CO-008

SELECTED ISSUES OF GEODATA UNCERTAINTY VISUALIZATION EFFICIENCY

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UNCERTAINTY VISUALIZATION – BACKGROUND AND OBJECTIVES

Uncertainty is one of potentially critical factors of geospatial data visualization. Users have tendency to accept the computer created maps as more reliable and usually do not take into account the original data quality, generalization, modelling, and other issues of the whole cartographic production cycle. Using geographic information systems for geospatial data collection, analysis, and visualization even raises the chance of data uncertainty or poor quality, when more data sources are combined with insufficient or no data quality metadata.

Efforts to develop visualization methods and tools that can help understand and cope with information uncertainty have been under way for almost twenty years but so far without a comprehensive understanding of the parameters that influence successful uncertainty visualization.

MacEachren (1992) presented three possibilities of uncertainty representation (visualization) to be used separately or in combination:

• Map pairs in which a data map is depicted side- by-side with a map of uncertainty about the data – we call this representation maps compared in accordance with Slocum et al. (2005).

• Bi-variate maps in which both the data of interest and the uncertainty estimate are incorporated in the same representation – we call these maps combined.

• Sequential representation in which user might be informed about uncertainty with an initial map which is followed by a map of data – this type of representation is sometimes called “interactive” (Slocum et al. 2005, Pang et al. 1997) and out of the framework of this paper.

The first and second types of representation are often called “static” thus applicable in digital and analogue (printed) form, the last representation is “dynamic” and can be effectively used only within digital environment.

Besides the representation issues there have also been proposed a number of methods to visualize thematic and positional uncertainty. MacEachren (1992) has suggested the use of Bertin’s graphic variables to depict uncertainty and proposed even specialised variables for depicting uncertainty including crispness, resolution, and transparency. Gershon (1998) grouped these into intrinsic and extrinsic visual variables depending on whether the variable is visually separable from the variable depicting the actual attribute. While extrinsic variables are separable, intrinsic variables are not. Another logical step is to describe how these variables including possible additions or modification, might be logically matched with different components of data uncertainty (Buttenfield 1991, MacEachren 1992, Leitner and Buttenfield 2000). MacEachren for instance stated that the graphical variables size and colour value are most appropriate for depicting uncertainty in numerical information, while colour hue, shape, and perhaps orientation can be used for uncertainty in nominal information. He also emphasised the colour saturation as important for uncertainty visualization. Saturation can be varied from pure hues for very certain information to unsaturated (light grey) hues for uncertain information. The role of graphical variables in mapping ecological uncertainty was further developed and documented by Buttenfield (2000).

MacEachren et al. (2005) specified that most research directed to uncertainty visualization had focused on developing representation methods (Pang et al. 1997, Hengel et al. 2004) software applications for the display of uncertainty (Haveulink et al. 2006), or on developing the uncertainty visualization theory (Pang 2001, Thomson et al. 2005). Much less has been done on the empirical evaluation and testing of use and usability. Based on their review and synthesis of literature on uncertainty visualization they identified seven core challenges requiring interdisciplinary efforts to be accomplished. One of these challenges deals directly with assessing the usability and utility of uncertainty representation and interaction methods and tools. Despite reasonable amount of work done in the field of uncertainty visualization testing (Evans 1997, Leitner and Buttenfield 2000), there is still a wide gap between the uncertainty visualization theory and widely accepted use of uncertainty representation with known effects on users. Hope and Hunter (2007a, 2007b) tested the effects of positional and attribute uncertainty on spatial decision making in both static and dynamic manners concluding that the method used to display uncertainty in spatial information can have extremely significant effects on decision making and that there exist subjective preferences for certain visual representations. They also strongly supported the need for further testing of visualization methods.

The influence of acute stress on cognitive processes and map reading was studied by Stachon et al. (2010), who concentrated on understanding the stress mechanism and its influence on particular cognitive functions, such as short-term and long-term memory, attention, perception, and decision making. They further explored possibilities and methods for testing the usability of maps and validated results by statistical analysis tools using a combination of quantitative and qualitative methods.

APPROACH AND METHODS

Following our previous work where we dealt with perception of different cartographic representation (Stachon et al. 2010) and testing of cartographic adaptation (Kubicek and Kozel 2010) we decided to focus on two static uncertainty visualization approaches – the maps compared and maps combined – and test their usability issues and user's ability to effectively cope with them.

We used soil sampling data originally collected and interpreted by Lukas et al. (2009, 2010) for visualization purposes. Soil depth samples were collected in irregular grids, in which the points have been selected subjectively.

