysis (EDA), and geographic information systems (GISystems) to provide theory, methods and tools for visual exploration, analysis, synthesis, and presentation of geospatial data"* [530]. Others take a more human-centered view and describe geovisualization as *"the creation and use of visual representations to facilitate thinking, understanding, and knowledge construction about geospatial data"* [515] or as *"the use of visual geospatial displays to explore data and through that exploration to generate hypotheses, develop problem solutions and construct knowledge"* [474]. There are a few immediate observations from these definitions. It is clear that geovisualization research is a multidisciplinary task. Since it is the human who uses visualizations to explore data and construct knowledge, effective geovisualization techniques must above all take the user needs into account.

The chapter is structured as follows. First, the range of possible goals of geovisualization and its driving forces are described in Section 6.1 and 6.2, respectively. Then, Section 6.3 looks at some perceptual issues and theoretical results in geovisualization. The main part of the survey, Section 6.4, covers a variety of suitable visualization methods from map-based and abstract techniques to animation. It also deals with interaction techniques and combined visual and computational mining of geospatial data. A number of existing geovisualization environments and tools are described in Section 6.5. Usability issues in the context of geovisualization, namely user-centered design, results from user studies, and geovisualization that supports group work, are reported in Section 6.6. The final part of this chapter looks at current and future challenges in geovisualization.

6.1 Goals of Geovisualization

The goals of geovisualization are manifold. The *map use cube* (Figure 6.1) by MacEachren and Kraak [530] models the space of visualization goals with respect to three dimensions:

– the *task* can range from revealing unknowns and constructing new knowledge to sharing existing knowledge;
– the *interaction with the visualization interface* can range from a rather passive low level to a high level where users actively influence what they see;
– finally, the *visualization use* ranges from a single, private user to a large, public audience.

The four visualization goals *exploration*, *analysis*, *synthesis*, and *presentation*, as identified in the International Cartographic Association's research agenda [530], are placed on a diagonal in this map-use space. On the one extreme, exploration can be found as a private, highly interactive task to prompt thinking and to generate hypotheses and ultimately new scientific insight. The other extreme is formed by presenting knowledge in low-interaction visualizations to a wide audience, e.g., on a professional conference or in a publication. DiBiase et al. [195] described these two extremes as *visual thinking* which creates and interprets graphic representations, and *visual communication* which aims at distributing knowledge in an easy-to-read graphic form. The former task is exploratory, while the latter one is explanatory.

In the beginning of the 1990s, geovisualization research focused on exploratory methods and tools. Communication was the realm of traditional cartography. Every map communicates a message by stressing certain aspects of the underlying data. Cartographers, due to the lack of interaction in paper maps, had the goal of finding an optimal map for the intended message. In exploration, where the 'message' is yet to be discovered, there is no optimal map in the beginning. The early focus on exploration has expanded recently to include the whole range of visualization tasks as Dykes [220] observed. The reason is that sophisticated interactive geovisualization methods are now recognized as useful not only for exploration but also for presentation of knowledge through *guided discovery*. The *visualization experience* [220] offers great benefits for understanding and learning as it enables both experienced scientists and students to (re)discover knowledge through interaction. The map is now frequently seen as an interactive

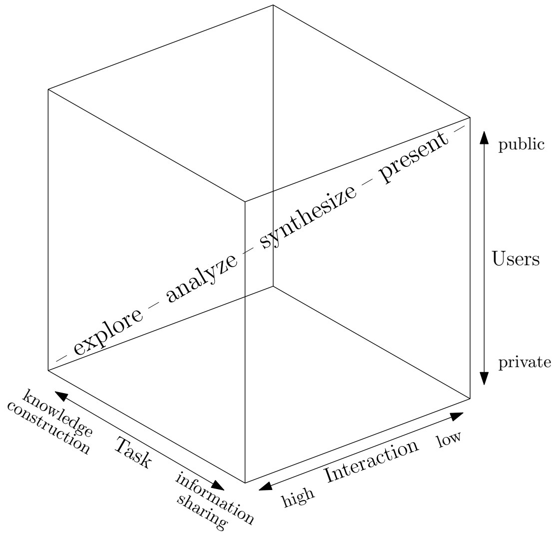

Fig. 6.1. The map use cube after MacEachren and Kraak [530] characterizing geovisualization objectives in a three-dimensional space by their level of interaction, their audience, and the addressed tasks.

interface to access and explore geospatial data while it still retains its traditional role as a presentational device [474]. Dykes argued that interaction appears to be the key defining characteristic of geovisualization today and MacEachren and Kraak [530] stated that geovisualization is characterized by interaction and dynamics. Concerning previously private tasks such as exploration, a shift from individual use towards support of group work has been demanded in the ICA agenda [530]. So recently, in terms of the map use cube, more research efforts have been attracted by the high-interaction and group-use (or public) parts of the geovisualization space.

6.2 Driving Forces of Geovisualization

So what is the reason for the increasing interest in geovisualization over the last 15 years? There are three driving forces for geovisualization.

The first is the rapid advances that have been made in *graphics and display technology*. The availability of both low-cost 3D graphics hardware in personal computers and the development of highly immersive 3D virtual environments resulted in investigating the potential that these technologies have for visualizing geospatial data. However, this emphasis on realism contrasts with the history of cartography that points to centuries of successful abstraction making the world easier to understand according to MacEachren [522]. Indeed, maps filter out unnecessary details of the environment in order to highlight interesting information. For example, a road map based on satellite images would be extremely hard to use. The challenge is to study the relative advantages and disadvantages of realism and abstraction in geovisualization and then, depending on the problem context, potentially integrate both abstract and realistic displays in a single geovisualization environment.

The second driving force for geovisualization is the need to analyze and explore a dramatically *increasing amount of geospatial data* that are routinely collected these days by a multitude of scientific and governmental institutions, private companies, and individuals. This is due to an increasing availability and decreasing cost of technology to acquire, store, and process these data. For example, the location of a credit card purchase or a mobile phone call is recorded by computers. A majority of the data, MacEachren and Kraak [530] estimated up to 80 percent, contain geospatial references, e.g., coordinates of environmental measurements, census data, positions of vehicles, ships, planes, and parcels, addresses of customers, etc. These data, often characterized by a high dimensionality, are a vast source of potentially valuable information for research and decision making, e.g., in studying disease incidence patterns, traffic flows, credit card fraud, or climate change. Privacy issues with these data are an important concern but they are out of the scope of this chapter. The large volume of many data sets poses challenging problems for their exploration. While computers are well suited for processing large amounts of data or finding well-known patterns, they perform rather poorly in detecting and interpreting unknown patterns in noisy data—at least in comparison to the human brain [399]. On the other hand, with increasing data volume and complexity humans quickly reach the limit of their capacities in analyzing raw numeric and textual data. The goal of geovisualization is to combine the strengths of human vision, creativity, and general knowledge with the storage capacity and the computational power of modern computers in order to explore large geospatial data sets. One way of doing this is by presenting a multitude of graphic representations of the data to the user, which allow him or her to interact with the data and change the views in order to gain insight and to draw conclusions, see Keim et al. [439].

Finally, the third driving force for geovisualization is the *rise of the Internet* and its development into the prominent medium to disseminate geospatial data and maps [474]. On the one hand, the Internet facilitates collaboration of expert users at different places, which is one of the ICA Commission's research challenges [530], and, on the other hand, it enables geovisualization applications to address the public. Reaching the public is an important aspect both for governmental agencies and for business companies who provide and sell services based on geospatial information, see for example Steiner et al. [796] who developed web-based tools to publish census data.

In general, there has been a shift away from technology-driven visualization towards more human-centered approaches that base on usability engineering principles and apply theoretical results from cognitive research as demanded by Slocum et al. [776]. To exploit the full potential of geospatial data, geovisualization tools need to adapt to their users. The question of what is a suitable map or visualization method depends not only on the visualization task at hand but also on the user's background. According to Griffin [305], there are different types of map readers who use geovisualization systems differently and who bring different knowledge to the map reading process. Hence, this chapter will not only present different methods and techniques applied in geovisualization, but also focus on usability testing and user-centered design of geovisualization systems.

6.3 Cognitive Aspects

This short section describes a cognitive framework for visualization in general and geovisualization in specific. The first part discusses visual thinking, i.e., how human vision perceives maps and images and how it finds patterns. The second part describes Bertin's concept of graphic variables for traditional paper maps and extensions for dynamic visualization techniques.

6.3.1 Visual Thinking

Visual thinking describes mental information processing through images instead of words. DiBiase [194] saw the origins of the potential power of visual thinking in the biological evolution where individuals with a quick reaction to visual cues survived. While we communicate mostly through words, we are connected to our environment primarily through vision. Hence, our visual perception has evolved into a powerful system that actively seeks meaningful patterns in what we see, sometimes even imposing them where they do not exist. Visual thinking often does not follow a logical train of thought and hence has not been appreciated for a long time in science. However, in 1990, MacEachren and Ganter [529] reported a renewal of interest in human vision as a tool of advancing science.

Prominent examples of successful visual thinking are Wegener's theory of continental drift prompted by the similar shapes of the facing coasts of Africa and South America, Kekulé's ring-shaped model of the benzene structure, or the discovery of the double helix structure of DNA by Watson and Crick stimulated by an x-ray photograph of DNA.

MacEachren and Ganter [529] developed a cognitive approach to geovisualization. They concentrated on the explorative side of visualization and thus on gaining new scientific insight through visual thinking. In their article visualization is seen in the first instance as a mental process rather than generating images using computer graphics. Nonetheless, computer graphics are a valuable tool to stimulate this mental process by creating graphics that facilitate visual identification of patterns or anomalies in the data. Visualization should not primarily focus on generating images but on using images to generate new ideas [194]. This also means that elaborate and highly realistic images are not necessarily required to generate valid hypotheses. Instead it is often abstraction, in the past achieved with pencil and paper, that helps to distinguish pattern from noise and thus makes a map or some other graphic useful. One key aspect in visual data exploration is to view a data set in a number of alternative ways to prompt both hypotheses and their critical reflection.

Fig. 6.2. John Snow's map of cholera deaths in London 1854. Deaths are marked by dots and water pumps by crosses. Version of Gilbert [294]. © *1958 Blackwell Publishing. Reprinted with permission.*

An early example of how a cartographic picture was used to gain new insight comes from medicine. In 1854 the London physician John Snow mapped cholera cases to a district map and made the link between cholera and a specific water pump that was used by the infected persons who 'clustered' around that pump on the map, see Figure 6.2. In fact, it was reported [456] that an anomaly of that pattern finally prompted his insight, namely the case of a workhouse with very few infections in the center of the cholera outbreak: it had an independent water source.

In order to successfully facilitate visual thinking it is necessary to understand how the human mind processes visual information. MacEachren and Ganter [529] and MacEachren [521] described visual information processing. Essentially, human vision produces abstractions from the complex input on the retina and these abstractions are matched to the mind's vast collection of patterns (or schemata) from experience.

MacEachren and Ganter [529] proposed a two-stage model for interacting with geovisualization tools in scientific exploration. At the first stage, called *seeing-that*, the analyst searches for patterns in the visual input. They distinguished two types of pattern-matches: a pattern is *recognized* if it is expected in the context; *noticing*, however, means detecting unexpected patterns that might lead to new insight. Once a pattern is recognized or noticed the analyst enters the second stage called *reasoning-why*, also known as the confirmatory stage of scientific inquiry. At this stage, the judgment made before is carefully examined to identify errors or to explain a pattern or anomaly. These two steps are iterated to collect more evidence for or to modify a judgment.

