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# For your eyes only? Evaluating a coordinated and multiple views tool with a map, a parallel coordinated plot and a table using an eye-tracking approach

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## ABSTRACT

Geographic visualization tools with coordinated and multiple views (CMV) typically provide sets of visualization methods. Such configuration gives users the possibility of investigating data in various visual contexts; however, it can be confusing due to the multiplicity of visual components and interactive functions. We addressed this challenge and conducted an empirical study on how a CMV tool, consisting of a map, a parallel coordinate plot (PCP), and a table, is used to acquire information. We combined a task-based approach with eye-tracking and usability metrics since these methods provide comprehensive insights into users' behaviour. Our empirical study revealed that the freedom to choose visualization components is appreciated by users. The individuals worked with all the available visualization methods and they often used more than one visualization method when executing tasks. Different views were used in different ways by various individuals, but in a similarly effective way. Even PCP, which is claimed to be problematic, was found to be a handy way of exploring data when accompanied by interactive functions.

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Coordinated and multiple views; geographic visualization tool; eye-tracking; user studies

## 1. Introduction

Geographic visualization (geovisualization) tools that integrate several visualization methods and are equipped with a number of interaction techniques are usually known as coordinated and multiple views (CMV) tools. Integrating various views can be more helpful than using individual displays (Edsall 2003a), but users may become confused and overwhelmed when using a CMV tool (Baldonado *et al.* 2000) and even more so because of a growing diversity of representations (Griffin and Fabrikant 2012). Although several authors have addressed the issue of how CMV tools work for users (e.g. Andrienko *et al.* 2002, Guo *et al.* 2005, Robinson *et al.* 2005, Marsh *et al.* 2006, Demšar 2007, Bhowmick *et al.* 2008), we still need to know more about how users of CMV tools apply and understand different visualization methods that present the same input data.

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We revisited this issue by conducting a study on a CMV tool that consisted of a map, a parallel coordinate plot (PCP) and a table. We selected these three visualization methods for the following reasons: maps are canonical in geographical displays (Roberts 2008), data displays such as interactive PCPs serve as components in most CMV tools, while tables are well known to users and are useful if equipped with the proper interaction techniques (Rao and Card 1994). We wanted to know whether users would willingly use a variety of displays that had different visualization methods, or reluctantly refer to different views in order to reduce the cognitive effort connected with context switching. Context switching is when a user switches from one display, based on one particular visualization method, to another display, based on another visualization method (Baldonado *et al.* 2000). Three research questions motivated our efforts:

- (1) Do individuals make use of several visualization methods even though they present the same input data?
- (2) Does the use of visualization methods differ between the types of tasks being executed?
- (3) Do individuals avoid working with a PCP if the same content is displayed simultaneously in other views?

By addressing these questions we hope to contribute to an increased understanding of how CMV geovisualization tools should be designed in order to support users effectively.

## 2. Background

### 2.1. Coordinated and multiple views

Visualization methods in CMV often include map displays, charts, graphs and PCPs, as well as networks, trees, hierarchies, routing diagrams and tables. Typically, all these visualization methods are interactive since they assist users in exploring the data sets in various ways (Baldonado *et al.* 2000). Of special interest to our study are situations in which CMV tools contain a set of views presenting the same data but in various forms, and whether or not this makes visualization more effective. An effective visualization is characterized by the use of minimum cognitive effort, but may be violated due to context switching (Baldonado *et al.* 2000). There is a risk that a user, when exploring the data, may not take advantage of the CMV tool and use only one view where it presents the same data as the other views, assuming that using only one view reduces demand on cognitive attention.

Some authors, nevertheless, report that the time cost for context switching may not be significant (Convertino *et al.* 2003) or that users tend to perceptively integrate information given in various components (Opach *et al.* 2014). In the latter study, however, the authors admit that cognitive shortages may occur if a CMV tool is composed of both static and animated map components. Yet they applied a limited number of visualization methods in their studies.

## 2.2. Effectiveness of parallel coordinate plots in the context of CMV tools

Two of the three selected visualization methods for our study (map and table) are widely applied in CMV tools and recognized for their usefulness (Edsall 2003a, Koua *et al.* 2006). However, some GIScience studies have revealed that the third visualization method, PCP, is confusing and difficult to use (Convertino *et al.* 2003, Robinson *et al.* 2005). Other studies have shown that when used together with maps, PCP may facilitate the understanding of spatial characteristics (Edsall 2003a, Opach and Rød 2014).

Users may select and apply a method that is not the most effective for a task (Mendonça and Delazari 2012) and, therefore, may not discover 'the richness of the underlying data' (Roberts 2007, p. 61). People may not take full advantage of CMV tools and may avoid using some views if they are perceived as challenging to learn. In order to fully exploit CMV tools it is important to understand how users work with CMVs in situations where they are free to use any of the implemented visualization methods.

