

Exploring the Micro-Social Geography of Children's Interactions in Preschool: A Long-Term Observational Study and Analysis Using Geographic Information Technologies

Environment and Behavior
45(5) 584–614
© 2012 SAGE Publications
Reprints and permissions:
sagepub.com/journalsPermissions.nav
DOI: 10.1177/0013916512438885
eab.sagepub.com


Paul M. Torrens¹ and William A. Griffin²

Abstract

The authors describe an observational and analytic methodology for recording and interpreting dynamic microprocesses that occur during social interaction, making use of space–time data collection techniques, spatial-statistical analysis, and visualization. The scheme has three investigative foci: Structure, Activity Composition, and Clustering. In each case, these are associated with either acquiring resources or using socioenvironmental features to influence social intercourse. For each point of focus, the authors provide an analytic strategy and demonstration of its usefulness, using data generated from a 2.5-year observational study of young children's play behavior. Each tool, and its associated concepts, is used to illustrate how early socializing behavior is embedded in time and space. The results show that geography is a significant catalyst for social dynamics in young children: It provides the opportunity for novel interpretations of sociality along with a better understanding of the influence that geographical factors (location, space, place, spatial structure,

¹University of Maryland, College Park, USA

²Arizona State University, Tempe, USA

Corresponding Author:

Paul M. Torrens, Geosimulation Research Laboratory, Department of Geographical Sciences, 2181 LeFrak Hall, University of Maryland, College Park, MD 20742, USA.

Email: torrens@geosimulation.com

spatial composition, landmarks, site) have on the evolving reciprocal interplay between individuals and groups.

Keywords

geographic information systems, spatial analysis, social networks, behavioral geography, human geography, children, playgroup

Introduction

Despite keen interest in the topic, scientists have garnered relatively little insight into the mechanisms that generate micro-social processes—those fleeting behaviors occurring among individuals in a social situation that modify the subsequent likelihood and trajectory of any particular or similar exchanges (Hartup & Laursen, 1999). Indeed, we know even less about how these interactions translate to group-scale phenomena. Calls for additional attention to these issues have come, in particular, from study of children's geographies, where it has been argued that social interactions have been relatively overlooked (Ansell, 2009; Barker & Weller, 2003; Skelton, 2009) and that sociality has been ill served by classic methods of inquiry (Gallacher & Gallagher, 2008; James, 1990). This increased attention to children's socio-spatial behavior comes at a time when the topic is of growing concern in a range of domains, including public health (Atladóttir et al., 2007; Latner & Stunkard, 2003; Pate et al., 2006), social development (Kinderman, 1998) and adjustment (Ladd, Kochenderfer, & Coleman, 1997), behavioral geography (Thomson, 2005), and education (Legendrea & Munchenbach, 2011).

This paucity in understanding is, in part, a consequence of several larger, broader, and thorny scientific challenges. First, the social phenomena in which behaviors are embedded are complex evolving structures generated by many-to-many interactions among and between people and their environments. The complexity of these interactions, which are often characterized by inconsistency in form and usually unpredictable outcomes, present a major conundrum for contemporary social science: how we might reliably and efficiently investigate the microscale of sociality and catalyze that insight, from the bottom-up, to meso- and macroscale social phenomena (Butts, 2009; Lazer et al., 2009). The second challenge relates to geography. Geography ascribes unique space-time context to environments (Hägerstrand, 1975); yet, social processes derive from the mixing and evolving of behavioral structure and environment—producing unique aggregations at each point of observation (Andrews, 1977). Third, subtle behavioral nuances embedded in relevant

evolving micro-social processes are difficult to observe and record as they unfold in natural settings (Willis, Gjersoe, Havard, Kerridge, & Kukla, 2004). Fourth, even with data in hand, appropriate analytic strategies for treating complex social processes that cross scales from the individual to the group are not well established in the literature (Epstein, 2007).

We describe herein a toolset that, in aggregate, allows investigators to record, analyze, and visualize micro-social data in a way that preserves time, space, and behavior—facilitating its use as explanatory context. We will also demonstrate how additional value can be added to these data, using analyses that focus on the space–time structure, composition, configurations, and trajectories of social behavior. We will demonstrate the applied usefulness of the approach in building insight into the fundamental features of sociality in young children. Specifically, we focus on group dynamics in preschool children, an age period when socializing behavior is initially developed (Kinderman, 1998), and we emphasize the interaction between behavior and space as a substrate and catalyst for social dynamics (Moore, 1986). Our methods couple long-term, coded, behavioral observation (Schwartz & Schwartz, 1955); location tracking in a space–time geographic information system (GIS; Longley, Goodchild, Maguire, & Rhind, 2001); spatial and spatial-statistical analysis (Wong & Lee, 2005); and qualitative geovisualization (Dykes, MacEachran, & Kraak, 2005).