Finally, when the scientist has confirmed a hypothesis, he or she will usually want to share his insight with scientific peers through presentations and publications. Now, the goal is to lead fellow scientists to the same insight by invoking their seeing-that and reasoning-why process through well-designed graphics. If fellow scientists discover the patterns themselves the author's arguments will be much more convincing [529].

The model of MacEachren and Ganter implies that the success of a geovisualization tool in scientific inquiry depends primarily on its ability of displaying patterns that can be identified and analyzed by a human viewer [529]. However, individual users recognize and notice patterns differently based on their individual experience. Hence, explorative geovisualization tools must be interactive and permit a wide range of modifications to the visual display of the data. In the reasoning-why process, a key to insight or error detection is examining a judgment from different perspectives. Errors in pattern identification are divided into two categories: Type I errors mean seeing-wrong, i.e., to see patterns where they do not exist. Type II errors, on the contrary, denote not-seeing, i.e., missing patterns that are really there. Since human perception is adapted to seeing patterns all the time humans are susceptible to Type I errors (e.g., seeing shapes in clouds). Conversely, there is an effect known as *scientific blindness*, a phenomenon describing the tendency to overlook what one is not actively searching for. Consistency of patterns across multiple perspectives and modes is a cue to a valid pattern while inconsistencies demand reconsidering or rejecting the pattern [529].

6.3.2 Graphic Variables

On a map, information is usually represented by symbols, points, lines, and areas with different properties such as color, shape, etc. Bertin's concept of fundamental graphic variables for map and graphic design and rules for their use, published as "Sémiologie graphique" [83] in 1967, has proposed a basic typology for map design. This work was based on his experience as geographer and cartographer. For a discussion of Bertin's graphic variables see also Section 4.1 in this book. Since then his original set of variables has been modified and extended, see MacEachren [521, 522]. Bertin's fundamental graphic variables, namely *location*, *size*, *density/size of texture elements*, *color hue*, *color saturation*, *color value*, *orientation*, and *shape*, are means of communicating data to a map reader. Especially the different variables of color have been studied with regard to their efficiency in representing different kinds of data (categorical, sequential, binary, etc.). See Brewer [111] for detailed guidelines on how to represent data by colors. Variables can also be combined to represent the same information redundantly, for example using both size and color value. This provides better selectivity and facilitates the judgment of quantitative differences on a map in comparison to using just one variable.

Originally, Bertin's variables have been designed to describe information visualization on paper maps. Today, advances in graphics display technology provide a set of new graphic variables that can be utilized in geovisualization. Transparency and crispness are regarded as static graphic variables, the latter for example is suitable to represent uncertainty of some classification on a map [522]. However, geovisualization goes beyond static maps and therefore sets of tactile, dynamic, and sonic variables have been proposed, e.g., loudness, pitch, duration, temporal position, rate-of-change, etc. Most of these variables are analogs of graphic variables in another dimension, e.g., duration corresponds to size and temporal position to spatial location. However, both dynamic and sonic variables need to be observed over time and thus require more user attention than static representations.

6.4 Visualization Methods and Techniques

A number of techniques and methods adapted from cartography and scientific visualization are studied and applied in geovisualization. This section first introduces geospatial data and their unique properties. Sections 6.4.2 and 6.4.3 discuss 2D and 3D map-based visualization techniques, respectively. A selection of different techniques to display abstract multivariate attributes of geospatial data is covered in Section 6.4.4. Animation as a dynamic visualization technique that utilizes time as a visual dimension is the focus of Section 6.4.5. Spatial data often contain temporal attributes and hence Section 6.4.6 discusses the display of time, using animation as well as graphic variables like space or color. Interaction is considered as one of the key characteristics of geovisualization. Interactive methods and interfaces that control and link different visual representations are introduced in Section 6.4.7. Finally, Section 6.4.8 deals with the combination of visual and computational data mining techniques to explore very large data sets.

6.4.1 Geospatial Data

In contrast to information visualization displaying any abstract data, geovisualization deals specifically with geospatial data, i.e., data that contain georeferencing. This is a unique feature and special methods and tools are needed to take full advantage of it. Haining [323] decomposed geospatial data into an abstract attribute space and a geographic space with two or three dimensions. According to MacEachren and Kraak [530] geospatial data and information are fundamentally different from other kinds of data since they are inherently spatially structured in two or three dimensions (latitude, longitude, and possibly altitude). In case of spatio-temporal data, time can be seen as a fourth dimension. Remaining dimensions are often unstructured and there are various visualization methods for these abstract data, compare Section 4.3. Note also that distances and directions have an immediate meaning in those dimensions in contrast to distances computed on abstract data. While general visualization methods may be applied to spatial data as well, they do not take into account the special characteristics of the attributes. The georeference is usually either to a single point or to a whole area. Whether geospatial data are defined as a point or as an area obviously depends on the geographic scale at which they are examined. For example, a village can be represented as an area on a large scale map, as a point on a map of its province, and not at all on a country level.

6.4.2 2D Cartographic Visualization

The most common visualization method for geospatial data is a cartographic display of some form, i.e., a map where the area under consideration is depicted, and onto which the data of interest are plotted at their corresponding coordinates. *Space* is used to depict *space* by mapping latitude and longitude to the coordinate axes of the map drawing area. This might seem to be the most natural way of using this graphic variable. However, there are good reasons of linking for example population to space resulting in a *cartogram*[1] where area on the map is not proportional to a certain geographic area but in this case to the number of people living in that very area. Still, cartograms usually try to preserve the users' mental map by keeping similar shapes and by preserving the adjacencies between the depicted areas. An example of a world population cartogram is shown in Figure 6.3. Tobler [832] gave an overview of algorithms to automatically create contiguous value-by-area cartograms and van Kreveld and Speckmann [853] studied drawing rectangular cartograms. Especially when the focus of a map is on social, economic, or political issues, cartograms help to draw the users' attention to population as the map's theme while avoiding to emphasize large but sparsely inhabited regions. MacEachren [521] described space as an indispensable graphic variable with a large influence on what the user of a map sees. He argued that therefore space should represent the map theme.

For both cartograms and geographic maps the interesting aspect is of course how to depict abstract attributes of the data or at least a subset of them. Among the most popular methods to represent categorical but also numerical data are *choropleth*[2] maps. A choropleth map uses the graphic variables describing properties of color or texture to show properties of non-overlapping areas, such as provinces, districts, or other units of territory division. A number of categories is mapped to distinct colors or textures which are used to fill the areas accordingly. Examples are land cover/use with categories like forest, crop land, housing, etc. or election results per district, e.g., displaying the percentage of

[1] Among the most widely used cartograms are schematic maps of public transport systems, e.g., the London Tube map [288] which emphasize the topology of the transport network.

[2] Greek from *choros* place and *plethos* magnitude.

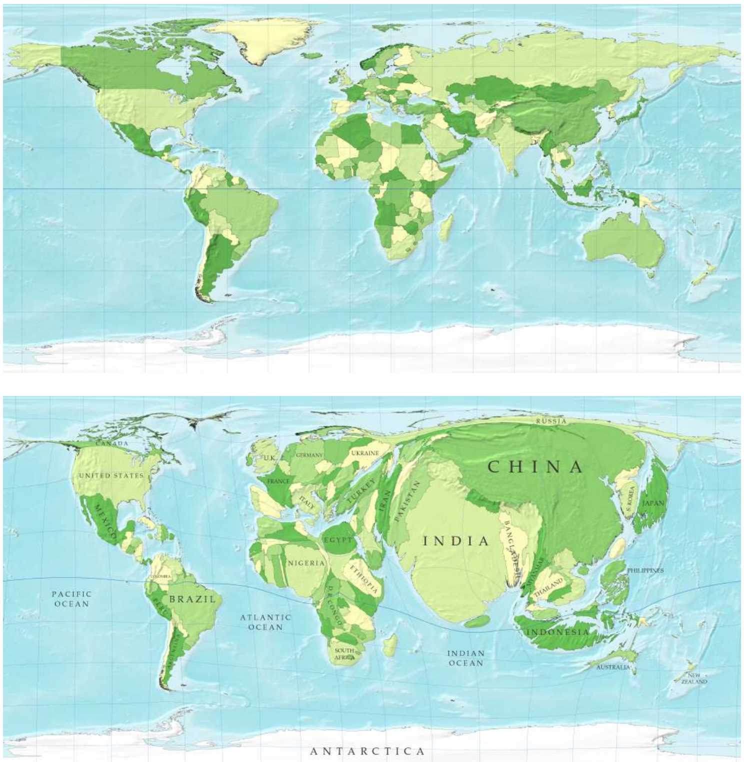

Fig. 6.3. Geographical world map (top) and world population cartogram (bottom). In the cartogram the size of a country is proportional to the size of its population. *Image courtesy of M. Newman.*

votes for a certain party or the voter turnout as in Figure 6.4. For unordered data well-distinguishable colors are needed while for ordered data it is important to find a lightness or hue scale that represents the original range of numbers efficiently, i.e., that the user can estimate values and differences from the colors. Alternatively, a continuous range of attribute values is mapped to a continuous color range without assigning values to a fixed number of classes. While choropleth maps help to show general trends in the data there is certainly a loss of information because the user cannot map a certain color to its exact numerical value. Furthermore, a choropleth map can only express one or two attributes of the data (by using a two-dimensional color scheme or by combining color and texture). Andrienko and Andrienko [21] described a selection of methods to represent single and multiple attributes in a map. Depending on the type of the attributes (logical, numeric, or nominal), they used bar and pie diagrams common in statistic visualization. Similarly, glyph-based techniques from visual data mining can also be combined with map displays. These techniques, described in more detail in Section 6.4.4, use compound glyphs to represent the values of multiple abstract attributes. Using their geospatial reference, glyphs or statisti-

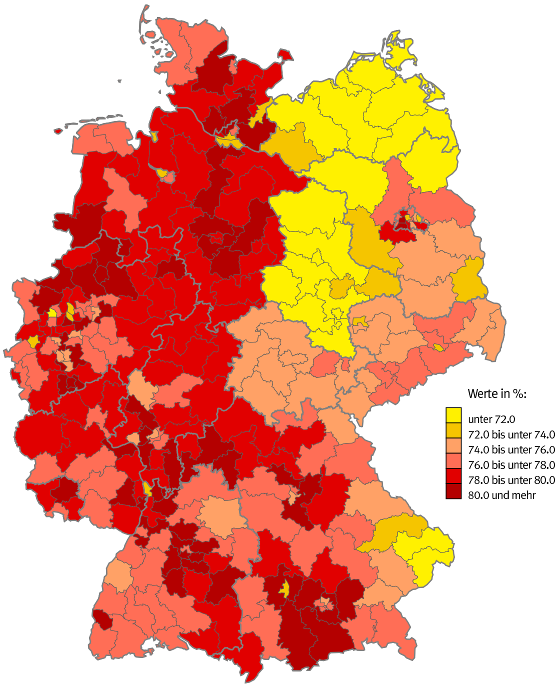

Fig. 6.4. A choropleth map showing turnout of voters in the 2005 federal elections in Germany [127]. *Image courtesy of Statistisches Bundesamt, Wiesbaden.*

cal diagrams are placed on the map and thus both spatial and multidimensional abstract attributes are represented on a single map. However, if the number of symbols or attributes exceeds a certain limit the symbols become hard to compare and other non-map based techniques from visual data mining should be applied in addition to the display of a map or cartogram, see Section 6.4.4.

Other approaches for displaying high-dimensional data reduce the dimensionality of the data, e.g., by applying statistical techniques like principal component analysis or by calculating compound indices representing, for example, the socio-economic development of a region. The disadvantage, especially for explorative visualization, is that through the loss of information potential patterns of some attributes might get lost.