## 3. Human-computer interaction and CMV tools

CMV tools are important in the explorative and analytical phases of the map use space (MacEachren and Kraak 1997) that is commonly enabled by interactive techniques with dynamic linking and brushing functionalities. However, due to the CMV tool's inherent complexity, such tools can be problematic for users and are therefore seldom used by non-specialists (Andrienko and Andrienko 2006a). For wider use of CMV tools, it is, therefore, necessary to understand how these tools are used, and usability studies that compare and evaluate selected user tasks (e.g. Tobón 2005, Koua *et al.* 2006) are recognized as appropriate (Slocum *et al.* 2001, 2003, Koua and Kraak 2004). This formal evaluative approach is complementary to an exploratory, insight-based approach, where users are engaged in free data exploration (Demšar 2007, Chang *et al.* 2009). It also provides precise metrics. For instance, error rates and response times refer to users' performance and provide information about effectiveness and efficiency, respectively (e.g. Çöltekin *et al.* 2009); whereas learnability focuses on the ability of users to understand the purpose of the tools and learn how to use them; while memorability refers to the ability of users to retain the acquired skills and utilize the tools after a period of time (e.g. Andrienko *et al.* 2002).

Tasks in a formal evaluation are typically derived from task taxonomies. For instance, Koua *et al.* (2006) assessed the usability of three visualization methods using Zhou and Feiner's (1998) visual task taxonomy. Çöltekin *et al.* (2010) used tasks from Gotz and Zhou's (2009) taxonomy when comparing differently designed geovisualization applications. The latter example shows that task taxonomies are helpful in studies that apply the eye-tracking method.

GIScience researchers often use eye-tracking in usability studies (Çöltekin *et al.* 2009, Ooms *et al.* 2012) and it still holds the promise of new insights (Montello 2009). Since this technique records the location of fixations (stable points of regard, held for a length of time, which suggests that a person is reading the content at this location), it provides insight into visual behaviour in an unobtrusive manner (Fabrikant *et al.* 2008). Eye-tracking data, when combined with usability metrics (the accuracy and time of response), give answers to what users tend to look at, and why they do so.

However, eye-tracking is seldom applied to studies of CMV geovisualization tools. An exception is Convertino *et al.* (2003), who investigated the differences between the most and the least successful individuals in respect to correctness when working with a dual-view layout. Although inspiring, Convertino *et al.*'s study applied eye-tracking in a basic way. To the best of our knowledge, more extensive studies using eye-tracking to understand how people work with CMV tools do not exist in GIScience literature.

#### 4. Empirical study

We conducted an eye-tracking study to learn more about how users of CMV tools apply three different visualization methods that present the same input data. As context switching may be an issue, we wanted to find out whether users of CMV tools tend to keep their attention within one visualization component or rather jumped across components in their search for information.

##### 4.1. Materials and methods

We used a web-based tool (Opach and Rød 2013) with map, table and PCP views (Figure 1) as the study material (<http://setebos.svt.ntnu.no/viewexposed/>). All views are linked, so that if a user selects one or more objects in one view, the same data items are simultaneously highlighted in the other views: for example, the map is centred on selected objects, and those objects are highlighted in the PCP and table views.

The tool contained information on integrated vulnerability to natural hazards in Norway. Integrated vulnerability combines indices on exposure to floods, landslides and storms with indices of social vulnerability; recognizing that the interaction between physical and socio-economic factors is essential in determining the outcome of extreme events. High values for any of these indices on exposure means that a proportionally high number of buildings are situated in a potentially dangerous place. The indices of social vulnerability represent the capacity of the municipalities to prepare for, respond to, and recover from extreme events. Combining information on integrated vulnerability with various visualization methods enables users to explore data in different ways: maps help to identify the most exposed and/or vulnerable places (answers 'where?'), PCPs help with understanding what makes a certain municipality exposed and/or vulnerable

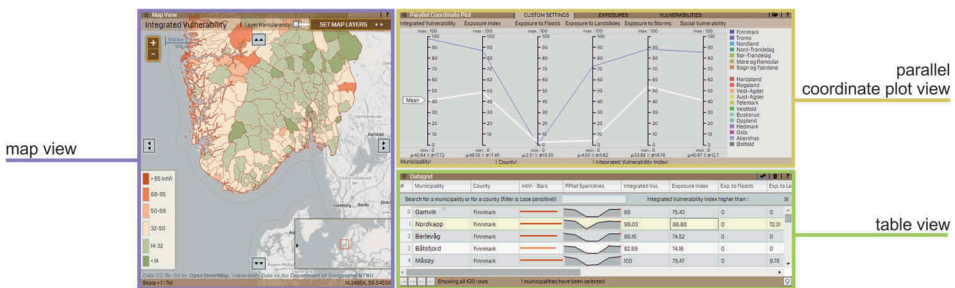


Figure 1. The layout of the CMV tool used as the study material.