This coupling of data and related “dataware” allows us to explore interrelated indices of social interaction: affect, group formation, place and space, the geography of activity, and their combined influence on the dynamics of social group formation, evolution, and disbandment. Each of these dimensions of socialization is important in discerning the evolution of social networks, irrespective of the population age. While developing the analytic schemes, we sought to elucidate specific temporal-spatial features that bind social interaction, specifically structure, composition, and space and time geography. We use children to illustrate the methods, but our objective is to emphasize the utility of the tools to discern the intricate features that characterize social dynamics. That is, although we demonstrate utility by analyzing behavior of young children, this toolset is applicable to any data that maps social behavior onto time and space.

The data used to verify our analytic approach were drawn from an observational study of preschool children forming playgroups (see “Method” for details). An initial examination of the observed behavioral propensities suggested that the interactions were tightly linked to either specific resources or general environmental features conducive to social exchanges (Cosco, Moore, & Islam, 2010). This conjecture is not unlike the suppositions empirically

upheld by social ethological and sociological traditions (see, for example, Santos, Vaughn, & Bost, 2008), but we extend the notion of ecological validity to include physical structures that have facilitator or inhibitory effects on socialization and networks.

In summary, the aim of the work is to explore a series of questions via data collection with space–time GIS and through informed exploration facilitated by spatial analysis and spatial statistics, but to pose these questions in novel ways with the support of novel methods. Specifically, we looked at how preschool environments (such as indoor areas, outdoor areas, specific design features) influence different forms of social interaction (such as solitary or interactive). We explored whether and how boys' and girls' behavioral and behavioral patterns might relate, given similar or different social and infrastructural environmental contexts. These questions are addressed as illustrations of how the technique can support exploration of person/place/activity combinations in new ways.

Method

To capture the dynamics of sociality in play, peer group formation, and the evolving nature of children's social behavior, we performed a 3-year observational study (half a year to prototype the scheme and 2.5 years to collect data) of children in a preschool. This was focused on coding children's social (or nonsocial) interactions, as well as tracking their movement and the locations of their activities.

Participants

Each participant had a maximum opportunity to be in the study for five semesters, although most were only present for one or two. (One of the six total semesters was used to pilot the scheme, and we do not include those data.) Participants ($n = 84$) were children ($M = 44.9$ months, $SD = 0.90$) who attended a university preschool in a Southwestern metropolitan area of the United States. Written informed parental consent was obtained before the onset of children's participation in the study, and the study followed Institutional Review Board guidelines and approval. Across all semesters of the study, the sample consisted of children who were European American (58%) with the remaining being Asian-, Mexican-, and African American in descending order; most were from two-parent households (69%) with an average household annual income of US\$116,000, and 50% were female.

Table 1. Overview of the Metrics Used to Analyze the Data.

Geography Type	Sociospatial Construct	Method	Appendix	Index	Range	Interpretation
Socioenvironmental	Structure	Semivariogram, variogram	2	Point-pair distance	$\geq 0, \leq \max$	0 at origin (lack dependence), increases until max is reached
Socioenvironmental	Activity	Dominance	3	Contagion	$\geq 0, \leq 1$	0: Maximal disaggregation; degree of clumping of attributes
Socioenvironmental	Activity	Intermixing	4	Interspersion— Juxtaposition	$\geq 0, \leq 100$	0: Extreme variability 100: Uniform activity
Socioenvironmental	Activity	Diversity	5	Shannon evenness	$\geq 0, \leq 1$	0: No diversity 1: Uniform
Resource	Clustering	Moran's I (global)	6	Global spatial autocorrelation	$\geq -1, \leq 1$	$0 < I \leq 1$: Clustered $I = 0$: Random $-1 \leq I < 0$: Dispersed
Resource	Clustering	Moran's I (local)	7	Point-point spatial autocorrelation	$\geq -1, \leq 1$	$0 < I \leq 1$: Clustered $I = 0$: Random $-1 \leq I < 0$: Dispersed

Procedures

Preschool children's naturally occurring free-play interactions were observed and recorded throughout fall and spring semesters; data used here are a subset consisting of only one and one-half academic years. Children were observed Monday through Friday for 5.5 hr each day of the 9-month academic school year. Observations commenced in concordance with the preschool's semester schedule; they occurred in the morning and afternoon during the times when most children were awake, in attendance (excluding lunch time), and engaged in free play (in the classroom or outside on the playground).