A combination of regular kriging interpolation method and interpolation uncertainty values is used for maps compared. Both variables (soil depth and uncertainty) are visualized using the hue saturation graphic variable (see fig.1) and lighter values are used for higher uncertainty. Kriging is widely recommended for uncertainty visualization because this method not only generates estimated field values (soil depth) at unsampled locations, but also provides information about their error variances (Zhang and Goodchild 2002). These properties are further explored as a source of uncertainty and used for alternative visualization source data.

Alternative approach is applied for maps combined. Whitening is a visualization method based on the hue-saturation-intensity (HSI) colour model and is supposed to be psychologically appealing (Jiang 1996) when hue is used to visualize values of thematic space and whiteness (paleness) is used to visualize uncertainty. A 2D legend was designed to accompany the visualisations. Unlike standard legends for continuous variables, this legend has two axis: (1) vertical axis (hues) is used to visualise the predicted values and (2) horizontal axis (whiteness) is used to visualise the prediction error (Hengel 2007).

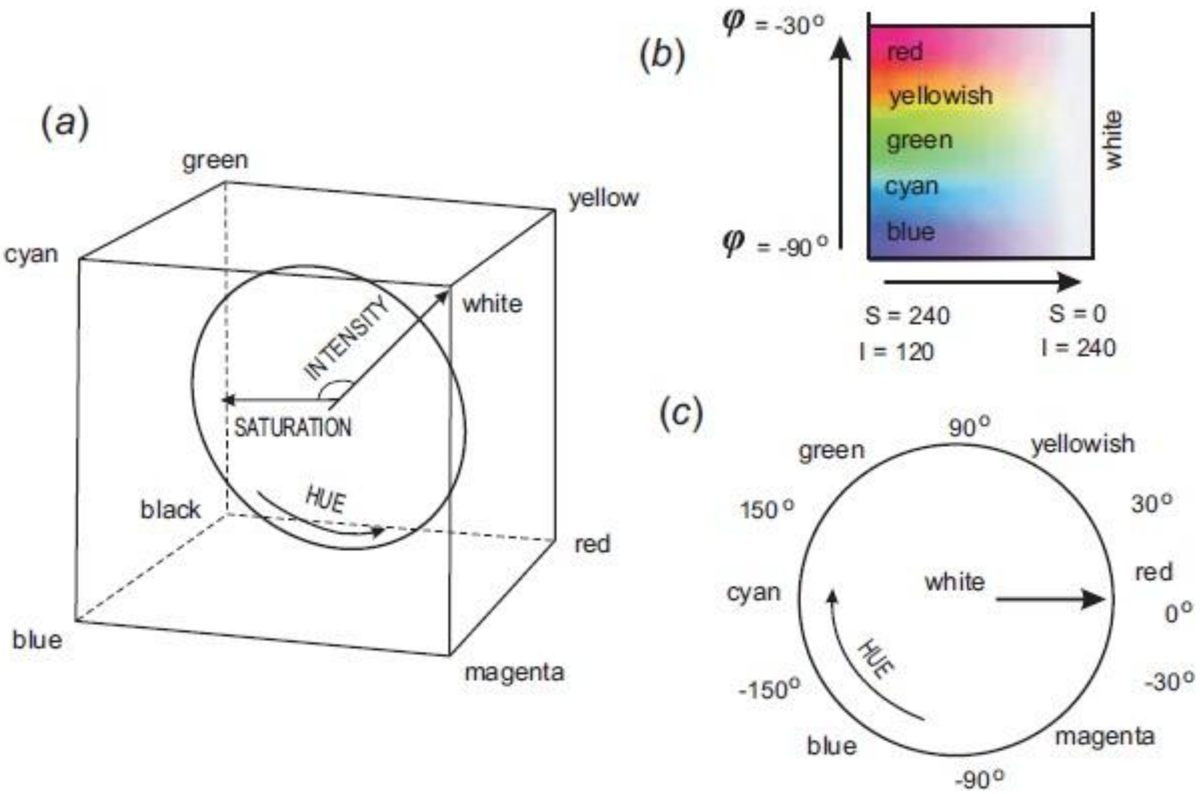


Fig. 1: Design of special 2D legend to visualize maps combined using whitening: (a) the HSI colour model, (b) the 2D legend and (c) the common types of Hues. Adopted from Hengel (2007)

The cognitive abilities of users are closely connected with psychology. Therefore besides the usability of uncertainty representation we also dealt with the question which cognitive processes are involved within the map reading and what causes the possible differences in the achievements. In the field of cognitive science is discussed always if human mind is capable of parallel processing of information and above all experimental techniques and tasks are explored which allow to distinguish between serial and parallel processes (see Snodgrass and Townsend, 1980, Egeth and Dagenbach, 1991, Townsend and Fifić, 2004). Townsend and Fifić (2004) argued in context of human memory research that „serial models assume that within the short-term memory search task, each item in memory is compared with the target in sequence, so that a comparison on an item must be completed before the next comparison can begin. Parallel models assume, in contrast, that all items are compared with the target simultaneously, although comparisons on different items can be finished at different times".