(answers 'why?'), and tables let the user access the raw data (see Rød *et al.* 2015 for details).

Since people tend to look at the things they are thinking about (Nielsen and Pernice 2010), we asked the participants to solve five tasks, and recorded their eye movements during task execution. As converging methods are essential for assessing complex geospatial interfaces (Buttenfield 1999, Robinson *et al.* 2005), we combined eye-tracking with usability metrics (time and accuracy of answers). The study was conducted in an area used for controlled audio and visual perception experiments: the Speech, Cognition and Language Laboratory (SCaLa) at the Department of Psychology of the Norwegian University of Science and Technology (NTNU). An SMI RED500 eye-tracker was used. The stimulus was displayed on a 21-inch screen with a resolution of 1680 × 1024 pixels while the recording sample was set at 120 Hz.

We used four analytical approaches to investigate the eye-tracking data that was collected. We divided the tools' layout into three areas of interest (AOI), covering each view: the map (33% of the layout), the PCP (31%) and the table (20%). A separate AOI called 'Task' (14% of the layout) was situated at the bottom part of the interface, and displayed the task questions. First, to get an overview of the tool usage, we compared total fixation lengths for each AOI.

Next, we applied sequence alignment analysis (SAA) to investigate how visual attention changes during task execution and to identify whether any patterns could be distinguished among visual behaviours. SAA allows for the identification of similarities between sequences of objects based on the frequency and position of the objects and the transition between them. It has previously been used within GIScience in general (Shoval and Isaacson 2007, Golebiowska 2015), and for eye movement studies in particular (Fabrikant *et al.* 2008, Opach *et al.* 2014). As did the latter authors, we too used ClustalG software (Wilson 2008) to determine the sequences of the viewed AOIs for each task.

Unfortunately, SAA does not include fixation duration. Hence, both a quick glance and a long fixation are treated equally. In order to verify whether the user groups distinguished in the SAA also differed when fixation duration was taken into account, we performed a task execution analysis (TEA). TEA is an approach that makes it possible to investigate the location of points of regard on a screen over time. To eliminate differences between particular task execution times, all eye movement recordings are standardized to one equal length.

Finally, we analysed viewing purpose (VPA) to identify the visualization methods used for conducting the two critical stages of tasks execution: selection and information extraction. The stages refer to the two parts for all possible tasks: the constraint (the conditions the information needs to fulfill) and the target (the information that needs to be obtained) (Andrienko and Andrienko 2006b). In order to get this data, we overlaid the animated eye-movement paths onto the screen recordings showing the interactions with the tool, and synchronized it with recordings of the participants' verbal answers. In this analysis we were also able to find out which visualization was successfully used in each task, since a high number or long fixation on a given view does not necessarily mean that it is helpful: the reason may be that it is problematic and time-consuming and thus users have to make more effort to get the information (Jacob and Karn 2003).

## 4.2. Tasks

As little research has focused on how humans perceive, understand and use geovisual analytics tools (including CMV) to gain insight into complex data and visualizations; we decided to start exploring the problem using a formal evaluative approach that demands less cognitive effort from the user than an exploratory usability evaluation (Marsh *et al.* 2006, Demšar 2007). We focused on the specific visual operations that are carried out in the process of exploring (large) data sets. The exploration process can be viewed as a set of basic tasks (Koua and Kraak 2004, Koua *et al.* 2006) such as checking the spatial positioning of elements of interest in order to verify spatial proximity among them, or obtaining an overview of how a target value measured at one particular spatial location varies for different attributes. To complete these various tasks, the user has to execute different types of visualization operations (Tobón 2005). Such operations have proved to be helpful in the evaluation of geovisualization tools (Tobón 2005, Koua *et al.* 2006).

We chose the taxonomy of Amar *et al.* (2005), which refers to low level operations, i.e., the ones that correspond to, or build up, tasks derived from other taxonomies (Table 1). This feature makes it easier to compare results between studies. Furthermore, since CMV tools are developed not only within the GIScience domain, we wanted to use a taxonomy that refers to visualization activities in general, not only those typical of geovisualization. Out of the 10 tasks in the taxonomy, we selected five that could be executed using all three of the visualization methods selected for the study. The tasks were not laborious, but they differ in terms of cognitive load. We believe that cognitive load is connected with the dimensionality of the task (number of variables) and spatial extent/scale (number of cases/objects) they involve. Therefore, the cognitive load increases from T1, which involves one variable and one case, to T5, which involves multivariate analysis of multiple cases (Table 1).

