The Cognition of Change: Scaling Deformations in Mind and Spatial Theories

Jinlong Yang\textsuperscript{1}, Alexander Klippel\textsuperscript{2}, Rui Li\textsuperscript{3}

\textsuperscript{1}Department of Geography, San Diego State University, San Diego, CA, USA
\textsuperscript{2}Department of Geography, The Pennsylvania State University, University Park, PA, USA
\textsuperscript{3}Department of Geography and Planning, State University of New York at Albany, Albany, NY, USA
jinlong.yang@mail.sdsu.edu, klippel@psu.edu, rli4@albany.edu

Corresponding address:

Jinlong Yang
305A Storm Hall
Department of Geography, San Diego State University
5500 Campanile Dr. San Diego, CA 92182, USA
Abstract. The dynamics of the earth and its inhabitants have become a core topic and focus in research in the spatial sciences. The spatio-temporal data avalanche challenges researchers to provide efficient and effective means to process spatio-temporal data. It is of vital importance to develop mechanisms that allow for the transition of data not only into information but also into knowledge. Knowledge representation techniques from artificial intelligence play an important role in laying the foundations for theories dealing with spatio-temporal data. Specifically, the advances in the area of qualitative spatial representation and reasoning (QSTR) have led to promising results. Categorical distinctions of spatio-temporal information identified by QSTR calculi potentially correspond to those relevant to humans. This article presents the first behavioral evaluation of qualitative calculi modeling geographic events associated with scaling deformations of entities, that is, changes in size by either expansion or contraction. Examples of such dynamics include a lake flooding its surroundings or an expanding oil spill in the ocean. We compare four experiments using four different semantic domains. Each domain consists of two spatially extended entities: One entity is undergoing scaling deformations while the other is static. We kept the formal (QSTR) characterization, which are paths through a topologically-defined conceptual neighborhood graph (CNG), identical across all semantic domains. Our results show that for geographic events associated with scaling-deformations a) topological relations are not equally salient cognitively; b) domain semantics has an influence on the conceptual salience of topological relations.

Keywords: topology, spatial cognition, scaling deformation, conceptualization, geosemantics
1. **Introduction**

Humans are embedded in dynamic, spatial environments. Dealing with spatio-temporal information is therefore a fundamental task that is omnipresent in daily lives. Technologies such as GIS have been developed to assist humans in processing spatio-temporal information. Formalisms designed for these technologies, however, tend to characterize space in quantitative ways while humans tend to conceptualize space in qualitative ways, which creates a gap in the interaction between human users and technical systems. This gap has been identified as being a critical barrier to advance spatial information theories (Galton 2003; Mennis, Peuquet, and Qian 2000; Robinson 1990). Incorporating theories from cognitive information processing into spatial information systems is a crucial step toward developing intelligent tools that allow human users to interact with systems in a more intuitive way. Seamless user interaction should be one of the key features in next-generation/current GIS (Egenhofer and Mark 1995b).

In response to this challenge, many formalisms have been developed to emulate how natural cognitive agents process spatio-temporal information (for an overview see: Cohn and Renz 2008). However, there are surprisingly few behavioral studies evaluating the cognitive adequacy of these formalisms (for overviews see: Klippel et al. 2013; Mark 1999). The importance of evaluating the cognitive adequacy of formalisms cannot be overestimated as these formalisms are often expected to enable an intuitive communication between machines and human users in terms of spatio-temporal information but are often developed based on researchers’ intuition or formal constraints.

Theories from cognitive science provide us with insights into various aspects of how natural cognitive agents process spatio-temporal information such as the particular focus on endpoints of movement patterns (Regier and Zheng 2007), factors that influence
the segmentation of continuous events (Shipley 2008), and how natural language terms are related to particular spatial relations (Egenhofer and Shariff 1998; Mani and Pustejovsky 2012; Mark and Egenhofer 1994; Zhan 2003). However, experimental results from studies in the psychological sciences are not necessarily applicable to evaluate formal approaches in the spatial sciences. This article addresses this issue by comparing artificial and natural cognitive spatio-temporal information processing directly.