6.4.3 3D Cartographic Visualization

In contrast to traditional paper maps and two-dimensional visualization methods, geovisualization can go one step further and use the potential of increasingly experiential representation technologies. 3D visualization includes the full range from regular 3D graphics hardware in desktop computers to immersive 3D displays, CAVEs (Cave Automatic Virtual Environments), and Power Walls providing stereoscopic views. For an overview on display technology, the reader is referred to Section 3.2. Since humans live in a three-dimensional environment our perception and cognition is adapted to processing 3D visual stimuli. But there is still little known about when 3D visualization is appropriate and how it can effectively enhance visual thinking.

Cartography has a long and successful tradition using abstraction to depict a wide range of data on maps. In contrast, the focus of computer graphics technology is on producing increasingly realistic images and virtual environments. Virtual reality techniques are widespread, for example, in architecture and landscape planning where realism is very important. Depending on the geovisualization task, realism can be a distraction and insight is more likely when using abstract visual symbolism. But as MacEachren et al. [527] pointed out, there had been only few efforts exploring abstract visualizations of geospatial data in 3D.

In terms of the 3D representation of the data, MacEachren et al. [527] distinguished between using the three dimensions of the representation to display the three dimensions of physical space, using one or two dimensions for non-spatial data, e.g., income or time, and using all three dimensions for abstract data. Representing time as the third dimension is common and will be discussed in Section 6.4.6 on spatio-temporal visualization.

Today, the most widespread use of 3D is at the level of visual representation while the display is a 2D screen. It is important to be aware of the implications that the projection of a 3D representation onto a 2D plane has. Depth cues such as perspective and occlusion also cause problems because distances are harder to estimate, and occlusion hides objects depending on the viewpoint. Ware and Plumlee [886] observed that due to occlusion humans cannot perceive much information in the depth direction while the x- and y-directions, orthogonal to the line of sight, can convey complex patterns. A set of interactive navigational controls are necessary to move within the 3D representation, e.g., zooming or flying, cf. Section 3.1 of this book or Bowman et al. [102]. As Wood et al. [912] pointed out the effectiveness of the virtual environment metaphor relies to some extent on navigational realism. While moving (e.g., walking or flying) slowly through the visual space maintains a sense of orientation, faster modes of movement such as teleporting lose the context and the user has to reorientate.

6.4.4 Visual Data Mining Tools

Visual data mining, also denoted as exploratory data analysis (EDA) in statistics by Tukey [843], is a human-centered task that aims at *visually* analyzing data and gaining new insights. This contrasts computational data mining techniques which use algorithms to detect patterns in the data. Effective visual data mining tools need to display multivariate data in a way that the human viewer can easily perceive patterns and relationships in the data. Visual data mining in general is not tailored specifically for geospatial data. See Section 4.3 for a general discussion of visualizing multivariate data. Since geospatial data usually have many abstract attributes (cf. Section 6.4.1) these general techniques can be applied for displaying non-spatial attributes of the data. Visualization techniques

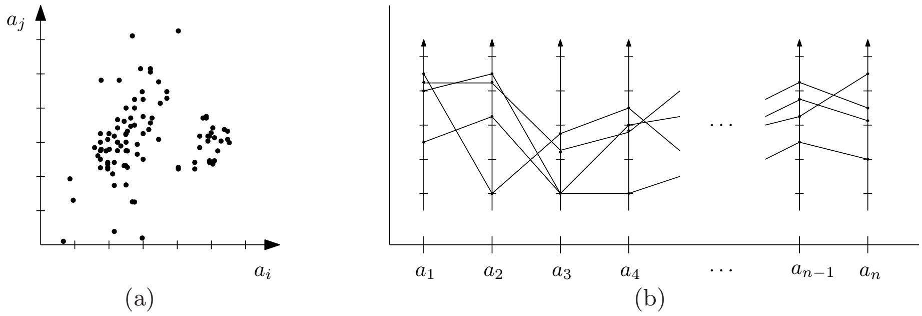

Fig. 6.5. Example of a 2D scatter plot in subfigure (a) and a parallel coordinate plot in subfigure (b).

for multivariate data were broadly classified as geometric, glyph- or icon-based, pixel-oriented, and hierarchical by Schroeder [745] and Keim and Kriegel [438]. In a geovisualization context, geometric and glyph-based techniques are most common. Graph-drawing techniques that depict relationships between individual data items are also covered in this section.

Geometric Techniques Two geometric techniques commonly used in geovisualization are scatter plots and parallel coordinate plots. Scatter plots in their basic two-dimensional form depict objects as points in a coordinate system where the axes correspond to two selected attributes, see Figure 6.5(a) for an example. Elements in the data set with similar values in these attributes form visual clusters in the scatter plot. The idea of a scatter plot can be extended to three dimensions but then phenomena as occlusion and different perception of depth as described in Section 6.4.3 may occur. The extension to more than three dimensions is often implemented by drawing a scatter-plot matrix containing one scatter plot for each pair of attributes. This, however, makes the identification of multidimensional patterns difficult because many plots in the matrix need to be linked mentally.

Parallel coordinate plots (PCP) [388] are a means of displaying high-dimensional data in a single plot. In a PCP, one dimension is used to place multiple parallel axes, each of which represents one attribute of the data. Each element of the data set is then characterized by the values of its attributes which are connected along the axes and thus build a geometric profile of that element as depicted in Figure 6.5(b). Since all elements are plotted in this way, the user can identify similar objects by comparing the geometric shape of their profiles. However, depending on the number of profiles, overplotting occurs and may result in poor legibility. Keim and Kriegel [438] estimated that about 1,000 items could be displayed at the same time. Moreover it becomes difficult to compare profiles based on an increasing number of attribute axes. Another important aspect of PCPs is the order of the attributes plotted along the parallel axes since this order has a strong influence on the shapes of the profiles. Hence, a user should be able to rearrange the attributes manually or based on sorting algorithms.

Glyph-Based Techniques Glyph-based or icon-based techniques use a mapping of multiple attribute values to a set of different visual features of a glyph which in turn represents one data object. Two examples of such techniques are Chernoff faces [154] and star plots [253]. In a Chernoff face, different variables of the data are related to facial features of an iconic face, such as size and shape of mouth, eyes, ears, etc., see Figure 6.6(a). The motivation of using faces to depict multidimensional data is that human mind is used to recognize and compare faces. However, different features, e.g., shape of the eyes and area of the face, are hard to compare and Chernoff faces are, in contrast to human faces, not perceived pre-attentively [574] such that there is no advantage over other types of glyphs.

Star plots depict the value of a set of attributes by the length of rays emanating from the center of the glyph. The endpoints of the rays are connected to create a closed shape as depicted in Figure 6.6(b). While the maximum number of facial features in Chernoff faces is reached quickly, star plots can display data with higher dimension by increasing the number of rays. Again, as for parallel coordinate plots, the order of the attributes influences the shape of the star plots.

A nice property of glyph-based techniques is that they can be easily combined with map displays described in Section 6.4.2 by placing each glyph according to its geospatial coordinates on the map. However, with an increasing number of symbols or attributes glyph-based techniques are of limited use due to the difficulty of visually recognizing patterns and distinguishing features on a display with too many glyphs or glyphs with too many features.

Graph-Drawing Techniques Geospatial data often contain links between related elements, e.g., routes, trade connections, etc. Exploring such data sets includes the search for patterns in the link structure between items. Data containing relationships between elements are mathematically modeled as a graph consisting of a set of nodes, the data elements, and a set of (weighted) edges, the links between elements. The research area of graph drawing provides a multitude of algorithms for visualizing such graphs, see di Battista et al. [192]. Section 4.4 discusses visualization of graphs from a human-centered perspective and Rodgers [717] gives an overview of graph drawing methods and their application to geovisualization. In general, for graph drawing the emphasis is on finding a layout, i.e., positions of nodes and edges of a given graph that satisfies certain aesthetic criteria, e.g., few edge crossings. In geovisualization, there are usually certain constraints on such a layout since nodes already have a spatial location. In that case, finding a legible layout for the edges is of interest, for example in schematizing road networks [137]. In other cases, such as drawing metro maps [362, 618, 803], the network topology is more important and node positions are only required to satisfy certain relative positions (e.g., left, right, above, below) in order to preserve the user's mental map. Finally, some data is best analyzed by putting no restrictions to node positions and using a general algorithm to find a graph layout in which link patterns can be identified visually. Such methods are applied in visual social network analysis, see for example Brandes and Wagner [108]. In the latter cases, where node positions are modified, a

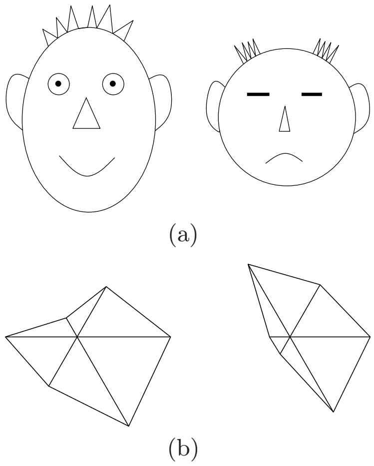

Fig. 6.6. Two examples of glyph-based techniques: subfigure (a) shows two Chernoff faces and subfigure (b) shows two star plots on six attributes.

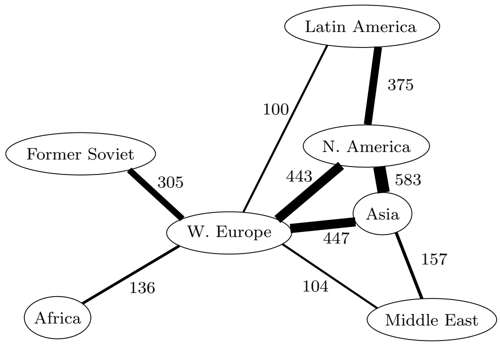

Fig. 6.7. A graph showing trade relationships. Edges are weighted by trade volume and drawn shorter and thicker with increasing weight. Only edges with at least 100 billion dollars trade volume are shown.

map display of the true geography in combination with a graph layout focusing on the link topology is helpful for identifying both spatial and link-based patterns. An example by Rodgers [717] visualizing trade volume between regions of the world as a graph is shown in Figure 6.7. The stronger a trade relationship between two regions the more they attract each other in the graph layout.

6.4.5 Animation

The methods described so far are primarily static displays of geospatial data. They can all be printed and studied on paper. In geovisualization, however, dynamic and interactive displays are core concepts today. Since the 1930s cartographers are experimenting with map movies and animated maps. Leaving interaction aside, which is covered in Section 6.4.7, animated maps are using time to add another visual dimension to the display. It is intuitive to relate time to time, just as space depicts space in most maps [333]. In this case, the time period of the data is mapped to the animation time. Each scene or frame of the animation shows the state of the data at one moment accordingly. Thus, the temporal change of the attributes becomes visible. It may be necessary to smooth the animation using interpolation to generate intermediate frames. Scenes can also be reordered from chronological order to an order based on attribute values. This may be helpful for studying at what points of time events with similar properties took place. For example, earthquake data can be ordered by the number of human fatalities in such a way that the beginning of the animation shows the least and the end the most catastrophic earthquakes [195]. Animation can also be used to display spatial features, e.g., animations of flights over the terrain. In other cases, the temporal dimension is used to display quantitative attributes by mapping their values to the blinking frequency of symbols or to highlight classes in a choropleth map by blinking. The presence of the temporal dimension in dynamic visualizations also introduces the potential to use acoustic variables. Although visualization is mostly concerned with visual aspects, using sound to complement dynamic graphics expands the possibilities of visualization. Krygier [480] summarized the role of sound in geovisualization from attracting attention over narrative voice and representing quantitative attributes (e.g., using the variable pitch) to sound maps for visually impaired.