## 4.3. Participants

Taking part in the study were 29 participants (11 females and 18 males), aged from 22 to 41 years (with an average of 27 years). All of them were geography students at either masters (79%) or PhD level (21%). The sample size was based on recommendations from usability engineering literature (Nielsen 1994) regarding final testing that involves actual use. It is also in accordance with the sample sizes used in successful empirical studies of geovisualization tool evaluation (Koua *et al.* 2006, Çöltekin *et al.* 2009).

In the background questionnaire participants reported using interactive maps mainly to locate interesting places, plan journeys, or for fun. They were also asked to estimate their level of training in several fields using a scale ranging from 1 (no training) to 5 (full training). The average score for training in cartography was 2.8, for computer graphics, web-mastering and user interface design they scored: 2.0, 1.5 and 1.7, respectively. All users were provided with a 10-minute introduction to the general tool interface directly before solving the tasks.



**Table 1.** Task questions and the task types they represent according to different task taxonomies.

Task	Task question	Amar <i>et al.</i> (2005)		Wehrend and Lewis (2000) (applied by, for example, Koua <i>et al.</i> 2006)	Dimensionality of the task (applied by, for example, Edsall 2003a, Tobón 2005)
		Task type	Description		
T1	What is Trondheim municipality's score for the Exposure to Flood Index?	Retrieve value	Given a set of specific cases, find the attributes of those cases.	Locate	One case, one variable
T2	Give the names of three municipalities with scores above 85 on the Integrated Vulnerability Index.	Filter	Given some concrete conditions for attribute values, find data cases satisfying those conditions.	Locate	Three cases, one variable
T3	How does the composite Exposure Index vary in Finnmark County?	Characterize distribution	Given a set of data cases and a quantitative attribute of interest, characterize the distribution of that attribute's values over the set.	Distinguish	Many cases, one variable
T4	Indicate one common characteristic of the municipalities with scores below 20 on the Exposure to Storm Index?	Correlate	Given a set of data cases and two attributes, determine a useful relationship between the values of those attributes.	Distribution	Many cases, two variable
T5	Are municipalities in Sogn og Fjordane County homogenous in terms of exposure to physical threats? Are there any municipalities that stand out with regards to exposure to some physical threats?	Find anomalies	Identify any anomalies within a given set of data cases with respect to a given relationship or expectation.	Non-applicable	Many cases, many variables

## 5. Data analysis and results

### 5.1. Areas of interest analysis: total fixation length

The AOI analysis revealed that the participants tended to look at all views when executing tasks T1 through T5 (see Table 2). A factorial ANOVA yielded the main effect for the visualization method on fixation length. The table view received the longest fixation length among the implemented visualization methods (see last row in Table 2). The main effect of the task type was also significant ( $F = 9.992$ ,  $p = 0.001$ ), fixation length was the longest for T5 and the shortest for T2 (see last two columns in Table 2). Moreover, the factorial ANOVA confirmed an interaction effect for visualization method and task type for fixation length ( $F = 36.221$ ,  $p = 0.001$ ), indicating that the visualization method effect differs between tasks. For T1 (retrieve value) the participants viewed the table for significantly longer than the map ( $F = 3.383$ ,  $p = 0.041$ ), in T2 (filter) the table was viewed for significantly longer than the map ( $F = 35.682$ ,  $p = 0.001$ ) and the PCP ( $p = 0.001$ ), whereas in T3 (characterize distribution) the map was viewed for a significantly shorter time than the PCP ( $F = 9.513$ ,  $p = 0.020$ ) or the table ( $p = 0.001$ ). In T4 (correlate) users viewed the table for the longest period ( $F = 15.059$ ,  $p = 0.001$  for both the map and the PCP). Finally, in T5 (find anomalies), the map was viewed for a significantly shorter time than both the PCP ( $F = 10.742$ ,  $p = 0.001$ ) and the table ( $p = 0.003$ ). Moreover, the map view was viewed significantly longer in T4 than in T2