Usually, three coders collected data during each shift. Coders rotated throughout the classrooms, remaining unobtrusive and uninvolved in children's activities. Each semester, the children quickly acclimated to the presence of observers. Data were recorded using Tablet PCs (see Figure 1) with direct interaction to an underlying spatial database infrastructure that we developed for the project; this permitted us to efficiently collect time-stamped and location-stamped behavioral data quickly and with minimal recording error.

Observational Measures. Codes were selected to encompass a wide and relevant range of indoor and outdoor behaviors that have been shown to occur in children of this age range. Coding was done using a scan procedure (Mize & Ladd, 1988), a method common in the naturalistic observation of children (Pellegrini, 1996) and other social animals (Martin & Bateson, 1996). Specific codes were drawn from multiple observation coding schemes, most prominently from the work of Fagot (Fagot & Hagan, 1991), Dishion (Rusby, Estes, & Dishion, 1991), and Walker (Walker & Severson, 1991; Walker et al., 1994), and our own laboratory work (Griffin, Greene, & Decker-Haas, 2004). A similar system has been successfully used in the study of peer relationships (Martin & Fabes, 2001). After initial training, interrater reliability was assessed throughout data collection. Kappa scores ranged from .70 to .99 for all coding structures and remained consistent over the span of the study (additional information about codes, coding structure, and reliability can be obtained from the second author). The coding procedure was designed to be intuitive: Using the Graphical User Interface (GUI) shown in Figure 1, a drop-down box identified a target child, randomly selected, who was observed for 10 s. Immediately after the time interval ended, the data were entered into a series of appropriate drop-down boxes. The procedure then continued with the next randomly selected child. The coding options are overlaid on a GIS view of the environment to facilitate annotation and orientation during observation. The same interface was used to facilitate route tracing of children's movement and coding of their socialization. During the 10-s period,

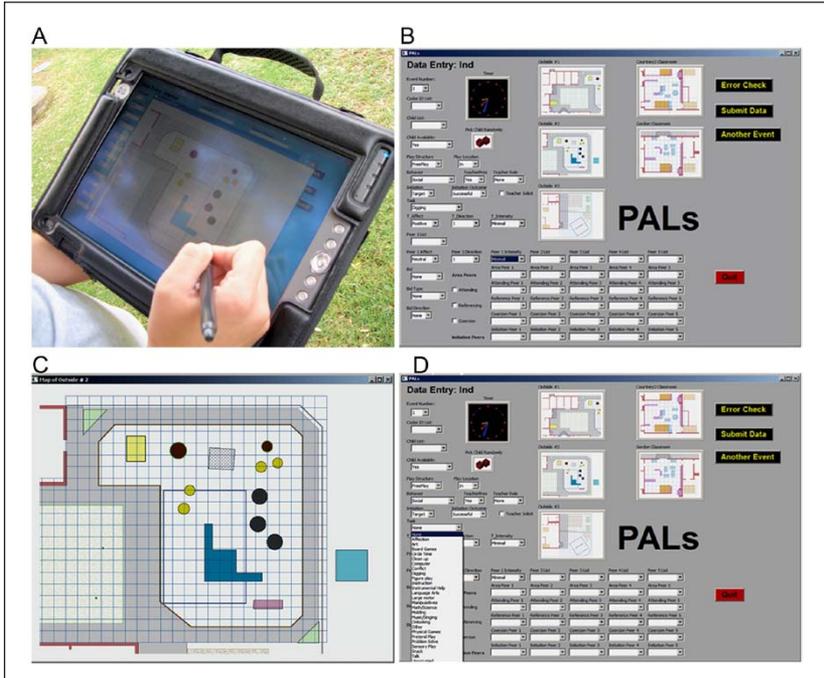


Figure 1. (a) Observational data are entered on a Tablet PC by coders, and the data are immediately registered in a geographic information system. We developed software to present coders with (b) a unified interface that coders can use to collect data in the field, (c) a gridded map to assist geocoding of children's locations, and (d) a set of tasks. In each case, observed children can be registered to structures, locations, and instructional activity. Their behavior can also be tagged by affect, direction, bids, and intensity. The presence of teachers and other children can also be noted.