Bertin's notion of visual variables [83], as introduced in Section 6.3.2, has been extended to dynamic animated displays, see MacEachren [522] and Chapter 6 of MacEachren [521]. Six dynamic variables are suggested: (1) temporal position, i.e., *when* something is displayed, (2) duration, i.e., how long something is displayed, (3) order, i.e., the temporal sequence of events, (4) rate of change, e.g., the magnitude of change per time unit, (5) frequency, i.e., the speed of the animation, and (6) synchronization, e.g., the temporal correspondence of two events.

Animation and its set of additional visual variables represents a powerful tool for map designers. However, animation should not be used carelessly and it is always worth asking *"why do I need to animate these data?"* [334]. From a user's perspective, things that change on a map attract more attention than the static background and moving objects attract more attention than objects that appear and disappear. The fact that animated displays change over time has an important disadvantage, especially if there are no interactive controls: there is always the risk that the user will miss important information. While a static display can be analyzed at an individual speed, an animation has to be followed at the predefined pace. Therefore, it is hard to compare data displayed at different points of time as the human brain usually forgets most details of previous frames of an animation. A study by Rensink et al. [705] showed how difficult perceiving changes in an animation can be.

Harrower [334] gave some guidelines for designing effective animated maps. Because dynamic variables attract more attention than static variables the information conveyed by static variables should be kept simple, e.g., by using a choropleth map with only few data classes (*high*, *medium*, and *low*) and a rather low level of detail. Details are often more effectively displayed using static visualization techniques. Temporal exaggeration, i.e., displaying durations not to scale, is often necessary since otherwise a short event, e.g., an earthquake, in an animation spanning several decades will be missed by the viewer. Directing the user's attention to critical events can be done for example by initially flashing new symbols on the map. In general, animated maps are better suited to depicting geographic *patterns*, e.g., growth or shrinkage of an area, rather than specific *rates of change* according to Harrower [334]. Finally, he observed that people are less confident with animated maps than with static maps, due to less experience and training.

Many of the above problems can be avoided by giving the control of the animation to the user. In interactive animations, where the user can control the displayed level of detail and the speed of the animation, information is less likely to be missed and users feel more confident with the animation. Still, the study of dynamic displays with regard to their geospatial expressiveness is identified as one of the challenges in the ICA research agenda [530] and further usability studies are required, see Section 6.6.

6.4.6 Spatio-Temporal Visualization

Spatio-temporal data are very common in the earth sciences and related disciplines. The goal of many studies is to reveal, analyze, and understand patterns of temporal change of phenomena, such as global warming, population development, or spread of diseases. The previous section has presented animation as a means of displaying temporal data. Animation works well in displaying patterns if they are based on the same temporal sequence as the animation itself, e.g., showing trends like urban growth over time. However, Andrienko et al. [26] criticized that for less evident patterns it is necessary to compare the data at different points in time which involves memorizing a large number of states in an animated display, even if interactive controls allow to pause, jump, and step through specific points in time. Thus it might be more effective to statically display selected moments in time simultaneously using small multiples. Then, an analyst can directly compare attribute properties of different points in time at his or her own speed. However, the number of simultaneous images on the screen is limited and long time series have to be evaluated piecewise. Andrienko et al. argue that, for all these reasons, spatio-temporal data exploration must be supported by a variety of techniques, possibly in combination with an animated display [26].

Andrienko et al. [25,26] classified spatio-temporal data according to the type of temporal changes: (1) existential changes, i.e., appearance and disappearance of features, (2) changes of spatial properties, i.e., change of location, shape, size, etc., and (3) changes of thematic properties, i.e., qualitative and quantitative changes of attributes. Following this classification, they presented corresponding visualization techniques. All techniques involved a map display to visualize the spatial attributes of the data.

Data of existential changes usually consist of events or observations at specific moments or time periods during which a certain property holds, e.g., road congestion data. Hence a map showing these data always considers a selected time interval. If data items are represented by glyphs, one way to display the time associated with them is by using textual labels. Another possibility is using a color scheme to represent the age of the data. A 3D representation of space and time is a third and common method [521]. In such a *space-time cube*, the third dimension corresponds to time while two dimensions represent geographical space. The reference map is usually displayed in the coordinate plane corresponding to time 0 and data items are positioned above the map depending on their spatial locations and their times of appearance. An example of a space-time cube is

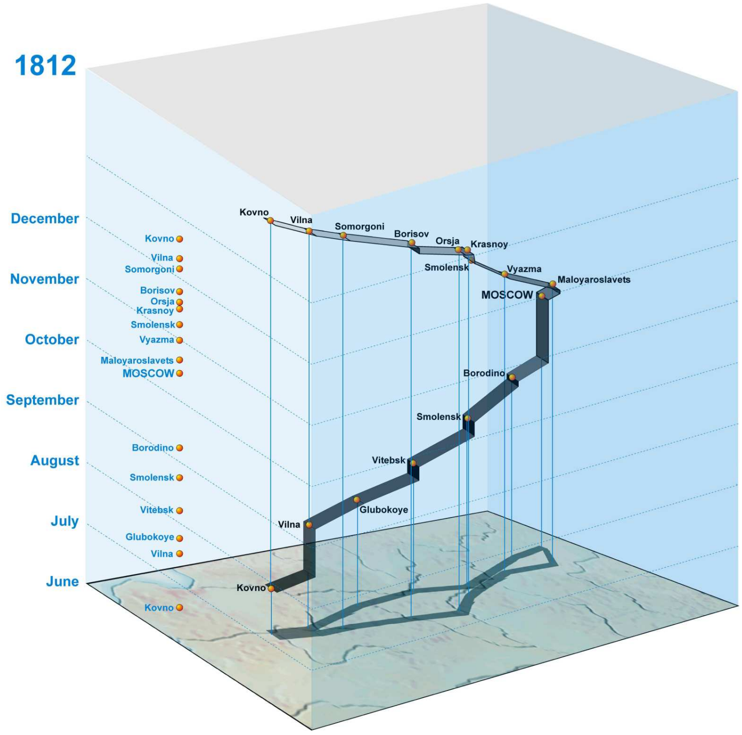

Fig. 6.8. A space-time cube visualization of Napoleon's march in Russia. *Image courtesy of M.-J. Kraak.*

shown in Figure 6.8. It shows the trajectory of Napoleon's troops during the French campaign against Russia in 1812.

For data that contain moving objects, comparing object trajectories is of interest. Static 2D maps are able to show the trajectories of a small number of objects but in this simple form it is not possible to evaluate aspects like speed or whether two objects met at a crossing or just visited at different points in time. Andrienko et al. [25] suggested animating object movements, either as a sequence of snapshots in time in which at each moment objects are shown at their current positions or using the movement history and showing the trajectories up to the current point in time. Movement history can optionally be limited to a specified time interval. It was found that the snapshot technique was suited for a single object while several objects were better observed displaying also the movement history. MacEachren [521] suggested using the space-time cube to display trajectories which avoids the disadvantages of 2D trajectories mentioned above as it shows *when* and not just *if* an object visited a point.

There are several methods of displaying thematic attributes on a map. A very effective and common method is the choropleth map, see Section 6.4.2. Animating a choropleth map is able to give a good overview of the values in a selected attribute. However, it is difficult to estimate trends in a particular

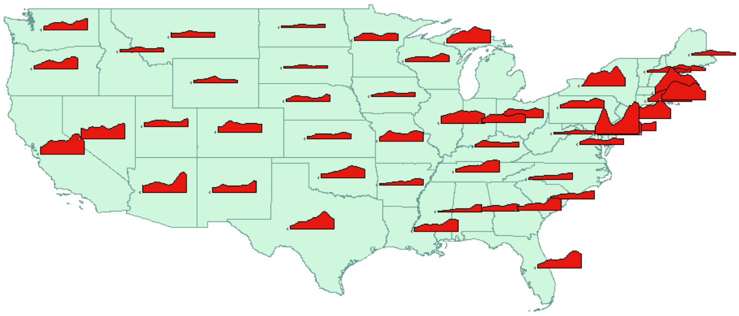

Fig. 6.9. Cartographic representation of the spatial distribution of the burglary rates in the USA. *Image courtesy of G. Andrienko.*

area on the map or to compare trends between different areas [26]. *Change maps* [25], adapted from conventional cartography, use the choropleth map to show the differences of an attribute between two selected points in time. Mapping increase and decrease in attribute value to shades of two different colors allows to evaluate regional changes for two moments. Such a map is restricted to two points in time and the map can be misleading because information on the actual attribute values is lost, e.g., concerning crime data two areas can have very different burglary rates but still be colored the same if the rates both decrease by the same value. Andrienko and Andrienko [23] combined time-series graphs with maps to avoid these disadvantages. A time-series graph is a two-dimensional plot of the temporal variation of attribute values, where time is represented on the x-axis and attribute values on the y-axis. Plotting all data in the same time graph gives an overview of the dynamics of the whole data set. To assess local behaviors, Andrienko and Andrienko plotted the time-series data individually for each area on the map and used the closed shape of the plot as a symbol superimposed on each area similarly to the glyph-based techniques in Section 6.4.4, see Figure 6.9 for an example. This technique allows to evaluate changes and actual values of an attribute for the whole time period under consideration. The user can explore both spatial patterns and patterns in the attribute space in the same view.

Shanbhag et al. [757] presented three techniques that modify choropleth maps in order to display temporal attribute data. They did not color each district area in the map uniformly but partitioned it into several regions, each representing one point of time in the data. Their first technique builds on a cyclical, clock-like metaphor for perceiving time and partitions the area polygon into wedges. The second technique draws from the metaphor of annual rings of a tree trunk and assigns time points to 'rings' of the polygon. Finally, they suggested time slices for a linear perception of time, i.e., polygons were partitioned into vertical slices. Using any of the three techniques, temporal trends in each area could be detected by observing the variation (e.g., brightness) of the different regions of the district area. However, for an effective visualization the number of simultaneously displayed time points must be limited with respect to the size of the polygons in order to avoid clutter [757].

For detecting periodic temporal patterns, Hewagamage et al. [348] suggested using spirals to depict time in a 3D representation similar to MacEachren's space-time cube [521]. They used this technique to display events, i.e., data with existential changes like the sight of a bird at a specific time and place. Depending on the semantics of the data, events often show some periodic appearance patterns, e.g., bird migration depends on the season and observed birds may rest at a certain place every year. Hewagamage et al. took a linear time line and coiled it such that one loop of the resulting three-dimensional spiral corresponded to a user-specified time interval, e.g., a year or month. At each location of interest such a spiral was positioned, and the events at that position were placed as small icons along the spiral. Thus, points in time whose temporal distance was a multiple of the selected time period were vertically aligned on the spirals. Since parts of the spirals were occluded the display needed to have interactive controls for zooming and panning, as well as for changing the period of the spirals.

6.4.7 Interactive User Interfaces

Interaction is paramount in geovisualization, especially for visual exploration, recall the map-use cube in Figure 6.1. The communication aspect of geovisualization is also shifting towards higher levels of interaction. Dykes introduced guided discovery as a communication task [220]. For example, consider a student who is learning by interactively (re-)discovering known relationships in a data set. Dykes saw interaction as the key defining characteristic of visualization early in the 21st century and according to MacEachren [522] interaction is a key factor distinguishing geovisualization from traditional cartography. He continued that geovisualization *"is an active process in which an individual engages in sorting, highlighting, filtering, and otherwise transforming data in a search for patterns and relationships"* [522]. In this sense, the present section focuses on common interaction principles and interactive user interfaces in current geovisualization systems.