The remainder of this article is structured as follows: The Background section details related work and introduces the basis of our experiments. The Methods section describes the design as well as the procedure of our four experiments. Several analyses are presented in the Results section followed by a Discussion and Future Work section.

2. Background

Topology is one of the most prominent formal theories that is acknowledged by the label cognitive adequate. Brugman and Lakoff (1988), for example, note that “The topological properties of the concepts [over] are necessary to characterize ‘image-schema transformations’ in terms that are cognitively natural, rather than in terms of an arbitrary calculus.” (p. 479). Many topology-based spatial calculi have been developed in QSTR. Among these calculi, two are arguably the most prominent ones: Intersection Models (IMs) by Egenhofer and Franzosa (1991) and the Region Connection Calculus (RCC) by Randell, Cui, and Cohn (1992).

Although these two approaches use different theoretical frameworks that IMs are based on point set theory while RCC uses regions as its atomic elements, both agree on eight basic topological relations when applied to region-region relations. These relations can be used to characterize static as well as dynamic spatial relations (Muller 2002),
which is an important aspect for this article.

To formally reason changing topological relations, it is helpful to introduce conceptual neighborhood graphs (CNG) (Cui, Cohn, and Randell 1992; Egenhofer and Al-Taha 1992; Freksa 1992). In Cohn’s (2008) definition of conceptual neighborhoods, two relations, $R_1$ and $R_2$, are conceptual neighbors if it is possible for $R_1$ to hold over a tuple of objects at a certain point in time, and for $R_2$ to hold over the tuple at a later time, with no other (third) mutually exclusive relation holding in between.

A number of behavioral studies have been conducted to shed light on the cognitive adequacy of these two topological calculi (For overview see: Klippel et al. 2013; Mark 1999). None of these studies, however, have addressed scaling deformations, which are the focus of this article. Thus, we keep the review short. Egenhofer and Max (1995a) conducted experiments on the cognitive adequacy of the 9-intersection model for modeling line-region (a road and a park) relations. Their results indicate that the 9-intersection model forms a sound basis for modeling the cognitive conceptualization of spatial relations between a road and a park. Knauff and collaborators (1997) investigated the conceptualization of static relations between two regions and concluded that the eight topological relations defined in both Intersection Model and RCC-8 appear cognitively relevant. Research by Klippel and Li (2009) centered on the conceptualization of translation movements (e.g., a hurricane crossing a peninsula). Their results revealed that not all topological relations are equally salient in dynamic situations such as translation movements. In a follow up study Klippel (2012), showed that this saliency is also changing depending on the semantics of the domain (e.g., whether the moving entity is a boat or a hurricane).

One of the important aspects for the research reported in this paper is identifying critical information in dynamic spatial processes to advance understanding of cognitive
conceptualizations. Research from the cognitive sciences shows that, in both perception and language, endpoints of spatial motion events are privileged over starting points (Regier and Zheng 2007; see also Klippel and Li 2009). Other theories from psychology, such as the peak-end rule (Do, Rupert, and Wolford 2008) and the recency effect (Murdock Jr 1962) also indicate that not the starting but the ending phase of experiences or more recent experiences are more influential in judgments about current situations/events. Hence, the dynamics (here, scaling deformations) we are focusing on in this article are distinguished on the basis of the topological relations that two involved entities end in.

Figure 1. Left: RCC-8 / IM based conceptual neighborhood graph (CNG). Right: scenes showing a sequence of topological equivalence classes that potentially capture salient discontinuities in a flooding event.