the target child was coded for behavior, peers (up to five, if applicable), activity, affect, and physical location. More specifically, coders indicated whether the child was absent or unavailable during that observational period. A child was marked as unavailable if they were sleeping, in the bathroom, or with a parent. These data allowed us to control for differences in interactional qualities that might be attributed to absenteeism for instance and not how a child relates to peers and teachers. Next, coders noted the child's context category: solitary, parallel, social, or teacher oriented. If a target child was observed with one peer regardless of category, we coded who the child was playing with, the

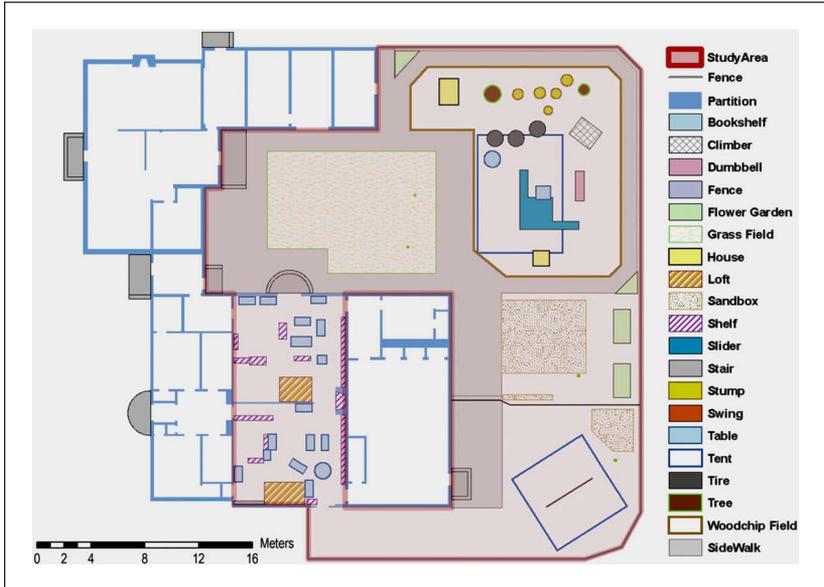


Figure 2. A map of the preschool structure (some of the furniture in the classrooms was rearranged over the study period; the map reflects the locations in which the furniture remained for the longest period of time).

activity, the affective exchange between the target and peer, and the physical location (i.e., in x,y coordinates of the preschool and time t of their trajectory; see Figure 2) of the interaction based on the target child's location.

As briefly mentioned above, the child's primary activity (i.e., their activity for five or more seconds) was observed and recorded in each 10-s interval; this length was found to be appropriate (based on previous studies and our pilot work) because it was short enough to capture the relevant behavioral and geographic data in a packet of time; it did not burden the observer with trying to remember too much, thus allowing fast and accurate data entry, which insures high interrater reliability; it also allowed ample opportunity to observe each participant. Also, because the codes were not, a priori, hierarchical, behaviors could co-occur; coders were trained to observe which behaviors occurred first and longest, the behavior best meeting those criteria was cataloged for the interval. At first blush, this seems difficult, but our coders were able to quickly grasp the concept and generate codes reliably.

Activities (i.e., coded behaviors) encompassed all developmentally appropriate behaviors including several gross motor (e.g., Walking, Physical Games),

Table 2. Observed Activities With Brief Definitions.

-
1. Affection (hugging, holding hands, patting on the back, tickling)
 2. Art (coloring, painting, collage, gluing)
 3. Board Games (Candyland, Ants in the Pants, Connect Four, playing cards)
 4. Clean Up (putting toys away, wiping down tables)
 5. Conflict (hitting, biting, scratching, verbally arguing, pulling hair, threatening gestures)
 6. Digging (sandbox, garden)
 7. Figure Play (dolls, action figures, people figures, toy animals)
 8. Instruction (e.g., “go get that shovel,” or a teacher saying “put that in your cubby.”)
 9. Instrumental Help (tying shoes, getting sunblock, tissues)
 10. Language Arts (books, writing, books on tape)
 11. Large Motor (running, climbing, swinging, bikes, wagon)
 12. Manipulatives (blocks, legos, lincoln logs, connects, puzzles)
 13. Math/Science (magnets, counting bears, space theme, balance scale)
 14. Molding (play-dough, goop, clay)
 15. Music/Singing (listening to the radio, singing, dancing to music, playing instruments)
 16. Onlooking (target is watching another kid(s) and/or a teacher—must be a PERSON, not an object)
 17. Physical Games (ring around the rosey, red rover, tag, sports)
 18. Pretend Play (getting married, being Superman, playing kitchen, dress up with a theme)
 19. Problem Solve (working out or negotiating a disagreement or physical altercation)
 20. Sensory Play (shaving cream, water, bubbles, dump and pour materials like corn kernels)
 21. Talk (conversation—If they are talking about what they’re doing, code that task instead)
 22. Walking (moving between locations—You do not have to know the destination, just distinguish from aimless walking)
-