Map use in traditional cartography, too, has been benefiting from interaction albeit to a far lesser degree than current geovisualization. For example, drawing with a pencil or using colored pins to mark spots on a paper map is a way of interactively changing the map. For centuries using these and similar techniques were the only way of exploring geospatial data. However, such manual interaction techniques are time consuming and often give only very limited insight into the data. Generating individual maps on demand had to be done manually by cartographers and at a prohibitive cost for most explorative purposes. This has changed drastically in computer-based geovisualization.

Buja et al. [126] introduced a taxonomy for general interactive multivariate data visualization. In the following, interactive visualization techniques are grouped using this taxonomy. Their two main classes are *focusing individual views* and *linking multiple views*. For a detailed description of interaction methods see Chapter 3 of this book.

Focusing By focusing Buja et al. [126] mean any interactive modification that selects what to see in a single display and how it is seen. They compared focusing

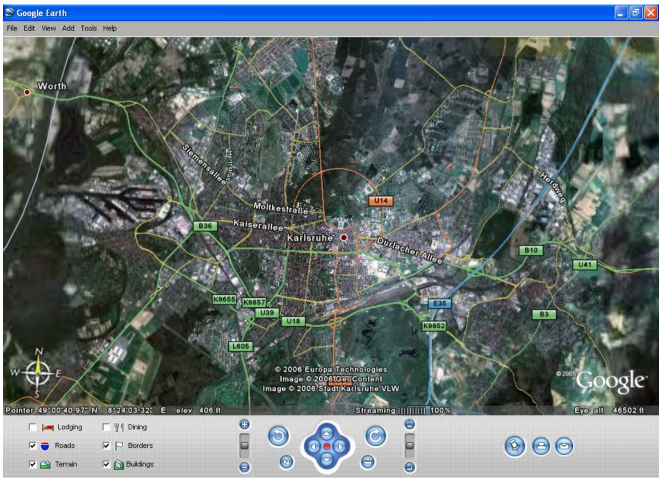

Fig. 6.10. Screenshot of Google Earth [300].

to operating a camera: choosing a perspective, deciding about magnification and detail, etc. The individual visualization methods introduced in the previous sections all profit from one or the other form of interaction—as static displays most of them are of very limited use. Two- and three-dimensional maps (see Section 6.4.2 and 6.4.3) usually come along with a set of navigational controls to move within the map space either by scrolling, shifting, or rotating a map or by walking or flying through a virtual 3D environment. Further controls allow users to zoom in or out of the map and thus to increase or decrease the level of detail and the amount of generalization of the underlying geographic features (rivers, cities, lakes, etc.). Once a perspective on the map is chosen, its appearance can be modified further, depending on the type of map. The display of geographic background features such as rivers, mountains, roads, etc. can be switched on or off. Depending on the user's task such surface details may be informative or distracting. In Figure 6.10, a screenshot of the satellite image viewer Google Earth[3] [300] is shown. With the navigational controls in the bottom of the figure the user can move around and change the scale. The check boxes on the left can be used to hide or show information like roads or borders.

The next mode of interaction concerns the way that the actual data items are displayed. For the general case of multivariate data the user must be able to select the attributes of interest and the type of their visualization, such as choropleth map or glyph-based map. Deselected attributes as well as the actual numeric values of selected attributes should be accessible, e.g., as tool tip information when moving the mouse over a symbol or area on the map. *Dynamic isolation* was used by Andrienko and Andrienko [21] to highlight a subset of data items in maps that use different symbols to depict different classes of data items, e.g., to select only coal mines in a map of natural resources. Spatial patterns may be

[3] `http://earth.google.com`

cluttered in a map of all resources while they become evident once dynamically isolated.

Modification of the color scheme in a choropleth map is another important aspect. Assigning colors to classes or color ranges to numerical ranges is a very simple way of interacting with choropleth maps. While traditional paper maps use well-established color schemes that are suitable for the majority of map users these schemes may still not be optimal for an individual analyst and hence should be adaptable. In an *unclassed* map, i.e., numbers are mapped to color shades directly, Andrienko and Andrienko [21] used *dynamic visual comparison* to display attribute values with respect to a number N in the value range. To this end they applied a diverging color scheme which maps N to a neutral color, e.g., white, values lower than N to shades of red, and values higher than N to shades of green. The greater the difference the darker the color. This is a way to visually split the areas on a choropleth map. The reference value N can be selected by clicking on an object in the map to select its value or by using a slider unit representing the value and color range. Statistic values like mean, median, or quantiles are typically used as reference value. In *classed* maps the value range of an attribute is partitioned into a set of intervals and a distinct color is assigned to each interval. Here *dynamic classification* was applied, i.e., interactive modification of the underlying classes by shifting interval boundaries or changing the number of classes.

Finally, the mapping of a numeric value range to color shades in a choropleth map or to height in bar maps can be modified. This mapping is usually a linear function and hence outliers in the value distribution may cause a poor color resolution for the bulk of values. To reduce this effect Andrienko and Andrienko [21] used *dynamic focusing* to map the full scale of colors to a subrange of values with the outliers removed. Values to the left or right of the subrange are simply colored by the minimum or maximum color value. Using non-linear functions to map values to colors, as it is common for statistical graphics, is undesirable for choropleth maps as visual analysis greatly depends on the immediate expression [21]. Similar colors would no longer necessarily reflect numeric closeness of values. For scatter plots, however, non-linear transformations (e.g., logarithmic scale) are acceptable if the goal is to find a functional relationship between two attributes.

As mentioned in Section 6.4.4, visual tools like the parallel coordinate plot (PCP) or glyph-based techniques depend on an order of the attributes. Ordering the axes in a PCP or star plot and assigning facial features to attributes in Chernoff faces has an important effect on the geometric shape of PCP profiles and glyphs. Giving users the opportunity to change these properties allows them to see the same data from multiple perspectives. Concerning outliers and visual resolution, similar arguments and solutions as for mapping a value range to a color range in choropleth maps apply for the scale of PCP axes.

For animated maps there is a need to give control of the animation to the user. Even simple animations have VCR-like interfaces to control the animation speed, to pause the animation, or to select individual scenes. Harrower [334] described these abilities to navigate in time as equivalent to navigating in space, i.e., zooming and panning on static maps. Tools to navigate in time vary from linear time lines with sliders, which the user can move to select points or intervals in time, to more sophisticated devices like the time wheel[4]. The time wheel supports a cyclic view of time and consists of three concentric circles, the innermost representing hours, the next one days, and the outer circle represents months. In each circle, the respective time units can be marked and thus it enables to select recurring periods in time, e.g., the hours between 7 and 9 p.m. on the first five days of January, April, and May.

Linking and Brushing The full potential of interaction in geovisualization lies in linking multiple views of the same data on the screen which is the defining criterion of the second class of Buja et al.'s taxonomy of interactive multivariate visualization [126]. See also Section 4.5 which discusses multiple and integrated views from a more general perspective. *Linking* basically means simultaneous highlighting of data items in multiple views. It is usually combined with *brushing*, i.e., selecting display objects by pointing on them or encircling them on the screen. Brushing was originally used for scatter-plot matrices, where points highlighted in one scatter plot are simultaneously highlighted in the other plots of the matrix to evaluate for example whether a relationship in two attributes also holds for other pairs of attributes. Monmonier [568] extended this idea as *geographic brushing* and links a map with scatter plots or other visual data mining tools. An example of linking and brushing is shown in Figure 6.11, where an outlier point in the scatter plot of per-capita income and percentage of poor is selected. The map shows the geographic location of the corresponding county New York, which has the highest average income in the USA. The PCP in the bottom of the screenshot allows to evaluate the remaining statistical attributes of New York.

Different views should be linked in a geovisualization system. Highlighting a point cluster in a scatter plot or a cluster of PCP profiles thus shows the spatial pattern of the corresponding objects in the associated map view. If there is, for example, a set of objects that are visually similar in a PCP the analyst might ask whether these object are located in the same region on the map or whether they are spread over the whole country but only in rural areas etc. Consequently, outliers that deviate from a general pattern can be located and examined more thoroughly. Similarly, one can select spatial object clusters on the map and subsequently analyze their behavior in attribute space using the remaining views. If the map is a choropleth map then linking and brushing can be done automatically using the same color scheme for the representations of objects in all views. Then, the analyst can mentally connect multiple views because the classes of the choropleth map are marked identically in all views. Changing the class assignment in the choropleth map immediately updates the linked displays. Conversely a scatter plot can be used to define new class boundaries for the map. A very simple example is the *cross map* [521]. It divides the value ranges of both

[4] Demonstration applet by Rob Edsall available at `http://www.geovista.psu.edu/products/demos/edsall/Tclets072799/cyclicaltime.htm`.

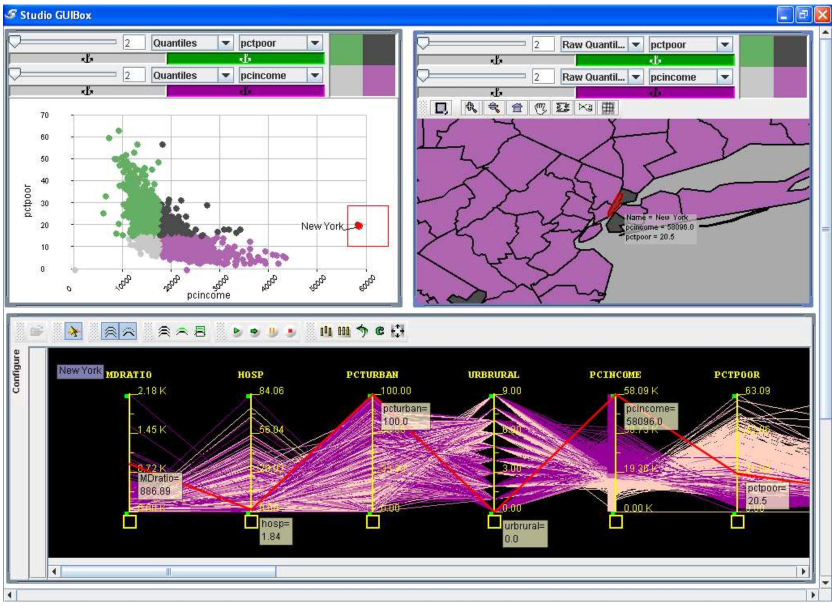

Fig. 6.11. Screenshot of GeoVISTA Studio showing linking and brushing between a scatter plot, a map view, and a PCP. The red item marked in the scatter plot is simultaneously highlighted in the other views.

attributes in a scatter plot into a lower and upper range thus defining four classes, each of which is represented with a distinct color on the map. Changing the class assignment is as simple as moving the class-break point, i.e., the center of the cross separating the four classes in the scatter plot.

The possibilities of interacting with multiple linked views through highlighting and brushing are numerous. The number, type, and arrangement of the views depend on the specific geovisualization task, the individual user, and the available space on the screen. In any case, it is linking and brushing that make the use of multiple views more than simply the sum of its parts. The interactive principles introduced in this section all concern a core aspect of geovisualization: stimulate visual thinking by presenting the data in different ways and from a large number of perspectives. This is a key aspect of avoiding both Type I (seeing-wrong) and Type II (not-seeing) errors as false patterns are unlikely to be visible from many perspectives and patterns hard to see in a single view are more likely to be discovered in other views.