Figure 1 shows a CNG applied to characterize one of the geographic events used in our experiments (further details are provided below). On the left side, five topological relations between two spatially-extended entities are organized into a CNG. Assuming the initial relation between two entities, $A$ and $B$, is disconnected (DC), and that $B$ can only contract after it fully envelopes $A$, nine topological equivalence classes can be
distinguished based on the corresponding paths with different ending relations through the CNG. While it would be possible for entity $B$ to contract at any stage of the scaling deformation, we simplified the scenario by considering contraction only after entity $B$ fully envelops entity $A$. Hence, the nine topological equivalence classes are (see Figure 1: $t_1$ to $t_9$):

Ending relation: $DC1$;
CNG path: $DC (t_0-t_1)$;

*The lake stops expanding before it touches the house.*

Ending relation: $EC1$;
CNG path: $DC – EC (t_0-t_2)$;

*The lake stops expanding when it reaches the edge of the house.*

Ending relation: $PO1$;
CNG path: $DC – EC – PO (t_0-t_3)$;

*The lake stops expanding when it engulfs part of the house.*

Ending relation: $TPP1$;
CNG path: $DC – EC – PO – TPP (t_0-t_4)$;

*The lake stops expanding when the house is fully enveloped by the lake (the edge of the house is attached to the shoreline of the lake).*

Ending relation: $NTPP$;
CNG path: $DC – EC – PO – TPP – NTPP (t_0-t_5)$;
The lake stops expanding when the house is fully enveloped by the lake (the edge of the house is not attached to the shoreline of the lake).

Ending relation: TPP2;
CNG path: DC – EC – PO – TPP – NTPP – TPP (t₀-t₆);

The lake first expands until the house is fully enveloped, and then contracts until it reaches the relation of TPP for the second time.

Ending relation: PO2;
CNG path: DC – EC – PO – TPP – NTPP – TPP – PO (t₀-t₇);

The lake first expands until the house is fully enveloped, and then contracts until it reaches the relation of PO for the second time.

Ending relation: EC2;
CNG path: DC – EC – PO – TPP – NTPP – TPP – PO – EC (t₀-t₈);

The lake first expands until the house is fully enveloped, and then contracts until it reaches the relation of EC for the second time.

Ending relation: DC2;
CNG path: DC – EC – PO – TPP – NTPP – TPP – PO – EC – DC (t₀-t₉);

The lake first expands until the house is fully enveloped, and then contracts until it reaches the relation of DC for the second time.
To summarize, comparable to more frequently employed translation movements, scaling deformations of entities and resulting changes in spatial relations between entities can be characterized as paths through a CNG.

To the best of our knowledge, no previous behavioral research has investigated how formal spatial information theories of topological calculi relate to cognitive conceptualizations of scaling deformations. This is in contrast to the omnipresence of this type of earth dynamics found in events such as flooding, glacier development, or desertification.

Additionally, contextual influences, for example, on the use of prepositions, have been identified in theories such as the extra-geometric functional framework by Coventry and Garrod (2004). Coventry and Garrod considered extra-geometric information as an equally important component in defining the correct use of prepositions as the geometry itself. Research by Lautenschütz and collaborators (2007) found that the aggregate state of objects (e.g., solid versus liquid) involved in a spatial relation influences the use of spatial language. While context effects have demonstrated significant influence on the cognitive conceptualization of spatial relations, they, too, have not received much attention in studies evaluating the cognitive adequacy of QSTR calculi.

Hence, the research questions addressed in this article can be summarized as follows: First, can we identify salient topological relations in the conceptualization of scaling deformations in geographic events? Second, do these saliencies change if the semantic domain changes? Given that there is currently no theory for predicting how the saliencies of topological relations might change across different semantic domains, we chose a geometric-based experiment with abstract figures as a baseline and compared it to three semantic experiments in which certain relations could be either neutral or negative:
- A gray circle scaling in relation to a black diamond shape area (geometric experiment);
- A desert scaling in relation to a recreational park (desert experiment);
- A lake scaling in relation to a house (lake experiment);
- An oil spill scaling in relation to an island (oil spill experiment);

3. Methods

3.1 Participants

20 participants were recruited for each experiment (i.e., 80 participants in total) from introductory level geography courses at The Pennsylvania State University. All participants were reimbursed $10 for their participation. Each participant was assigned to work on only one of the four experiments. To ensure that participants were clearly aware of the semantics of the experiment they worked on, we checked the linguistic descriptions provided by each participant, and consequently recruited 14 new participants to replace 14 participants who did not mention the correct entities in their description. The numbers of females in the four experiments are: five (desert), seven (lake), eight (oil spill), and ten (geometric); average age is 21.5 (desert), 19.7 (lake), 20.6 (oil spill), and 20.6 (geometric), respectively.