It might be expected that tasks on the maps performed in our study will evoke differences in the way of information processing. Serial processing of information is expected for maps compared, where map user is forced to decode the predicted value, maintain this information within memory and consequently identify uncertainty level at the corresponding spatial location of second map. Both comparison and synthesis processes are being performed. On the other hand, the second method (maps combined, whitening) offers both variables in the same place and the user has all information available at the same moment. This configuration makes possible the parallel processing of information.

Testing environment

The formalization of cartographic knowledge usually involves some kind of empirical research like interviews or text analysis, which is in most cases very tedious and time-consuming. Since no multidisciplinary environment enabling both cartographic inputs and psychological measurement and testing is currently available, an interactive web based testing tool (GP Test) was designed and an early prototype developed. The tool was devised in order to test a wide variety of inputs from isolated cartographic symbols or symbol sets to complex map compositions both static and interactive.

Application core was developed above the framework of Google Web Toolkit and the cartographic part relies on Open Layers libraries. Overall architecture consists of three basic modules – client, server, and database. The client module communicates with server site and its GUI works within standard web browsers (IE, Firefox). Server module processes the client requirements and returns demanded data or information.

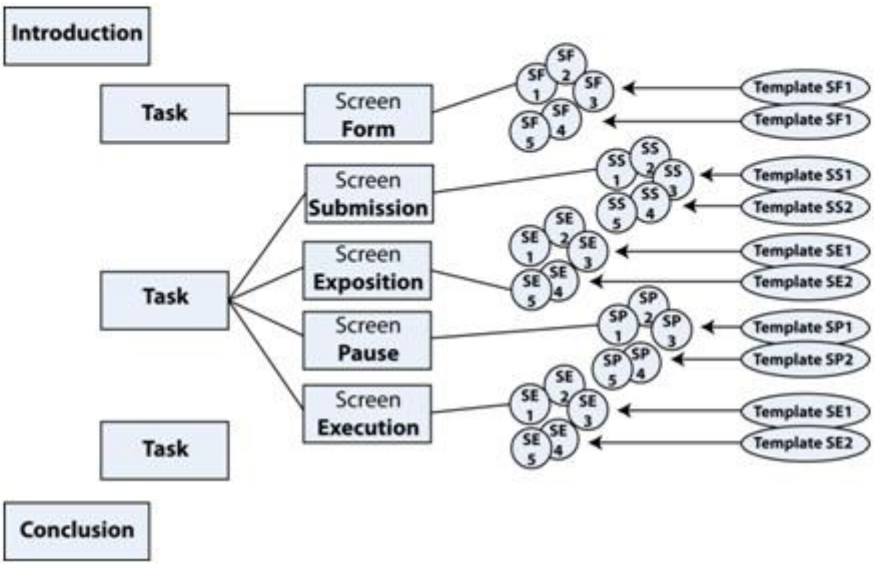


Fig. 2. General schema of usability testing - GP Test templates (adapted from Kubicek and Kozel 2010).

Individual tests are stored in database and consist of tasks and scenes (Fig.2). Each task embraces at least one scene but usually four scenes in a standardised sequence – assignment, exposure, pause, and realization. Each scene is based on XML template supplemented by the specific scene content. Both template and content together constitute the graphic interface. Map compositions can be possibly defined by three different types of cartographic inputs - Google Maps (standard topographic and street map, satellite and aerial images, hybrid map), WMS sources, and static images substituting the analogue map composition.

Basic test functionality includes the test person identification and pre-test calibration of individual computer and cartographic abilities. Within the test environment there are three basic types of tasks – forms with pull-down menus with predefined testing answers; visual choice scenes, where the test person is forced to choose one or more possibilities of visual variables; and localisation tasks, where the test person must place the symbol to the right position or draw the line or polygon of certain task. After choosing an appropriate test, the overall content is downloaded from the server to the client site and initialized. The test person passes the tasks and each interaction (mouse click) is recorded on the event log. Both reaction times and positional accuracy are stored and further processed. The technological background of the system is further described in Kubicek and Kozel (2010).The test results are stored within PostgreSQL and further exported via exporting module as *.csv files for statistical processing.