6.4.8 Combining Visual and Computational Exploration

The visualization and interaction techniques described so far seem most successful for data exploration tasks in small and medium-sized data sets, i.e., up to a few hundred items and a few tens of attributes. Geospatial data sets in practice, however, are continuously growing in size and are often characterized by a high number of dimensions as a report by the US National Research Council observed [601]. In such large data volumes with high-dimensional attributes human vision cannot be successful in isolating patterns [530]. Visualizing large data sets result in maps and other displays that are cluttered with overlapping items and small symbols such that properties of data items are hardly visible. Zooming is no remedy to these problems: it does help to avoid information overload and magnifies small symbols but at the cost of losing the overall view of the data which is just as important.

On the other hand, computational methods have been developed in areas like machine learning and data mining that can analyze large data volumes and automatically extract knowledge. But data mining methods have limited pattern interpretation abilities. They are susceptible to missing patterns with unusual, non-linear shapes. Interpreting potential patterns is also extremely difficult for computational methods which do not have the domain knowledge of a human expert.

With their strengths and weaknesses, computational methods and visual approaches complement each other. The integration of both approaches to combine their advantages promises further advances in the exploration of geospatial data. MacEachren and Kraak [530] reported *"integrating advantages of computational and visual approaches for knowledge discovery"* as one of the four primary themes on the ICA research agenda. Data exploration with tools that integrate both approaches is an iterative process. Results of the initial computational analysis are displayed graphically for further examination by an analyst. Using visual tools the patterns detected automatically need to be explored and interpreted. Questioning the results of a single run is very important. The user must be able to verify patterns and their stability by interactively changing the parameters of the data mining methods.

Examples of this integrative approach comprise the use of self-organizing maps (SOM) as a form of neural networks by Guo et al. [315] and Koua and Kraak [472] as well as applying k-means clustering by Andrienko and Andrienko [22]. Both methods are used for detecting *clusters* in a data set. A cluster denotes a subset of data items that are similar to each other and different from items in other clusters. This implies the need for a similarity measure on the attribute space, e.g., based on the Euclidean distance. In an explorative environment, where the goal is to discover unknown relationships, patterns have no predefined shape. Therefore, it is important to apply computational methods that do not impose a-priori hypotheses about the shape of patterns and instead let the data speak for themselves [315]. Kohonen's SOM is an example of such a method. The basic idea is to project high-dimensional data to a given grid of nodes on a two-dimensional surface such that (potentially non-linear) similarities are preserved and transformed into spatial proximity: data items within the same node are most similar, and the similarity between an item in one node and items in other nodes decreases with increasing grid distances to these nodes. A detailed description of SOMs can be found in Hastie et al. [340].

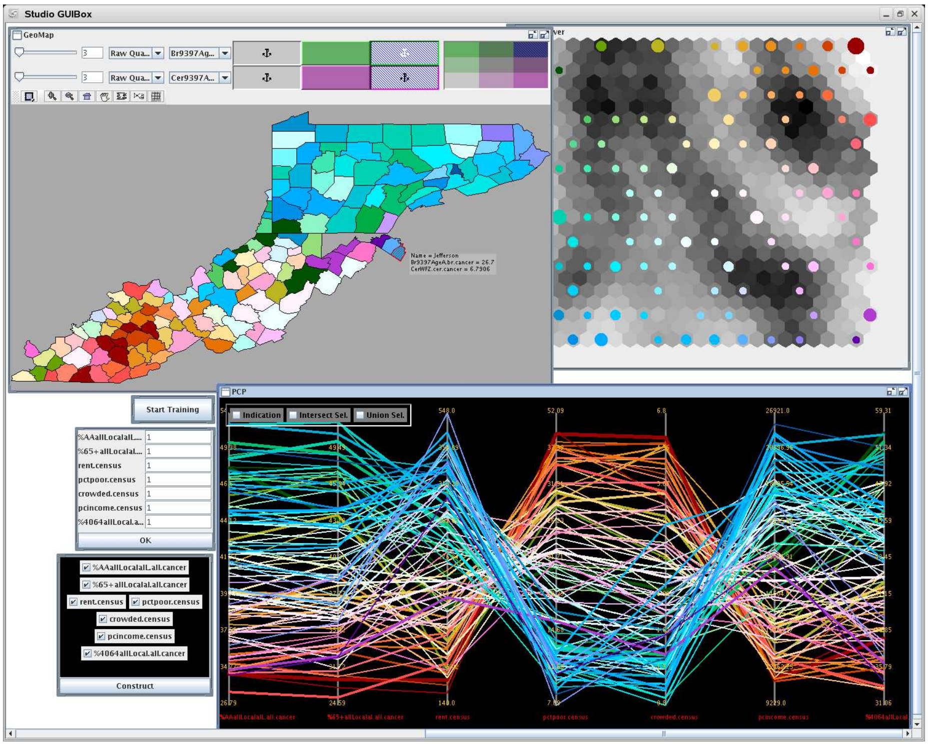

Fig. 6.12. Visualization of a cancer data set with a choropleth map, a parallel coordinate plot, and a SOM view. Screenshot of an application built with GeoVISTA Studio [816].

A SOM for geospatial data by itself is missing some important information. First, the geographic locations of clustered items cannot be extracted from the SOM view and second, the attribute values representative for a node cannot be displayed. Guo et al. [315] solved this problem by linking a view of the SOM with a map and a PCP view which provided the missing information. A screenshot of their tool is shown in Figure 6.12. The map depicts 156 counties in the US states Kentucky, Pennsylvania, and West Virginia. They used an appropriate (user-adjustable) 2D color scheme to color SOM nodes such that nearby nodes have similar colors. This can be seen in the upper right window in Figure 6.12. The hexagons in this windows colored with shades of grey depict the distance in attribute space between adjacent SOM nodes. In the choropleth map view, each county is colored according to the SOM node it belongs to. This enables the user to compare proximity in attribute space with proximity in geographic space in a single view. A PCP is used to display the summarized attribute values of all SOM nodes. Summarizing data items in the same node avoids overplotting in the PCP since the number of SOM nodes (e.g., 10×10) is usually much smaller than the number of data items. The profile of each node is again colored identically and the line thickness is adapted to the number of items in that node. Brushing and linking of the three views are supported and the user can select either counties on the map, profiles in the PCP, or nodes in the SOM. The corresponding objects in the other displays are immediately highlighted.

The example of Guo et al. [315] shows that the integration of a computational data-mining technique into a geovisualization system allows the exploration of large geospatial data sets. The visual information load is reduced by automatically clustering the data and only displaying summary information while details are still available on demand. Users can explore the data and generate hypotheses by interacting with the system and by bringing in their expertise.

6.5 Geovisualization Tools

In the previous section, a wide range of methods and techniques used in geovisualization have been presented. However, the challenge for designers of geovisualization tools is to put these methods together effectively in order to help users solving their respective tasks. It has become clear that both users and tasks vary considerably. Hence, there cannot be a universal tool that fits all users and tasks. Instead, tools need to be flexible and easily configurable by users in order to be applicable to more than just a tightly defined problem. Users should be able to select freely from the methods discussed in the previous section and to link multiple views. In the following, five examples of geovisualization systems are briefly described to show how multiple views are combined and linked in practice.

ArcView. ArcView[5] is a commercial tool for visualizing and analyzing geographic data. It is a component of ArcGIS, one of the world's leading geographic information systems. ArcView offers a range of methods for creating customized thematic maps and analyzing spatial data. It is primarily used in administrative and industrial settings, e.g., for emergency planning, site planning, or marketing.

XGobi. XGobi [814], initially released in 1996, is a general data visualization system supporting linked scatter-plot matrices and parallel coordinate plots. XGobi is a freely available tool, and it can also be linked to ArcView.

Cartographic Data Visualizer. The Cartographic Data Visualizer (CDV) [219] integrates the mapping and abstract data visualization components into a single application. Its latest release is from 2000, and it is freely available on the Internet. CDV offers dynamic choropleth maps, population cartograms, and statistical graphics like PCPs. Graphic symbols serve as interface elements to access detailed information or to select subsets of items. The views are linked such that highlighting items in one view is passed on to the other views.

CommonGIS. CommonGIS [24] is another integrated geovisualization environment developed at Fraunhofer AIS which is in practical use in academic, administrative, and commercial settings. It combines a multitude of geovisualization techniques from (multiple) dynamic choropleth maps, optionally combined

[5] More information at `http://www.esri.com/software/arcgis/arcview`.

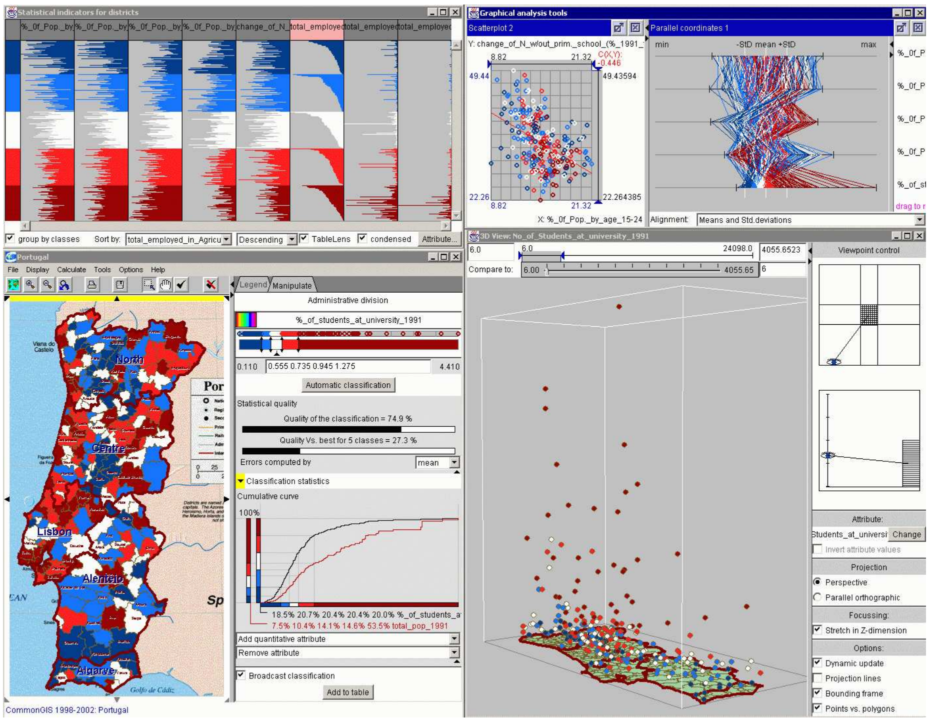

Fig. 6.13. Screenshot of CommonGIS. *Image courtesy of G. Andrienko.*

with bar plots and pie plots, over animated maps, time-series diagrams, and space-time cubes to multivariate visualizations like PCPs or scatter plots, see Figure 6.13. The user interface of CommonGIS supports interaction through focusing, brushing, linking of multiple views, and dynamic range selection for attributes. It is also possible to complement the visual data analysis by computational data-mining techniques. One focus in the development of CommonGIS was that it could be used even by users with no expertise in cartography and geosciences. The tool is commercially distributed, but it is free of charge for academic users.