3.2 Materials

A set of animated icons was designed for each experiment using Adobe Flash 8 (see Table 1 for details):
Table 1. Four sets of animated icons used in four experiments: a desert expending in relation to a recreational park, a lake expending in relation to a house, an oil spill expending in relation to an island, and a gray circle expending in relation to a black diamond.

<table>
<thead>
<tr>
<th>Experiment</th>
<th>Sample Icon</th>
<th>Dynamic Entity</th>
<th>Reference Entity</th>
</tr>
</thead>
<tbody>
<tr>
<td>Desert</td>
<td>![Desert Icon]</td>
<td>A desert area</td>
<td>A recreational park (symbolized by a letter ‘R’ which is enclosed by a red boundary)</td>
</tr>
<tr>
<td>Lake</td>
<td>![Lake Icon]</td>
<td>A lake</td>
<td>A house</td>
</tr>
<tr>
<td>Oil</td>
<td>![Oil Icon]</td>
<td>An oil spill</td>
<td>An island</td>
</tr>
<tr>
<td>Geometric</td>
<td>![Geometric Icon]</td>
<td>A gray circle</td>
<td>A black diamond</td>
</tr>
</tbody>
</table>

For each experiment, 72 animated icons were created for the nine unique paths detailed in the Background section (i.e., eight animated icons for each unique path). All icons were 120 by 120 pixels in size. Within each animated icon, there was a dynamic (scaling) entity and a reference entity. The reference entity (e.g., house) was placed in the center of the icon while the central coordinates of the dynamic entity (e.g., lake) were randomly selected from a starting region (see Figure 2). The starting relation of the two
entities was always disconnected (DC). When the animation started, the dynamic entity expanded at a constant speed until one of the nine ending relations was reached. To ensure that the scaling deformations were perceptually clear, the duration of each deformation was at least 2.0 seconds, followed by a 1.5 second pause to show the ending relation before the animation restarted.

Figure 2. Design layout of icons. The reference entity is located in the central region of the icons while the starting position of the dynamic entity is randomized within the starting region shown in the figure.

3.3 Procedure

All experiments were carried out as group experiments in a GIS lab at The Pennsylvania State University. We used CatScan, a freely available software tool (Klippel, Worboys, and Duckham 2008) that allows for administering static/dynamic grouping experiments. A demo version of CatScan for the lake experiment can be downloaded at tinyurl.com/CatScanDemo (Java installation required).

At the beginning of all experiments, participants were asked to provide basic personal information (e.g., gender, age). Subsequently, participants were provided with a written introduction explaining the scenario and the experiment. To familiarize participants with CatScan, they were asked to perform a grouping trial on a set of animal icons. Once the participants finished the trial, they were able to proceed to the main experiment.
Figure 3. Two screenshots of CatScan interface. Top: Initial screen of the main experiment. Bottom: Mock-up of an ongoing experiment.

In the grouping interface of the main experiment (Figure 3), all 72 animated icons were initially presented in the left panel of the interface. Animated icons on the left panel could be placed into groups created by participants on the right panel. Participants were able to create new groups and delete existing groups. All groups created by participants were automatically surrounded with frames in distinct colors to assist participants remembering a group they previously created. Participants were informed in the instructions that there were no right or wrong answers with respect to their grouping criteria or number of groups they created. After the participants finished the grouping task, they were shown the groups they previously created, one group at a time. They were asked to provide a short label (no more than five words) for each group and a detailed description to explain the criteria they employed to create that group.
4. Results

4.1 Basic Statistics

Table 2 shows means and standard deviations of a) the number of groups created; and b) the time spent on the grouping task of the four experiments.