Testing methods

Both above mentioned methods were tested on three different levels. On the first level the intuitiveness of whitening method was questioned visualized as map combined (fig.3). Users were asked to mark the area with the highest uncertainty level. Our intention was to test whether the association between uncertainty and paleness (see Jiang 1996 and Hengel et al. 2004 for comments) is really intuitive or not without prior knowledge of uncertainty visualization methods. Map legend was simplified in order to inform about visualized variables (soil depth, uncertainty) but not about the scale and order.

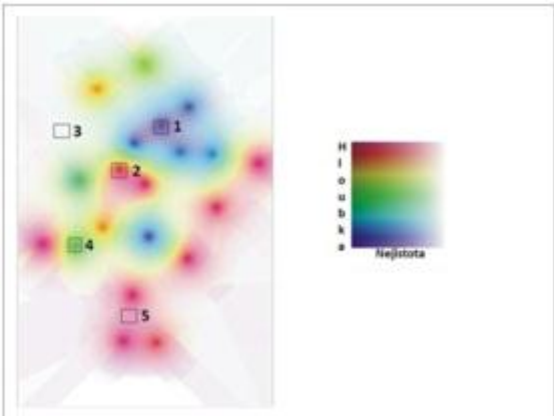


Fig.3: Uncertainty visualization intuitiveness

In the following section users were informed about the basic principles of uncertainty visualization and both methods (maps combined and maps compared) were presented together with examples and legend.

On the second level both visualization methods were compared starting with map compared followed by map combined. Testers were asked to mark the polygon exceeding certain level of soil depth (50 centimetres), the uncertainty level (70 %), and find the combination of certain soil depth and uncertainty at the same time (more than 70 cm and 40 %). These cases were tested in 6 successive tasks – two for each case.

Tests were focused on the following user's abilities:

- uncertainty level decoding (soil depth uncertainty);
- simple decoding of predicted value (soil depth interpolation results);
- comparison of combined values (both soil depth and uncertainty, fig.4).

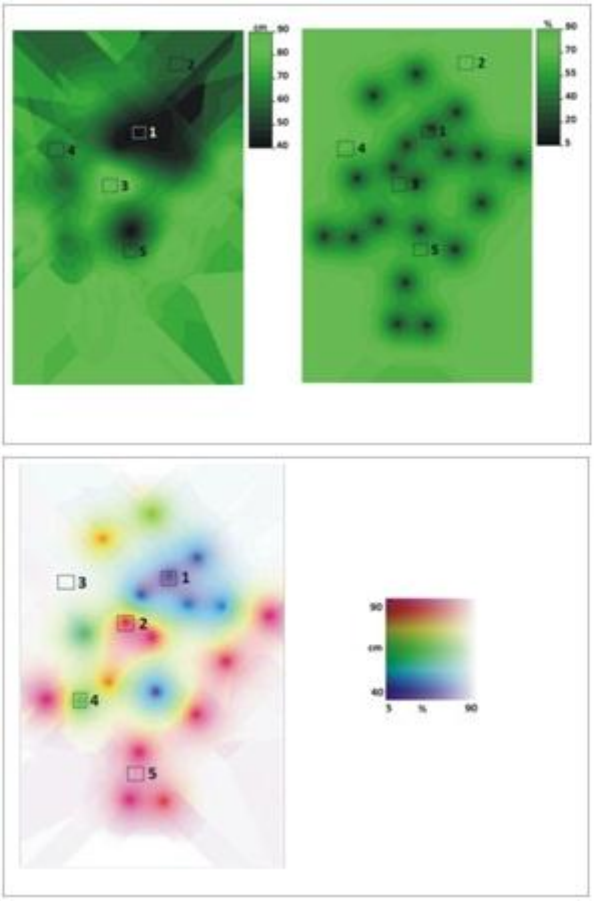


Fig.4: Examples of visualizations for both value and uncertainty testing for maps compared (left) and maps combined (right).

While the tested level of soil depth and uncertainty was identical for both visualization types, the placement of testing polygons was different both for tasks and visualization methods. Correctness and processing time was recorded in order to enable further statistical processing.