GeoVISTA Studio. The approach taken by GeoVISTA Studio [816] is different. It is an open source software development environment for geovisualization rather than a static application. It is a component-oriented system with the goal to integrate a wide range of both computational and visual analysis activities and ultimately to improve geoscience research. Creating custom applications is done via a visual programming user interface that allows to connect different geovisualization components, provided as Java Beans, according to the desired data and control flow. Visual programming is a key aspect according to Takatsuka and Gahegan [816] because it allows geoscientists with little computational background to rapidly create prototypes when they are searching for useful insight. GeoVISTA Studio comes with a range of standard components, such as choropleth maps, 3D renderers, PCPs, scatter plots, color maps, spreadsheet views, and computational tools as k-means clustering and self-organizing maps. Additionally, Java Beans created by third-party developers can easily be plugged in. Once a specific application or applet has been designed, its deployment over the Internet, for example to students for educational purposes, is supported. Sample applications can be downloaded from the project web site[6]. One example is the SOM-based tool by Guo et al. [315] described in Section 6.4.8 and shown in Figure 6.12 which is built using GeoVISTA Studio.

6.6 Usability of Geovisualization Systems

In the early days of geovisualization, the development of new tools was mainly technology-driven. New features of computer hardware had to be used extensively just because they were available. The tools were often seen as proofs of concept or designed for personal use and not really intended to be utilized in practice by geoscientists and other professionals. Currently, this scope is shifting away from innovators and early adopters towards a broader audience of pragmatic and conservative users [274]. Hence, it becomes increasingly important to provide geovisualization systems that are useful and usable for their target users. As Slocum et al. [776] put it, *"the most sophisticated technology will be of little use if people cannot utilize it effectively"*. In other words, considering cognitive and usability issues throughout the whole development process of a geovisualization tool is highly important for its success with the users. Cartography has a long tradition of applying perceptual and cognitive principles to map design, e.g., devising color schemes [111]. However, the cognitive theory for static maps does not easily generalize to current geovisualization systems. Slocum et al. [776] argued that cognitive and usability issues had to be considered in the context of (1) dynamic interactive maps, (2) immersive geovisualization environments, (3) interface design, (4) individual and group differences, (5) collaborative visualization, and (6) the effectiveness of geovisualization methods.

Usability issues and evaluation of visualizations are covered in depth in Chapter 2 of this book. Here, only the most important aspects with respect to geovisualization are discussed. Usability and usefulness are terms originating from the field of human-computer interaction (HCI) which are increasingly influencing geovisualization research after being put on the 2001 ICA research agenda [530]. Usability in the HCI community refers to the *effectiveness*, *efficiency*, and *satisfaction* with which specified users can achieve specified goals in a software system. This is not to be confused with usefulness which denotes the system's ability to achieve the specified goal in principle. A tool can be useful for some spatial analysis task (it provides all necessary information) but still not be usable e.g., because of poorly designed interfaces or because users don't understand its intended usage. Usability engineering in HCI refers to a human-centered design process in which the usability of the system at different stages is evaluated, see

[6] `http://www.geovistastudio.psu.edu`

Nielsen [609] for a comprehensive introduction. Quantitative usability evaluation, as introduced in Section 2.4 of this book, is successfully applied for tasks that are well defined. However, in geovisualization well-defined tasks are hard to identify when it comes to data exploration and knowledge discovery. These scenarios are inherently poorly defined and goal achievement becomes difficult to assess. Fuhrmann et al. [274] gave an overview on how principles of usability engineering could be modified to take the characteristics of geovisualization into account. Common quantitative measures like the required time to complete a task or the number of correctly answered questions are often not directly applicable. Rather are system developers interested in whether their tool supports the user's abilities to understand the data and to uncover hidden patterns. Therefore, qualitative assessment methods using various interview and discussion techniques, participant observations, or thinking-aloud protocols proved to be suitable for evaluating geovisualization tools, see the results reported in Section 6.6.2.

One difficulty of usability testing in geovisualization, reported by Andrienko et al. [27], is that often the goal is to evaluate a concept, e.g., a parallel coordinate plot, but the actual test must be performed with an implementation of that concept. A positive result provides evidence in favor of the concept (and the implementation), but a negative result does not imply the failure of the concept. It could simply mean that this implementation of the concept is not appropriate. It is therefore important to evaluate preliminary prototypes qualitatively to reduce the risk of poor implementations of a concept.

A user group that may not be forgotten—and one of the most challenging according to Plaisant [654]—is the general public. Problems that need to be addressed in this context mainly deal with the diversity of users. But reaching every citizen is becoming important for governmental agencies and companies offering geospatial services for end users. Such services need to be distributed to a wide audience, most likely over the Internet. However, users range from children to senior citizens, have different levels of education, speak different languages, and—not to forget—may have visual disabilities like color blindness. Additionally, they use different technology in terms of network bandwidth, processor speed, screen size, etc. Scientific visualization methods such as scatter plots or PCPs are hard to understand for the average user. Simple interfaces and displays are paramount to keep the required training as low as possible. In general it is important that the visualizations are adjustable for the needs of the specific user group. All these challenges are subsumed in the term *universal usability* by Shneiderman [764].

6.6.1 Involving Users in the Design of Geovisualizations

Evaluating a geovisualization tool according to usability principles right before its release should only be one of the final stages of usability testing in a human-centered design process. Fuhrmann et al. [274] reported that carrying out 'last-minute' evaluations often revealed major flaws and thus caused timely and costly repairs. In order to avoid this, user participation should take place right from the early stages of tool development as discussed in Section 2.4 of this book. Fuhrmann et al. identified setting an early focus on users and tasks involving their participation and empirical testing iteratively during the whole design process as common principles in the literature on user-centered design approaches. Determining the characteristics of the target user group in a user analysis is one of the first steps. Variables that are important range from cultural background and sex over domain expertise and education to computer literacy and potential disabilities. Learning about users and their needs is usually done in individual interviews, user observations, or group discussions (called *focus groups*). Narrative story telling is another method to gain insight into a user's subjective view on a problem by listening to users' reports of critical incidents and personal experiences. These methods usually require that users have already been using a similar geovisualization system. For novel technologies like virtual environments or highly dynamic geovisualization systems this is, according to Slocum et al. [776], often not the case. Hence, users cannot be interviewed about or observed during analogous situations.

During later stages, such as concept development and prototyping, domain experts' feedback gives valuable hints about the usefulness of the system. In the beginning, this comprises discussing drafts and paper and pencil prototypes. Later on, prototypes with still limited functionality can, for example, be tested in a situation where one of the designers acts as the interface to the tool for expert users who perform their actions verbally. Once the desired level of usability for all parts of the product can be ensured, the final implementation takes place. If similar systems are available comparative evaluations are common in practice. Otherwise the tool is evaluated on its own by users interacting directly with the full product or with certain components individually. Depending on the specific visualization goal the tool is built for, a set of representative user tasks may be defined and subsequently be solved by the test participants. In this case, results can be measured quantitatively. Alternatively, users are asked to explore a data set and report on their findings using methods like interviews, focus groups, etc. as described in Chapter 2 of this book.

The procedure described above is still vague and actual usability studies in geovisualization fill in the details differently. The reason for this is that the ideas of usability testing and user-centered design from HCI research are novel in geovisualization. The need for a comprehensive user-centered design approach and formal methods for usability assessment in geovisualization was expressed by MacEachren and Kraak [530]. A theoretical cognitive framework providing the basis for novel geovisualization methods and user interfaces is needed as well as the development of usability engineering principles for designing geovisualization tools [776]. Slocum et al. [776] also observed that authors of geovisualization tools often claimed that their methods facilitated science and decision making without providing empirical support for their claims. In the following section, some results from user studies that were inspired by these challenges are reported.

6.6.2 Results from User Studies

Griffin [305] studied how experts use geovisualization to explore epidemiological data with a tool using three types of displays: maps, scatter plots, and time-series graphs. The thinking-aloud method was used to generate protocols of the system usage of 18 experts from epidemiology and related domains. Participants were asked to use the model for exploring the data set and generating hypotheses after an introduction to the user interface. The main finding matches the intuition that users attending a greater diversity of displays also generated more complex and diverse hypotheses. Since facilitating hypotheses generation is an important goal of explorative geovisualization, Griffin's results provide evidence for including a wide range of different display types in such tools.

A study by MacEachren et al. [524] reported on the use of a single manipulable map by nine experts for the analysis of health data. The authors analyzed mortality rates and risk factors for three types of cancer between 1979 and 1993. The map display supported selection of up to two attributes represented in the choropleth map. Interactive controls comprised dynamic classifiers and a cross map to compare two attributes. Additionally VCR-like temporal controls were offered to analyze changes over time. Verbal protocols from participants were recorded as well as interaction logs during thinking-aloud sessions. Unlike in the study described above [305], participants were given six explorative tasks involving locating areas with certain properties, examining temporal trends, and making space-time comparisons. Depending on how users interacted with the tool they noticed or missed certain patterns. This study provides evidence that users who animated time-series data noticed trends missed by others, who used manual stepping to navigate through time.

Animations in comparison to static graphics, as examined in the previous study, have been the focus of several other studies. Koussoulakou and Kraak [473] compared the communicative expressiveness of animated maps versus static maps. In a study with 39 geodesy students using quantitative evaluation, they found that the correctness of answers was not influenced by the map type. However, spatio-temporal phenomena were perceived more quickly on animated maps. They also stated that using the full potential of animated maps requires an interactive user interface, which was not available in their study.

Harrower et al. [335] studied two interactive controls for animated maps: temporal brushing and focusing with temporal legends (linear and time wheel). In their test setting, 34 undergraduate students were using the interactive learning environment EarthSystemVisualizer. The advanced interaction methods had little impact on the students' performance. The reason is that many students were confused by the new interactive controls and hence did worse than students who did not use brushing and focusing. However, those students who understood the tools performed best in answering a series of objective questions. In contrast to the results from the main evaluation, a preliminary focus group using EarthSystemVisualizer gave mainly positive feedback about the interactive tools. This example of a useful but not very usable system clearly indicates the importance of sufficient user training, especially for novel techniques. A visualization system that is too complex for its users has rather negative than positive effects.

Perceptual salience[7] of dynamic displays was studied by Fabrikant and Goldsberry [242]. They applied a neural-net based and neurobiologically plausible computational model by Itti et al. [395] to predict the most salient locations on either static or animated maps. They found that the most salient locations determined by the vision model differ between static small multiples and non-interactive animations. Future plans include comparing these predicted results with empirical eye-movement measurements in a user study and exploring the perceptual differences of dynamic displays between expert and novice users.

Morrison et al. [581] compared several studies on the efficacy of animations in general. They observed that animation was not superior to static displays in studies where both displays provide equivalent information. Studies reporting positive effects of animation were using non-equivalent static displays, e.g., with the microsteps of an animation not being shown in the static graphics. So, these microsteps might be the power of animations. Slocum et al. [776] pointed out that the methodology of Morrison et al. [581] was limited by comparing only non-interactive animations to static graphics. However, just as users can control (in a sense interactively) the focus location in a static graphic, they should be able to do the same with respect to the temporal dimension of an animation.

Andrienko et al. [27] reported on an experimental usability study of interactive techniques in CommonGIS assessing tool learnability, memorability, and user satisfaction. Since they primarily wanted to test whether users are able to handle the tools and not whether the tools facilitate knowledge construction, users had to solve well-defined tasks and answer multiple-choice questions. In a first round, the authors gave a tutorial lesson to nine participants before the test which was repeated a month later with the same group to assess memorability of the tool usage. The third web-based test was taken by 102 students who did not receive the introduction to the tools. However, they could read illustrated explanations for each task series. Overall, the performance in the web-based test was much worse in comparison to the first two rounds. This confirms the findings of Harrower et al. [335] that demonstrating and teaching the novel tools is very important. Teaching users to interact with web-based tools is a challenging task. Many participants did not read the instructions thoroughly and interactive online tutorials were suggested instead. Positive results were reported for some of the tested techniques, such as visual comparison of values in choropleth maps and dynamic linking of map, scatter plot, and PCP. Negative results were obtained for the dynamic query technique. This technique allows to specify value ranges for attributes. Objects with values outside these ranges are removed from the display.