**Table 2.** Total average fixation times for the three views while executing tasks.

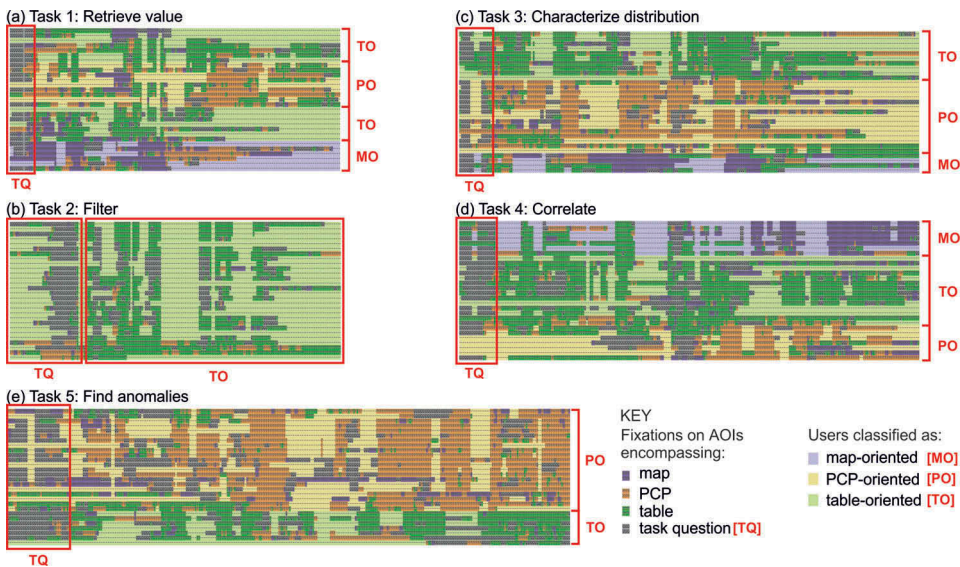
	Map		PCP		Table		Total	
	Mean (sec)	St. dev. (sec)	Mean (sec)	St. dev. (sec)	Mean (sec)	St. dev. (sec)	Mean (sec)	St. dev. (sec)
T1: Retrieve value	8.99	9.78	11.20	12.15	17.47	16.33	12.51	13.39
T2: Filter	1.88	6.76	1.98	3.69	25.76	20.05	9.88	16.67
T3: Characterize distribution	12.34	13.74	10.40	13.55	33.23	23.53	17.83	20.36
T4: Correlate	6.31	8.71	19.87	19.30	27.33	24.40	18.65	20.24
T5: Find anomalies	7.92	12.09	38.45	21.72	31.26	38.01	25.87	29.04
TOTAL	7.46	10.91	16.38	19.65	27.00	25.76	16.95	21.25

( $F = 3.831, p = 0.005$ ), the PCP view was viewed significantly longer in T5 than other tasks, and viewed longer in T2 than in T3 ( $F = 23.448, p = 0.001$ ).

### 5.2. Sequence alignment analysis

The SAA revealed that patterns representing participants’ visual behaviour varied depending on the task, except in the initial stages (marked with TQ in Figure 2) where individuals focused on the question AOI. For all tasks except T2, eye-movement recordings distinguished the participants into three groups of users: map-oriented, PCP-oriented and table-oriented (Figure 2). T2 resulted in a homogenous visual behaviour: all were classified as table-oriented as they worked mostly with this component.

We checked if particular participants were classified in the same group (map-, table- or PCP-oriented) across tasks. It turned out that most participants were changing their preferences, as only one participant was classified in the same (table-oriented) group for all five tasks.