Test participants

There were three different groups of test participant. The first group was composed of 15 students of university of defence (aged 19 – 23) with just a basic background in the field of spatial information. The second group was created by 39 geography and geoinformatics students (aged 19 – 23) with intermediate skills in the field of spatial information. Both student groups were relatively homogeneous as for age and skills. The third group of 50 participants was tested within the “open door day” and is heterogeneous both from the age (15 – 61) and education (spatial skills) point of view. Gender of participants was also recorded; the group was relatively well balanced in this respect – 63 males and 41 females in total.

RESULTS

Results gathered during the tests were processed and statistically tested. T-test for independent samples was used for the first level, while paired Student's t-test or Wilcoxon signed-rank test were used for the second level of samples. The Wilcoxon signed-rank test was used as an alternative to the paired Student's t-test when the samples were not normally distributed.

Results on the first level of testing (intuitiveness of uncertainty visualization with HSI method) confirmed, that more participants (63 %) acknowledged the lighter value to be more uncertain. Those preferring this result were also quicker and were able to decide within more condensed time variability (fig. 5). However the results were not confirmed as statistically significant either for the homogeneous or for the heterogeneous groups.

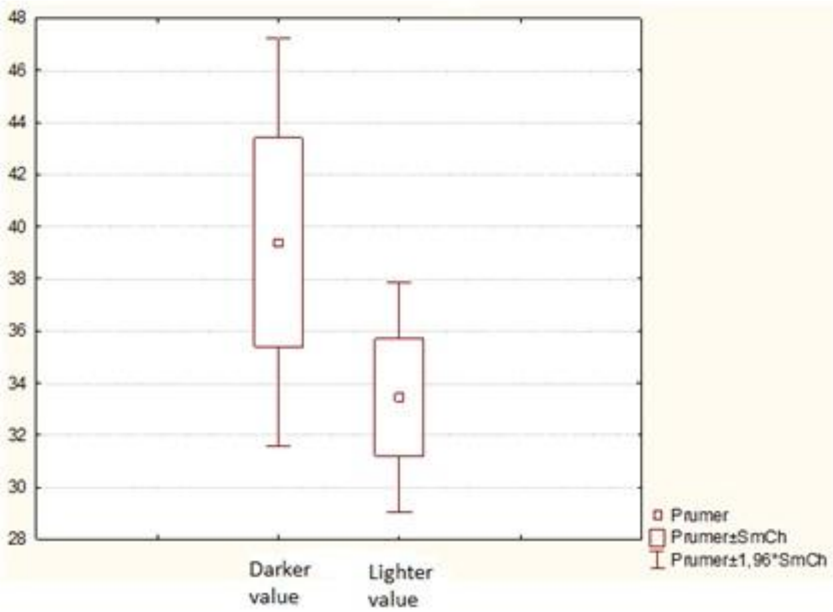


Fig.5: Box plots of uncertainty intuitiveness decoding (explanation in text).

Results on the second level of testing can be divided according to the tested variables. For simplification only correct answers were taken into account, thus a pair comparison for both methods (maps combined and maps compared) is always available. As for uncertainty level decoding there were significantly better results for maps combined (whitening) than for maps combined. This result is valid both for homogeneous groups (group 1 and 2) and for heterogeneous group (1-3 together, fig.6).

Decoding of predicted value testing (soil depth) brought slightly better results for maps combined (whitening) but without statistical significance. Again this is valid for both three tested groups if considering only correct answers. It is arguable whether slightly better results for whitening method are conditioned by the fact, that test participants had faced the whitening method within the first level testing.

The last part of testing dealt with comparison of combined values (both soil depth and uncertainty at the same time) and was the most controversial as far as the correct answers are concerned. Only 43% were correct for both methods at the same time. 64% correct answers were valid for maps compared and 56% for maps combined (see discussion for further details). Significantly better results were achieved by whitening methods, participants were not only quicker, but also more confident about the result – the standard deviation was only ½ in comparison to maps compared (fig. 7). The significant results were valid even if we took into account only 1 correct answer for a pair.