<table>
<thead>
<tr>
<th>Scenario</th>
<th># of Groups Created</th>
<th>Time Spent on Grouping Task</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>SD</td>
</tr>
<tr>
<td>Desert</td>
<td>6.1</td>
<td>3.7</td>
</tr>
<tr>
<td>Lake</td>
<td>7</td>
<td>2.7</td>
</tr>
<tr>
<td>Oil</td>
<td>6.6</td>
<td>3.2</td>
</tr>
<tr>
<td>Geometric</td>
<td>8.9</td>
<td>3.1</td>
</tr>
</tbody>
</table>

Analysis of variance (ANOVA) revealed that the difference in the number of groups created by each participant across four experiments is on the verge of being statistically significant, $F(3,76)=2.683$, $p=.053$. A post-hoc comparison of between group differences using Tuckey’s HSD test indicated that this effect could be attributed to the difference between the geometric and desert experiment. The average number of groups created in the geometric experiment ($M=8.9$, $SD=3.1$) is significantly higher than the average number of groups created in the desert experiment ($M=6.1$, $SD=3.7$).

A second ANOVA showed that the grouping time comparing the four experiments is statistically significantly different, $F(3,76)=2.784$, $p=.047$. Post-hoc comparisons using Tuckey’s HSD test further indicates that the average time of the desert experiment ($M=771.1$, $SD=343.9$) is statistically lower than the average time of the geometric experiment ($M=1150.9$, $SD=383.8$).
4.2 Heat maps of Raw Similarities

The grouping behavior of each participant was recorded in a 72 by 72 similarity matrix (72 is the total number of icons in each experiment). All possible similarities between pairs of icons are binary-encoded: ‘0’ indicates that two icons are not placed into the same group; ‘1’ indicates that two icons are placed into the same group. An overall similarity matrix (OSM) is obtained by summing over the similarity matrices of all 20 participants in each experiment. Hence, the value of each cell in the OSM ranges from 0 (none of the 20 participants placed this pair of icons into the same group) to 20 (all 20 participants placed this pair of icons into the same group).

Figure 4. Heat maps visualizing the raw similarity of four experiments. Dark red colors indicate high similarity whereas yellow to white colors indicate low similarities. (Note: DC – Disconnected, EC - Externally connected, PO - Partially overlap, TPP - Tangential proper part, NTPP – Non-tangential proper part.)
We visualized the OSMs in the form of heat maps with dendrograms - resulting from cluster analyses employing Ward’s method (Ward Jr and Hook 1963) using R (R-Development-Core-Team 2005). The heat map is a graphical representation of matrix data. The data values from the matrix are being translated into colored cells. The similarities between each pair of icons are color-coded using a red-to-white color ramp as shown in Figure 4. The red cells correspond to the highest similarity (i.e., 20) while white cells correspond to the lowest similarity (i.e., 0) between pairs of icons. The entries (i.e., icons) in heat maps were re-ordered to accommodate the structure of the dendrogram such that entries with high similarity always neighbor with one another. It is worthwhile to notice that icons from each topological equivalence class form an exclusive sub-cluster in the dendrograms without exception. The heat maps allow us to visually assess the similarities between topological equivalence classes by inspecting the color distribution. The most significant pattern across the four heat maps is the red 9 by 9 blocks along the diagonals from top left to bottom right, which perfectly corresponds to eight icons from each topological equivalence class. This pattern strongly indicates that icons from the same topological equivalence class were placed into the same group by most of the participants. In addition, the heat maps of the desert, lake, and oil spill experiments are dominated by yellow-to-orange color whereas the heat map of the geometric experiment is dominated by light-yellow-to-white color. This implies that the nine topological equivalence classes are conceptually clearly separated in the geometric experiment but form conceptual groups in the semantic experiments. This is a first indication that the nine topological equivalence classes may need to be generalized to a coarser level when comparing artificial and cognitive conceptualizations of geographic events.
4.3 Multi-dimensional Scaling