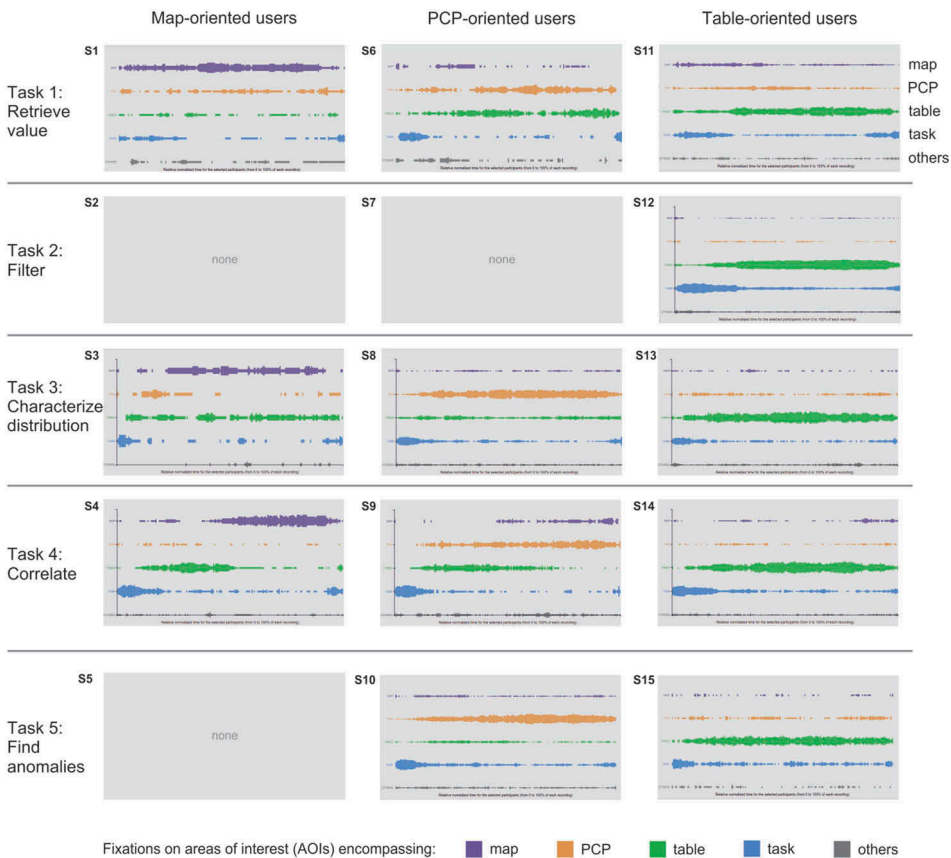


**Figure 2.** The sequence alignment analysis results with subgroups of the participants distinguished by tasks. Each row indicates a sequence of eye-fixations recorded for one participant.

### 5.3. Task execution analysis

The TEA approach enabled us to identify the dominant places of attention during the task execution's relative start, middle and end, and compare participants' visual behaviours. We developed the Eye Movement AOI Aggregation Tool (EMAAT) using JavaScript and HTML5 with a web browser-based interface, since available eye-movement software lacked the required sophisticated functionality (Fabrikant *et al.* 2008). The EMAAT filters eye-movement data based on tasks and the participants' IDs. The tool depicts aggregated AOI locations of fixations over standardized task execution times. Five AOIs were included in the interface as horizontal parallel axes (see screenshots in Figure 3).

The TEA confirmed the differences in individuals' visual behaviours that were revealed in the SAA (Figure 3). The behaviours were aggregated for user groups (columns) and arranged by the five tasks (rows). Only the table-oriented users focused mostly on one view in all tasks (screenshots: S12, S13, S14, S15). PCP-oriented users often referred to the table (S6, S8, S9), whereas map-oriented users often referred to two other views (S1, S3). Map-oriented users focused on the map, although not from the very beginning of



**Figure 3.** Screenshots from the EMAAT tool arranged by task number (rows) and user group (columns). The screenshots depict individuals' visual behaviour during relative task execution time: the thicker the line, the more the participants fixated on a particular AOI.

the task execution (S1, S3, S4). At the beginning and end of all task executions, there was higher attention targeted on the task AOI: participants first read the task questions, while at the end they double-checked the questions before answering.

#### 5.4. Viewing purpose analysis

Let's consider one case from Figure 3, screenshot S4, which summarizes the map-oriented users' visual behaviour in T4. First, the question area was frequently viewed. Subsequently, participants focused mainly on the table; and then the focus moved to the map. Such shifts may indicate that visual behaviour consists of stages where different views are preferred and used for different purposes. As was mentioned in Section 4.1, we divided each task into two stages (selection and information extraction), and identified which views were applied in each stage.

In all but one task, participants used most of the implemented visualization methods for both stages (Figure 4). Only T2 was solved through interacting with one view alone, the table (Figure 4(b)), which confirms the SAA outcomes. In T1 most participants used the table in order to select the required municipality (Figure 4(a)). A majority used the same view for both stages (mostly the table). Three participants used the PCP for information extraction, although the PCP-oriented group was higher (Figure 2). Even though certain participants started with the PCP, a portion of them moved their attention to other views where they finally managed to find the answer. T3 was executed mainly through the use of the PCP and table (Figure 4(c)). Most participants used the PCP for selection. Two-thirds of this group continued to work with this view for information extraction. Others shifted attention to the table and only one participant to the map. The latter finding differs from the SAA's outcomes where the map-oriented group included four individuals, but only one of them found the information searched for in the map. T4 was solved in the most heterogeneous way (Figure 4(d)). Of the participants, 67% used the table for selection, but only half of this group continued with this view, the rest of them worked mainly with the map for information extraction. Of the users, 28% used the map for selection and, except one, for the information extraction stage. Even though the SAA classified seven participants as PCP-oriented (Figure 2), the PCP was used by the lowest number of participants. In T5, 83% of participants used the PCP for object selection, and 62% of users also used this view for information extraction, which confirms the results of the SAA, classifying the majority of participants as PCP-oriented.