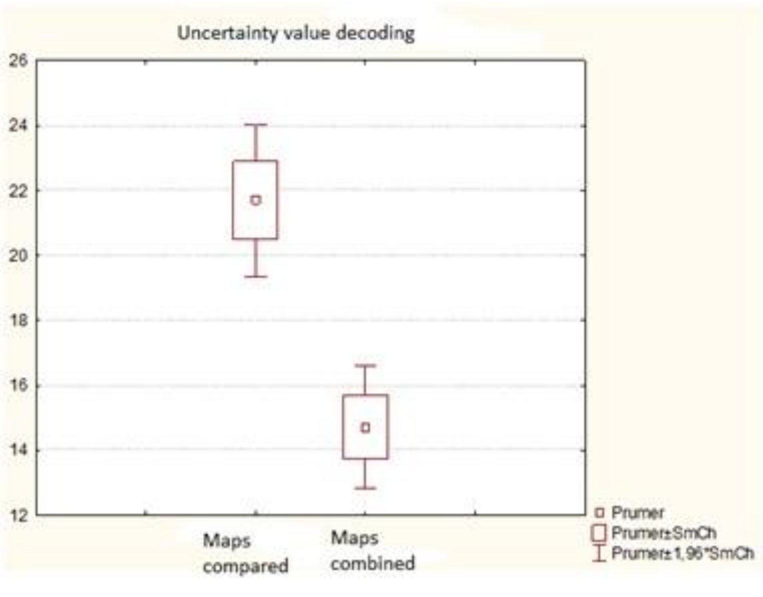


Fig.6: Box plot of uncertainty comparison for maps combined and maps compared.

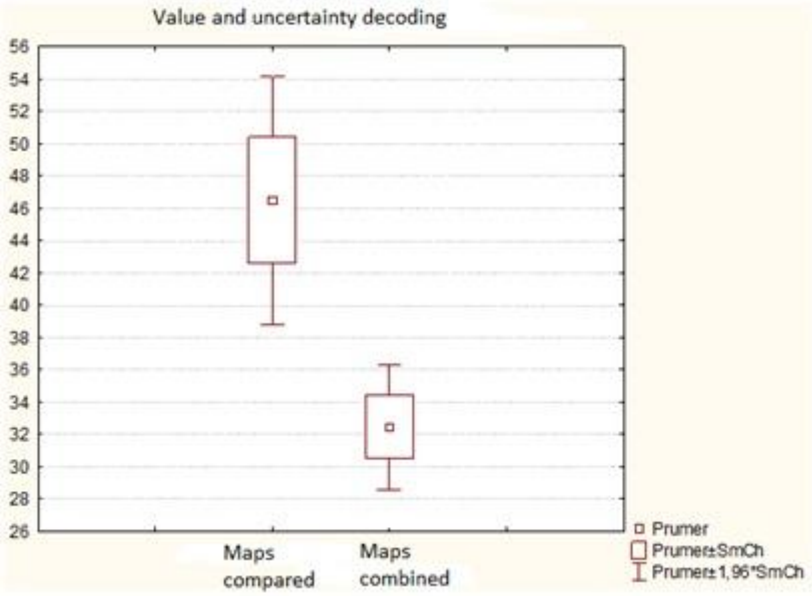


Fig.7: Box plot of combined value comparison for maps combined and maps compared.

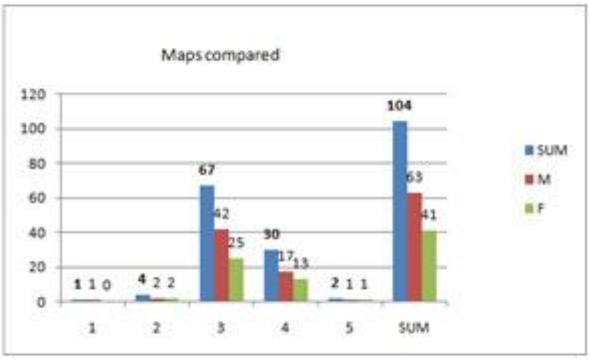
DISCUSSION

Leitner and Buttenfield (2000) recommended symbolization schemes for correct decision and proposed graphic variable value as the most appropriate and also supported the idea that more certain information should be visualized by lighter value. They were aware of the fact that this result appears to be counterintuitive, since darker value has been repeatedly suggested for the depiction of more certain information because it is perceived by map reader as being more prominent. Lighter value, on the contrary, is perceived as being less prominent (MacEachren, 1992). However they saw the main reason for this conflict in different testing environments and quoted, that the original MacEachren's assumption is correct if certainty information is depicted on printed paper and colours are perceived by reflected light. On a computer screen, however, where colours are perceived with emitted light the results might be reversed. Results achieved by our test (performed purely in digital environment), however have not verified their conclusions. Because of the statistical non-significance we can only state, that the use of light value for more uncertain information as proposed by MacEachren is more probable according our preliminary results.

Comparison of both methods – maps combined and maps compared – did not reveal significant differences for simple decoding of predicted value (soil depth). We can thus expect that there is no difference whether we use lighter-darker value for prediction (as in case of maps compared) or different hues across the spectrum (as in case of whitening). This assumption has not been significantly approved yet.