To explore the similarities among icons from a different perspective, we performed multi-dimensional scaling (MDS) analyses based on the overall similarity matrices (OSMs) using CLUSTAN™. MDS is a dimensionality reduction technique that helps visualize similarities within a high-dimensional dataset in a lower-dimensional space (e.g., 2-dimensional space). In this analysis, MDS was employed to reduce the dimensions in the OSMs to allow for a 2-dimensional visualization of the similarities between topological equivalence classes. The MDS algorithms used in CLUSTAN™ are MDSCAL (Multidimensional Scaling) and KYST (Kruskal, Young, Shepard, and Torgerson) (Carroll 1987). The results were further visualized into MDS plots with a program in CatScan. In the MDS plots, each icon is symbolized by a colored square and the color-coding corresponds to the nine topological equivalence classes. The Euclidean distance between each pair of icons on the plot represents the participant-rated similarity of that pair of icons: A short distance indicates high similarity whereas a long distance indicates low similarity (see Figure 5).
First, in all four experiments, icons belonging to the same topological equivalence class form their own clusters. In some cases, icons whose topologically defined ending relations are conceptual neighbors in the CNG overlap with each other in the MDS plots.

Second, in the MDS plot of the lake experiment, three main clusters can be clearly identified. The first cluster is formed by all of the DC1 and EC1 icons, in which the house has never been *enveloped* by the lake. We name this cluster *No Damage*. The second cluster is exclusively formed by all of the PO1 icons, where the house is partially

Figure 5. The MDS plots of four experiments. The legends for nine different topological equivalence classes are shown in the right side of the figure. (Note: the MDS plots of desert and lake have been mirrored and rotated such that the position of each major cluster is consistent across three semantic experiments. This modification should not affect the results as orientation of MDS plot is arbitrary.)
enveloped by the lake at the end of the animation loop. We name this cluster **Medium Damage**. The rest of icons in the lake experiment form the third cluster. A commonality shared by all these icons is that the house has been completely enveloped by the lake. We name this cluster **Serious Damage**. This three-cluster pattern also can be found in the MDS plot of the desert experiment (see Figure 5).

The MDS plot of the oil spill experiment, however, tells a slightly different story. While the three-cluster pattern exists here, too, all of the EC1 icons join in the **Medium Damage** cluster together with PO1 icons instead of falling into the **No Damage** cluster. From a semantic perspective, this can be explained as participants considered an oil spill touching the coast of an island to be **Medium Damage** instead of **No Damage**.

Lastly, the MDS plot of the geometric experiment shows an entirely different pattern. Icons from the same topological equivalence class form distinct clusters, and these clusters are more evenly distributed (separated) on the plot compared to the plots from the three semantic experiments. Intriguingly, icons that share the same topological ending relation, independent of whether it is at the beginning or at the end of a scaling deformation (i.e., DC1/DC2, EC1/EC2, PO1/PO2, or TPP1/TPP2), are neighbors on the plot. Furthermore, we found that the icons with number ‘1’ (i.e. DC1, EC1, PO1, TPP1) are populated at the peripheral area of the plot whereas icons with number ‘2’ (i.e. DC2, EC2, PO2, TPP2) are clustered in the central area. This pattern suggests that, although there is no difference from a topological perspective, relations toward the contracting phase of a scaling deformation are conceptually closer than relations at the expanding phase of a scaling deformation.
4.4 Statistical Significance Analysis

To further analyze participants’ conceptualization of scaling deformations and to provide a statistical significance analysis, we performed Chi-Square tests on similarity measurements (grouping behavior) for the first three sets of conceptual-neighbor-pairs (DC1-EC1, EC1-PO1, and PO1-TPP1) both within each scenario as well as for each pair across all four scenarios. The first analysis will demonstrate that different topological relations (and their corresponding conceptual neighbors) are differently salient within each scenario; the second analysis will show that semantics influences this saliency differently. We derived similarity data of the first three sets of conceptual-neighbor-pairs by summing over cell values from the sub-matrix of the OSM (overall similarity matrix) that correspond to these three conceptual-neighbor-pairs for each experiment. Since OSM encodes the number of times each icon pair placed into the same category, this data is essential count data - a large value indicates high similarity while a small value indicates low similarity. We refer to this similarity measurement as raw frequency.