Edsall et al. [231] assessed and compared the effectiveness of a map dynamically linked to a PCP with a map linked to a scatter plot. At first, the 37 participants of the study had to use either of the tools to accomplish a series of

[7] An object in a graphic is said to be *perceptually salient* if it can be detected quickly with respect to its surrounding objects.

well-defined tasks. In the second step, participants were observed during unrestricted exploration of a new data set with all available tools. They did not find a statistically significant advantage of one method over the other. However, scatter plots were slightly ahead for studying bivariate patterns while PCPs seem to be more suitable for multivariate data. In the second test, those participants were most successful in finding patterns who made extensive use of a variety of visualization tools and thus taking multiple perspectives on the data.

A software tool to visualize uncertainties of global water balance due to climate change on a wall-size display was described by Slocum et al. [777]. Their goal was to communicate scientific results to decision makers, e.g., to politicians or executives. They followed usability engineering principles and first built a prototype which was evaluated by domain experts. The prototype was followed by two software revisions, the first one evaluated by usability experts and the final version evaluated by decision makers. This approach clearly improved the software, however Slocum et al. recognized that decision makers, the actual users of the system, were involved too late in the design process. Their comments would have been of greatest value in evaluation of the prototype [777].

Another example of a system designed according to usability engineering principles is ESTAT (Exploratory Spatio-Temporal Analysis Toolkit) by Robinson et al. [716]. It was developed in a cooperation of geovisualizers and epidemiologists to facilitate cancer epidemiology research. ESTAT is built in GeoVISTA Studio, and it combines and dynamically links a bivariate choropleth map, a scatter plot, a time series plot, and a PCP. At all stages of the development end-users were involved to assess the usability of the system. A prototype of the PCP module was evaluated in a thinking-aloud study with a group of students and resulted in reorganizing the PCP interface. Then, a refined version of ESTAT was evaluated with a group of epidemiologists in a tutorial and task session and a focus group discussion. Participants expressed the need for more training with the PCP and the time series plot and the desire to see descriptive statistics of the data. it was decided to perform an in-depth case study with an epidemiologist to understand how users would like to work with a geovisualization tool. This case study emerged as a particular beneficial way of gaining a deeper understanding of an expert's analysis strategies and directed attention to previously neglected issues like loading and sorting data and interface icons and controls. All parts of usability evaluation resulted in redesigning significant parts of ESTAT, e.g., the scatter plot was enhanced by a number of descriptive statistics and regression methods. The study clearly demonstrates how important it is to adapt innovative methods to the needs of real users doing real work.

6.6.3 Geovisualization to Support Group Work

Another aspect of human-centered geovisualization is the design of systems that support collaborative use. While many potential applications of geovisualization require coordinated efforts by groups, most geovisualization methods are primarily designed for single users at a workstation. Technological advances such as large screen displays or high-bandwidth communication enable both same-place and different-place multi-user systems but current geovisualization systems often do not use these capabilities. MacEachren and Kraak [530] listed geovisualization methods that support group work as a fundamental multidisciplinary research challenge. Section 3.4 of this book discusses distributed collaborative visualization in general. Here, both same- and different-place collaboration is covered in the context of geovisualization.

Scenarios in which small groups collaborate can be found in scientific research, environmental and urban planning, education, or economic decision making. Commonly, group work is classified by same- or different-place and same- or different-time collaboration as described by Applegate [32], see also the discussion in Section 3.4.1 of this book. Current geovisualization research on group work focuses on both same-place/same-time and different-place/same-time collaboration. Same-place collaboration certainly provides the most natural mode of interaction between humans but in certain situations groups of experts with various backgrounds need to be consulted and it is often impossible to convene at a single place, particularly for time-critical tasks such as emergency management. Same-place collaboration often utilizes wall- or desk-based large screen displays and multimodal user interfaces. In contrast, different-place collaboration introduces the problem of synchronizing and linking the visualizations at multiple places. Brodlie [116] described three models of distributed visualization systems. A *single, shared* application runs on a single machine and the user interface is replicated to different displays, i.e., all collaborators see exactly the same image. Either a single user controls the application, e.g., for a demonstration, or control of the application is passed between users. A *single, replicated* application is executed at each location and parameter settings are shared. This is a more flexible approach, e.g., users can change their personal screen layout or language settings. Finally, *multiple, linked* applications allow the highest degree of flexibility. Users can work individually and share data and parameters as they wish. However, flexibility is also the disadvantage of this approach as it is hard for a user to get a feeling of what others are doing and that makes coordinated work difficult. MacEachren [523] suggested a *participant watcher* as a tool that shows each user's screen layout and currently active windows as well as activity displays that show for example the amount of time each user was in control of the joint display. Such a tool arises concerns about privacy and therefore its acceptance by users but it was not yet evaluated in a user study. Video conferencing is a another common mode of human-human interaction in such applications [116, 523].

Being the object of collaboration is not necessarily the role of geovisualization. MacEachren [523] listed supporting dialogue and supporting coordinated activity as alternative roles. In supporting dialogue, the display can be used, for example, to depict an argument directly or to serve as a framework for arguments. Geovisualization can support coordinated activity, for example, in an emergency response situation, where the command center staff needs to communicate with individuals in the field. The visualization environment serves to guide navigation, to input data and to provide an overall view for assessing the situation.

Collaborative geovisualization systems make different demands on usability and user-centered design in comparison to the single-user case discussed before in Section 6.6.1. Users, such as experts from different fields, are no longer homogeneous and tasks that support and mediate dialogue have not been considered before in single-user systems. MacEachren and Brewer [525] identified several research challenges for geocollaboration. For example, working with a large screen display requires more natural, multimodal user interfaces, such as speech and gestures, to support group work. See Section 3.3 of this book for a survey on multimodal interaction techniques. Furthermore, a theoretical understanding of cognitive and social aspects of collaboration must be developed as a basis for usability studies. In the following, two prototype systems designed for collaborative geovisualization tasks are described.

Brewer et al. [112] developed a prototype system to support same time/different place collaboration of a team of environmental scientists. The system was designed to mediate and enhance knowledge construction in a sample climatic time-series data set. A focus of their study was on usability and human-centered design aspects and they reported the results of a user-task analysis. They interviewed six domain experts and demonstrated their prototype to prompt discussion. The prototype presented a 3D map-based view of precipitation and temperature. The temporal dimension is controlled by a time wheel interface and the map can be animated accordingly. The environment can be displayed on regular displays as well as on an ImmersaDesk virtual reality system. In their user-task analysis, Brewer et al. found that drawing the attention of others is a crucial task [112]. Participants frequently used gestures to draw attention to features on the display. Joint interface controls were endorsed but users added that conflict avoidance is necessary, e.g., with a turn-based approach or separate windows for each user. Alternatively they suggested a single user to be in control. Concerning the display a workbench-like display was preferred over a wall-mounted solution. In terms of different place collaboration, the experts favored voice and video for communication. They expressed the need for a private workspace and for the ability to see what others are doing to the joint workspace, not just the outcome. Again, drawing attention, e.g., with the mouse cursor, was regarded as very important.

A second prototype system is DAVE_G (Dialogue-Assisted Visual Environment for Geoinformation) by MacEachren et al. [526]. DAVE_G was designed for a map-mediated crisis management scenario where decision makers need to coordinate the emergency response. Geoinformation systems (GIS) are used in practice today but they are operated by GIS technicians in response to requests from decision makers. Valuable time is often lost due to this indirect GIS usage. Hence, the goal of MacEachren et al. was to develop a multimodal, dialogue-assisted tool that uses speech and gesture recognition to enhance human-human collaboration around a large screen map display. In this approach, human-computer and human-human interaction use the same modalities which is an important aspect for user acceptance. An initial work-domain analysis with four emergency managers identified a set of required map functionality, e.g., zoom, pan, buffer, select data, and free-hand drawing. Challenges for the user interface include recognition of implicit commands ("we needed to view this in more detail") and sloppy speech. Speech and gestures are fused, i.e., a spoken command, e.g., "zoom in to this area", is associated with a pointing gesture. A dialogue manager requests missing parameters for incomplete commands. Technical details of the user interface can be found in MacEachren et al. [526]. Fuhrmann et al. [275] evaluated the usability and performance of DAVE_G in a user study with ten graduate students. The system was unknown to the participants. In the beginning, they set up individual voice profiles and completed a DAVE_G learning session of about ten minutes after which they felt comfortable with the system. They solved two unguided tasks where they had to load data, zoom, pan, and identify certain objects. About 70% of the requests were successful and 90% of the gestures were correctly recognized. In a subsequent interview, participants were positively describing their experience with DAVE_G and emphasized quick learnability. Fuhrmann et al. [275] reported that hand tracking sometimes lost the cursor and that the dialogue capabilities of DAVE_G needed to be improved.

6.7 Chapter Notes

This chapter aimed to give a comprehensive overview of the state of the art in geovisualization research. However, the abundance of developments and results in this lively research field cannot be covered completely within this book. A good starting point for further reading is "Exploring Geovisualization" [222], a book that contains the results of a cross-disciplinary workshop with the same title held in 2002 at City University, London.

6.7.1 Future Trends

How will geovisualization develop over the next years? In the future, Dykes et al. [221] still see the map as the primary tool to present, use, interpret, and understand geospatial data. However, it has become apparent in the past that the map can and will take a variety of forms, some of which quite astonishing. The map has evolved from its traditional role as a presentational device to an interactive and highly dynamic interface to access and explore geospatial data.

Another common feature of current geovisualization tools is that they consist of multiple linked displays, each depicting an alternative representation of the data under examination to stimulate visual thinking. This will certainly remain a central aspect in geovisualization.

Concerning the tasks and users of geovisualization tools a transition from explorative, individual use by experts towards the whole range of tasks from exploration to presentation and heterogeneous groups of users is taking place. While individual expert tools will continue to develop, there will be an increasing number of applications designed for the public and disseminated over the web. It is clear that the usability requirements differ significantly between research tools for specialists and public applications for the mass of non-expert users. Human-centered aspects need to play a key role in the design of future tools in order to make them fit the needs of their audience. The goal of universal usability, i.e., creating applications for wide ranges of users from children to senior citizens in different languages and respecting visually disabled users, remains a big challenge.

Advances in hardware technology will also have a strong influence on geovisualization. On the one hand, large 2D and 3D displays and virtual environments will be used for geovisualization tasks, especially for collaborative use by a group of experts and decision makers. Usability studies for these new technologies will have to investigate their advantages and disadvantages over traditional visualization methods as well as possible cognitive and social impacts. In particular, the right balance between abstraction and realism needs to be determined for 3D displays. On the other hand, portable devices like PDAs or mobile phones will provide location-based services, e.g., route finding in foreign places which build on some sort of map display. This means additional challenges for application developers in terms of efficient memory and bandwidth use as well as in terms of visualization design for multi-platform, small-size displays.

A last point that is raised by Gahegan [283] is the need for interoperability of geovisualization components. Following the efforts of the Open Geospatial Consortium[8] to define open standards for geospatial information systems, Gahegan promotes a similar initiative for geovisualization. Visualization components should define standard interfaces in order to be reused and integrated into a variety of geovisualization tools. A lack of interoperability means that for developing a new tool too much effort is spent on re-implementing basic functionality and too little effort can be invested in developing new methods.

The coming years will show what directions geovisualization research will take and how it will influence both research in the earth sciences and related disciplines and our everyday handling of geospatial information.

[8] See `http://www.opengeospatial.org`.