Another result to be discussed deals with response times of tested subjects on different complexity of information. Leitner and Buttenfield (2000) quoted that adding attribute information of any kind should slow down subject response times. However, adding attribute certainty did not increase response times in their original research. No significant differences in response times were found in comparing one class maps with attribute certainty maps. This finding implied that map readers do not assimilate attribute certainty in the same way as they assimilate added map detail. Inclusion of certainty information appeared to clarify the map patterns without requiring additional time to reach a decision. Fastest response times were discovered for certainty maps showing saturation, thus if a fast decision is the highest priority, attribute certainty should be symbolized by more pastel colours.

As for serial and parallel processing results – serial is more time consuming but gave better quality results (67 of 104 correct answers, 64%, fig. 8a). Parallel thinking for whitening method gave significantly better results as for the speed, but was less correct for answers (only 59 of 104 correct answers, 56%, fig. 8b). In both cases there were 5 possible answers within the test with only one correct – no.3 for maps compared and no.5 for maps combined. However, there were always secondary "champions" for test participants with close-to-correct-answers results – no.4 for maps compared (29% of answers) and no.4 for maps combined (26% of answers).



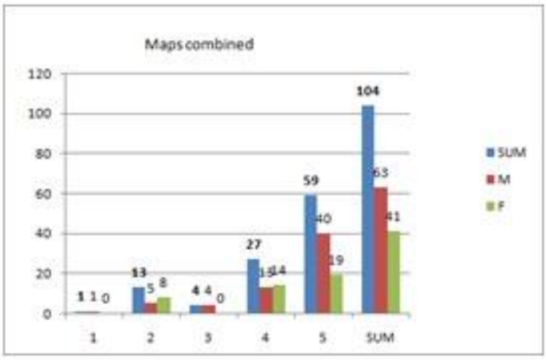


Fig.8: Correct answers for serial (maps compared) and parallel (maps combined) processing.

CONCLUSIONS AND FUTURE PLANS

Testing results confirmed the importance and relevancy of empirical testing and brought some preliminary results about the two basic uncertainty visualization techniques – maps compared and maps combined. According to our results there exist significant differences for both methods when decoding uncertainty, value, and both at the same time. The results presented within this article are still of a preliminary level and serve as a base for further exploration both for statistical processing and more extensive psychological testing of uncertainty visualization. It can be concluded that the whitening technique is not appropriate for direct decoding (reading) of interpolated values because of a complex legend where people with even minor colour sense malfunction are not able to recognise correct value of uncertainty.

Testing web based environment has proven its usability and will serve as a basic tool for ongoing research. Uncertainty visualization test presented here are still available for more extensive users' group testing and possible incorporation of other cartographic issues within the test environment.

Although the research population was large enough and homogenous, it could be not passing over the limitation by the interpretation of results. Our tasks which were focused on the users work with uncertainty were included in more complex test with others cartographic and psychological tasks. The number of the single items in the task was limited for this reason. More items in the tasks can aver possible risk that unexpected intervening variables (e.g. impact of learning, distribution of correct answers in the map field) will affect the results. It is suitable to increase the number of items in the future research.

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REFERENCES

Brown, J.D. and Heuvelink, G.B.M. (2007): The Data Uncertainty Engine (DUE): A software tool for assessing and simulating uncertain environmental variables. Computers & Geosciences, 33(2): 172-190.

Buttenfielf, B. (2000): Mapping ecological uncertainty. in Hunsaker, C.T., Goodchild, M.F., Friedl, M. A., and Case. T. J. (eds.) Spatial Uncertainty in Ecology. New York: Springer-Verlag: 116- 132.

Egeth, H., Dagenbach, D. (1991): Parallel versus serial processing in visual search: Further evidence from subadditive effects of visual quality. Journal of Experimental Psychology: Human Perception & Performance, 17(2): 551-560.

Gershon, N. (1998): Visualization of an imperfect world. Computer Graphics and Applications, 18(4): 43 – 45.

Hengel, T., Heuvelink, G., Stein, A. (2004): A generic framework for spatial prediction of soil variables based on regression-kriging. Geoderma, 120: 75–93.

Hengl, T. (2007): Practical guide to geostatistical mapping. JRC Ispra, 143 p.

Heuvelink, G.B.M. (2002): Analysing uncertainty propagation in GIS: why is it not that simple?. In: G.M. Foody and P.M. Atkinson, Editors, Uncertainty in Remote Sensing and GIS, Wiley, Chichester, pp. 155 – 165.