The results provide clear support for our more qualitative interpretation in the previous sections: All analyses (comparing raw frequencies of conceptual neighbors within and across scenarios) are statistically significant at $p < .001$ level (see results in Table 3 and Table 4).

<table>
<thead>
<tr>
<th>Scenario</th>
<th>$\chi$</th>
<th>df</th>
</tr>
</thead>
<tbody>
<tr>
<td>Desert</td>
<td>712.4</td>
<td>2</td>
</tr>
<tr>
<td>Lake</td>
<td>162.3</td>
<td>2</td>
</tr>
<tr>
<td>Oil</td>
<td>78.42</td>
<td>2</td>
</tr>
<tr>
<td>Geometric</td>
<td>239.5</td>
<td>2</td>
</tr>
</tbody>
</table>

Table 3. The results of Chi-square analysis on raw frequencies of conceptual neighbors DC1-EC1, EC1-PO1, and PO1-TPP1 within each scenario.
Table 4. The results of Chi-square analysis on raw frequencies of conceptual neighbors DC1-EC1, EC1-PO1, and PO1-TPP1 across scenarios.

<table>
<thead>
<tr>
<th>Conceptual neighbors</th>
<th>$\chi$</th>
<th>df</th>
</tr>
</thead>
<tbody>
<tr>
<td>DC1-EC1</td>
<td>297.7</td>
<td>3</td>
</tr>
<tr>
<td>EC1-PO1</td>
<td>688.3</td>
<td>3</td>
</tr>
<tr>
<td>PO1-TPP1</td>
<td>140.4</td>
<td>3</td>
</tr>
</tbody>
</table>

Additionally, we compared differences between conceptual neighbors at the beginning and at the end of each movement pattern. We focus on the pairs DC1EC1 / DC2EC2 and EC1PO1 / EC2PO2 for all scenarios, that is, eight comparisons in total. The results are similar to the other Chi-Square results above and comparisons are all significant at the $p < .001$ level ($df = 1$) with the exception of the comparison of oil EC1PO1 / EC2PO2 which yielded a $p$ value of .02 and the comparison of geometric DC1EC1 / DC2EC2 which was not significant ($p = .8$) (see results in Table 5).

Table 5. Results of Chi-square analysis of conceptual neighbors at the beginning and at the end of each movement pattern.

<table>
<thead>
<tr>
<th>Conceptual neighbors</th>
<th>Scenario</th>
<th>$\chi$</th>
<th>df</th>
</tr>
</thead>
<tbody>
<tr>
<td>DC1EC1/DC2EC2</td>
<td>Desert</td>
<td>78.7**</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>Lake</td>
<td>134.1**</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>Oil</td>
<td>166.1**</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>Geometric</td>
<td>.04</td>
<td>1</td>
</tr>
<tr>
<td>EC1PO1/EC2PO2</td>
<td>Desert</td>
<td>431.1**</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>Lake</td>
<td>45.7*</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>Oil</td>
<td>5.6*</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>Geometric</td>
<td>136.3**</td>
<td>1</td>
</tr>
</tbody>
</table>

Note: * significant at the .05 level; ** significant at the .001 level.

5. Discussion and Future Work

The results reveal important aspects about modeling cognitive conceptualization of scaling deformations associated with geographic events. First, we found that topological equivalence does play an important role comparable to findings addressing static relations (Egenhofer and Mark 1995a) and translation movement patterns (Klippel and Li 2009). As revealed by the heat maps as well as the MDS plots, topologically equivalent
representations are conceptually closer/more similar than representations belonging to different topological equivalence classes. However, individual topological equivalence classes form conceptual groups. This is reflected a) in the heat maps by the existence of dark orange blocks for pairs of certain topological equivalence classes; b) by different distances between topological equivalence classes in the MDS plots; and c) statistically significant similarities between the first three pairs of conceptual neighbors within each of the four experiments. This confirms the suggestions for translation movement patterns by Klippel (2012) that topology is an important aspect to formally characterize cognitive conceptualizations of movement patterns but that not all topological relations are equally salient. It has been acknowledged theoretically for some time (Li and Fonseca 2006) that certain topological relations are more or less similar to each other; we are now able to render these results more precisely for scaling movement patterns. These results are also in line with earlier findings from experiments by Egenhofer and Mark (1995a), who concluded that certain topological relations are conceptually closer than others in static scenarios (a road crossing a park). In contrast, our results contradict findings by Knauff, Rauh, and Renz (1997) who states that topological relations identified by RCC-8 or the finer level of Egenhofer’s Intersection Models (IMs) are equally salient from a cognitive perspective — even for the geometric case.