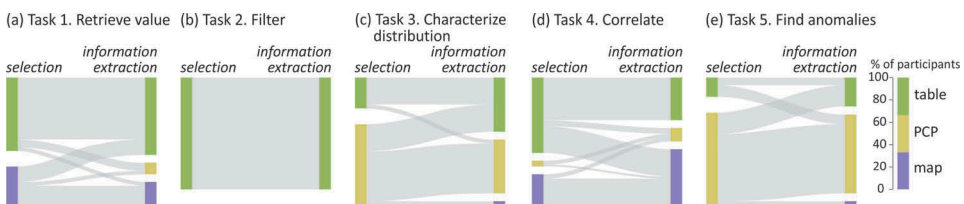


Figure 4. Visualization methods that users referred to in the two critical stages of task execution.

Despite the need for context switching, participants who applied different visualization methods for selection and for information extraction did not need longer response times for most of the given tasks. A factorial ANOVA showed the interaction effect between variables: 'number of visualization methods applied when executing a task' and 'task types' ( $F = 56.706$ ,  $p = 0.001$ ). Only for T4 did we find a significant difference between the scores of those who applied the same view ( $M = 64.97$  sec,  $SD = 24.46$ ) and those who applied different views ( $M = 139.87$  sec,  $SD = 66.11$ );  $t(27) = -4.451$ ,  $p = 0.001$ . Most of those who applied different views (7 out of 10) for this task used the table for selection and the map for information extraction. Table and/or map was thus the least appropriate for the correlate task, an issue we will further elaborate in the discussion section.

### 5.5. Answer correctness

Although most users gave correct answers, none of the tasks was solved correctly by all. As presented in Figure 5, T1 resulted in the highest rate of correct answers, whereas T3 resulted in the lowest value of correctness, as 35% of the participants answered it incorrectly.

There was no significant difference in answer correctness between participants who were classified as map, PCP or table-oriented in tasks 1–4. Only in T5 did users, classified as table-oriented, gave more incorrect answers than those classified as PCP-oriented ( $\chi^2(1, N = 29) = 24.22$ ;  $p < 0.01$ ). There was no statistically significant change in response time between the subgroups of participants. Moreover, any significant differences regarding answer correctness were observed between those who applied different visualization methods for selection and information extraction in tasks 1–4, and those who applied the same method in those stages. Again, in T5, users who applied the table for information extraction gave more incorrect answers than other users ( $\chi^2(2, N = 29) = 19.94$ ;  $p < 0.01$ ).

It turned out that most of the incorrect answers were given when the table was used for information extraction (Figure 6). The mistakes were primarily caused by referring to a wrong attribute (65% of incorrect answers) in the table. Other causes concerned referring to the wrong object, not analysing all the necessary objects, and incorrect data sorting.

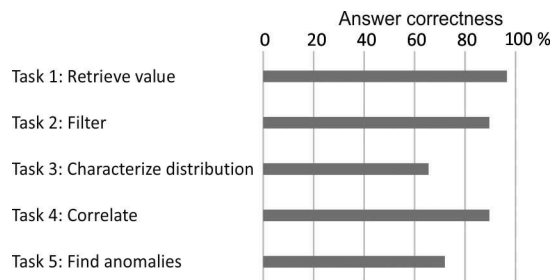


Figure 5. Answer correctness.

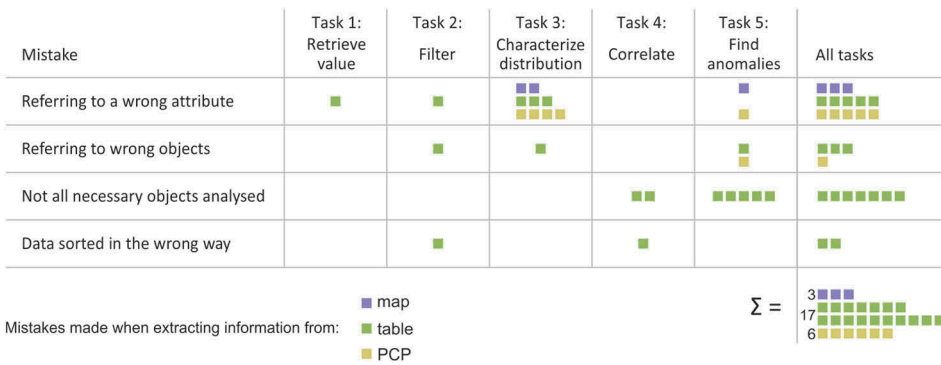


Figure 6. Mistakes and their causes.