Heuvelink, G.B.M., Brown, J.D., Van Loon, E.E. (2006): A probabilistic framework for representing and simulating uncertain environmental variables. International Journal of Geographic Information Science, 21(5): 497-513.

Hope, S., Hunter, G.J. (2007a):Testing the effects of positional uncertainty on spatial decision-making. International Journal of Geographical Information Science, 21(6): 645 – 665.

Hope, S., Hunter, G.J. (2007b): Testing the effects of thematic uncertainty on spatial decision-making. Cartography and Geographic Information Science, 34 (3): 199 - 214.

Jiang, B. (1996): Fuzzy overlay and visualization in GIS. PhD thesis, Utrecht University, The Netherlands.

Kubíček, P., Kozel, J.(2010): Cartographic techniques for adaptive emergency mapping. In Kremers, H., Susini, A. (eds.): Risk Models and Applications. Lecture Notes in Information Science Berlin : CODATA-Germany, p. 49 – 62.

Leitner, L., Buttenfield, B. (2000): Guidelines for the display of attribute certainty. Cartography and Geographic Information Science, 27(1): 3-14.

Lukas, V., Neudert, L.(2010): Soil pH sampling optimization using ancillary data. In Wery, J., Shili-Touzi, I. and Perrin, A. Proceedings of "Agro2010 the XIth Esa Congress", Montpellier, France: Agropolis International Editions, p. 237-238.

Lukas, V., Neudert, L., Kren, J. (2009): Mapping of soil conditions in precision agriculture. Acta Agrophysica 2009, 13(2): 393-405.

MacEachren, A. (1992): Visualizing uncertain information. Cartographic Perspectives, 13: 10-19.

MacEachren, A., Robinson, A., Hopper, S., Gardner, S., Murray, R., Gahegan, M., Hetzler, E. (2005): Visualising geospatial information uncertainty: What we know and what we need to know. Cartography and Geographic Information Science, 32(3): 139 – 160.

Montello, D.R. (2002): Cognitive map-design research in the twentieth century: Teoretical and empirical approaches. Cartography and Geographic Information Science, 29(3): 283–304.

Pang, A. (2001): Visualizing uncertainty in geo-spatial data. In: Proceedings of the Workshop on the Intersections between Geospatial Information and Information Technology. National Academies Committee of the Computer Science and Telecommunications Board, Washington, D.C.

Pang, A. (2008): Visualizing Uncertainty in Natural Hazards. Risk, Governance and Society, 2008, 14: 261-294

Pang, A., Wittenbrink, T., Lodha, K. (1997): Approaches to uncertainty visualization. Visual Computer, 13: 370-390.

Slocum, T. A., Blok, C., Jiang, B., Koussoulakou, A., Montello, D. R., Fuhrmann, S. and Hedley, N. R. (2001): Cognitive and Usability Issues in Geovisualization. Cartography and Geographic Information Science, 28: 61-75.

Slocum, T., McMaster, R., Kessler, F., Howard, H.(2005): Thematic Cartography and Geographic Visualization. Prentice Hall, New Persey, 576 p.

Snodgrass, J. G., Townsend, J. T. (1980): Comparing parallel and serial models: Theory and implementation. Journal of Experimental Psychology: Human Perception & Performance, 6(2): 330-354.

Stachoň, Z., Šašinka, C., Talhofer, V. (2010): Perception of various cartographic representations under specific conditions. In Konecny, M., Zlatanova, S., bandrova, T.L. Geographic Information and Cartography for Risk and Crisis Management; Towards Better Solutions. Berlin Heidelberg : Springer, 446 p. Lecture Notes in Geoinformation and Cartography.

Thomson, J., Hetzler, B., MacEachren, A., Gahegan, M., Pavel, M.(2005): Typology for visualizing uncertainty. In: Visualization and Data Analysis, 5669 : 146 – 157.

Townsend, J., Fifić, M. (2004): Parallel versus serial processing and individual differences in high-speed search in human memory. Perception and Psychophysics, 66(6): 953-962.

Wachowicz, M., Vullings, W., Bulens, J., de Groot, H., van den Broek, M.(2005): Uncovering the main elements of geo-web usability. In: F. Toppen, M. Painho (eds.). Proceedings of the 8th AGILE Conference on Geographic Information Science. Wageningen: Centre for Geo-Information.

Zhang, J., Goodchild, M. (2002): Uncertainty in Geographical Information.Taylor and Francis, Inc., London, 266 p.