Additionally, from a cognitive perspective, the nine topological equivalence classes are not equally salient across different scenarios. The similarities between equivalence classes are influenced by semantics of the domains and the nine topological equivalence classes are aggregated accordingly. In contrast, the geometric experiment exhibits almost no such influence, although the MDS plots show that even in the geometric case, certain topological relations are conceptually closer than others. Considering the fact that both IMs and RCC identify five topological relations on a
coarser level of granularity with some distinct differences (Knauff, Rauh, and Renz 1997), it is worthwhile to differentiate which approach deserves the label of being cognitively adequate (or more adequate) in a specific domain. Intersection models merge *meet* (equivalent to EC) and *overlap* (equivalent to PO) into *overlap*; this is supported by the results from the oil spill experiment. In contrast, RCC-5 merges *DC* and *EC* into *DR* (Discrete Region), which is supported by the results from the desert and lake experiments. These findings strongly support our conclusion that there is no universally acceptable formal approach to model cognitive conceptualizations across different semantic domains. To deserve the label *cognitively adequate*, qualitative spatial calculi need to be tailored to semantic domains (for an extended discussion of the influence of semantic domains on cognitive processes, see Hirschfeld and Gelman 1994; Klippel 2012; Zacks 2004; Coventry and Garrod 2004). To quantify the influence of semantics on the cognitive conceptualization of fundamental spatio-temporal relations is a challenging task for future research.

Finally, based on the results presented here, we also conclude that, for the same topological relation, it matters whether the relation is encountered at the expanding phase (e.g. DC1, EC1, or PO1) or at the contracting phase (DC2, EC2, or PO2) of a scaling deformation. In the MDS plots of desert, lake, and oil spill, DC2, EC2, and PO2 icons are clustered together whereas DC1, EC1, and PO1 icons are more separated from one another; toward the end of a movement pattern finer distinctions are less relevant semantically in our scenarios. In the geometric experiment, all relations with ‘2’ (e.g. DC2) are clustered in the central area of the MDS plot, indicating higher similarities between these relations than relations with ‘1’ (e.g., DC1). However, as these relations, in

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1 Egenhofer (personal conversation 09/13/13) does not agree with Knauff’s et al. interpretation of which topological relations are aggregated and states that both RCC and IM distinguish the same relations on the coarser level. However, for the purpose of this discussion it is a useful distinction.
the absence of semantic ‘glue’ are more individualized, differences assessed by looking at conceptual neighbors are not always significant. This result suggests that participants tend to make fewer distinctions toward the end of a scaling deformation. Movements seem to be a critical contextualizing factor that has not been sufficiently addressed for topological characterizations that are otherwise thought of as being rather universal.

Future work therefore includes assessing the cognitive adequacy of topological calculi in more experiments so that we can build an ontology of domains based on human’s conceptualization of topological relations. Additionally, the question of which spatially invariant characteristics such as size, direction, and speed is given preference from a cognitive perspective is important to formalize spatial and spatio-temporal similarity assessments. When more than one invariant exists in a scaling deformation, which invariant will be the dominant force anchoring cognitive conceptualizations? In addition to studies on the cognitive adequacy of topological calculi in translation movement patterns as well as scaling deformations (in this article), it would be interesting to investigate the cognitive adequacy of topological calculi in rotation movements, which is identified by Egenhofer and Al-Taha (1992) as one of the three major kinds of movement patterns. This would enable better representations of spatio-temporal information and foster interaction at the human-machine interface.

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7. References