### 6. Discussion

All five analytical approaches used to investigate the empirical data revealed that participants worked with the three visualization methods in CMV for most of the tasks. The VPA revealed that different visualization methods were applied for selection and for information extraction. In four out of five tasks, some participants used different views during the task execution and this behaviour did not result in lower answer correctness. Like Convertino *et al.*'s (2003) study, we did not find that using different views resulted in longer response times. The one exception was for T4, where a longer response time for users applying different views was observed, mainly when switching from the table to the map. Contrary to the visualization methods applied in other views, choropleth map display only one variable at a time. Consequently, CMV tools often use several layers of choropleth maps to present multivariate data. The variable required for T4 was portrayed on one of the map layers, but not the one enabled by default. Additionally, analysis of screen recordings revealed that participants who used the map for information extraction were unsure as to whether the units selected in the table were visible within the current extent of the map. They were panning the map to check the areas outside the map's display range, consequently resulting in a longer response time.

We also investigated whether there were any patterns regarding the way in which individuals interacted with the tested tools. Participants were classified as map, table and PCP-oriented in the SAA and confirmed by the TEA. Apart from T2, map, PCP and table-oriented users were distinguished by tasks. Participants' willingness to work with a particular visualization method in various task types supports Roberts's (2008) claim that users might find different methods better for data manipulation. Response times and accuracy did not differ for users who focused on different views and those who used only one view in a particular task, confirming Edsall's (2003a) conclusion that there is no difference in response accuracy between visualization methods. However, Edsall (2003a) examined PCP and scatterplot only, whereas we investigated map, PCP and table.

We further analysed how the use of visualization methods differed between stages of selection and information extraction for the five tasks. Only T2 resulted in a fairly homogenous users' attention, as all participants used the table for selection and information extraction. Although tables are often considered inconvenient and ineffective for

data display, data filtering and sorting implemented within the table made it preferable for many individuals. Koua *et al.* (2006), who tested map and PCP for similar tasks, found that individuals prefer the map and considered it suitable. However, those individuals were not offered a table for filter operations. A complex task, such as T5, was conducted mainly with the use of the PCP. Those who chose to use the table view for this task gave significantly more incorrect answers. The result confirms the usefulness of PCPs in the analysis of multivariable data (Edsall 2003a).

The participants were free to use any of the available visualization methods, allowing us to identify if participants avoided using the PCP. Although the use of PCPs is believed to be undesirable by people, our study suggests otherwise. Koua *et al.* (2006) reported that users working with PCP to solve the locate task (analogue to T1 in our study), required twice as much time as those who used the map for the same task. We concluded differently. The individuals classified in the SAA as map-oriented were not significantly faster than PCP-oriented participants. Participants willingly used the PCP, and we believe the efficient use of the PCP is a result of individuals being able to filter the PCP's polylines and dynamically brush them through other views. Furthermore, in T3, most participants were classified as PCP-oriented, i.e. they fixated most on the PCP, and the PCP was used by the majority of participants for object selection. This data filtering, implemented in the PCP, helped overcome its visual clutter (Heinrich and Weiskopf 2013). For T1 and T4, participants often selected data items in views other than the PCP. However, the dynamic linking implemented in the tool highlighted the selection in the PCP. Thus, selections made in other views overcame the visual clutter in the PCP and individuals frequently read the searched for information from the PCP. All these findings support Edsall's (2003b) claim that interaction techniques may remedy the negative effects of the visual clutter typical of PCPs. We therefore claim that tables as well as PCPs can be a handy way of displaying data even for simple tasks: if it is accompanied by interactive functions that help explore the data.

## 7. Conclusion

We examined the way in which people interacted with the CMV tool when they were free to use any of the three implemented visualization methods, even if they presented the same input data. It turned out that the individuals willingly worked with all the available visualization methods without any time cost for context switching. The freedom to choose a preferred visualization method (due to custom, experience, or just an on-the-spot decision) is the essential power of CMV tools. Different views were used in different ways by various participants, but they performed in a similarly efficient way. Such an outcome proves that integrating various visualization methods in a CMV tool can be more effective than using them separately.

Adequate interaction techniques are crucial to a CMV tool's effectiveness, even for visualization methods like PCP that is claimed to be challenging. A set of interaction techniques, for example, the ability to filter data and dynamically brush them through other views, made the PCP attractive to participants.

We hope that our results encourage a deeper investigation of how people interact with CMV tools. Having conducted an inquiry using simple visualization operation tasks that built up the process of data exploration, we have seen how three different



visualization methods were applied during the execution of five tasks. A further valuable investigation would be to study how users develop hypotheses (similar to e.g. Demšar 2007), without the predefined tasks, but still with the help of a CMV geovisualization tool. We believe that obtaining such knowledge will help identify issues and design solutions so that CMV geovisualization tools can be applied successfully.

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