Note: Codes not used in this analysis were Circle Time, Computer, Other, Snack, Unoccupied, Nondirected Physical, and Animal Observation. See text for exclusion criteria.

fine motor (e.g., Molding), relational (e.g., Talk, Pretend Play), educational (e.g., Math/Science), and solitary (e.g., Art) options. A full list of behaviors along with their definition is provided in Table 2. Also note that, based on one of four criteria, seven tasks were removed before commencing data analyses. Two tasks not included in all semesters (Animal Observation, Nondirected

Physical) were removed to create an equal-size task list for all semesters. The Computer task had zero frequency in all semesters except fall 2007, and so was excluded to avoid sparse cells in the matrix. Two tasks (Circle Time, Snack) were only coded during structured activities, meaning that the child did not have a choice of peer or activity. These codes were always teacher directed, so they provide no information about task selection. The fourth exclusion criteria pertained to Other and Unoccupied. These tasks were invoked while coding whether the activity could not be classified into any of the other tasks or if the child was completely uninvolved with activities or people in the preschool. Other and Unoccupied provide no information about an interaction. In addition, we removed all instances where the classroom was designated as structured time (e.g., children had to be engaged in certain activities as stipulated by the teacher). Last, any code with an unknown peer was removed. This occurred if the target child was interacting with a child not participating in the study (i.e., toddlers, siblings, or visitors).

Details regarding the start location (a $[x,y,t]$ point in space and time), stop location, and farthest distance traveled were recorded for the aforementioned observations. The farthest distance was included because we wanted to trace the typical amount of movement within the 10-s window; however, most interactions showed little movement beyond the initial x,y coordinate, at least at the recorded scale, and thus are not addressed in these analyses. To guide location recording, we developed a mobile GIS for use on coders' Tablet PCs. The System was accessible in the same GUI as the coding options. This included a cartographic representation of the preschool environment, with cues for location and relative distances between structures and objects in the environment (Figure 1). We tested the interface over the course of two weeks, and coders settled on a design that they felt would best maximize the efficiency of their work.

Data

This study concluded in June, 2009; it generated 178,565 codable events. To make it easier to understand the usefulness of our methods, we collapsed individual activities and analyzed the data at the level of the context category (i.e., teacher oriented, solitary), ignored affect, and only examined the frequency of the activities in space and time. Frequency of activity was deemed a proxy for preference. We also make distinctions between these behaviors when observed indoors (in the formal setting of a classroom) and outdoors (when children are in a free-play setting). Obviously, using higher dimensional data (for example, including various vector-structured

combinations of activity, peer selection, affective tone, and spatial indicators) increases the complexity of analysis and interpretation dramatically, a focus geared toward more substantive interpretations of the data, which is not the focus of this article.

In sum, while watching a randomly chosen child for 10 s, the observer coded several dimensions of the child's behavior in a naturalistic setting, recording both social and geographic information. Specifically, a coder recorded whether the child was alone (solitary behavior), with a teacher (teacher interaction), directly engaged in group (dyad) interaction with other children (peer interaction), or passively engaged in group behavior through parallel play (parallel interaction; in which children are playing in proximity to each other, but not with each other). And for solitary, teacher, parallel, and peer codes, a target child was observed for activity (see Table 2); affect (i.e., positive, negative, neutral; but not used here) while in the presence of social peers (i.e., peers involved in direct interaction) or area peers (i.e., peers in the physical vicinity but not interacting with the target child). This breath of information enabled us to analyze how the specific type of activity and physical location influenced micro-social processes in a manner that was reconciled empirically using GIS methods.

Concepts and Tools

To generate meaning and knowledge from the data that we collected, we developed and applied a series of analytical schemes for examining the relationships between geography and sociality implied in our observations.

Sociospatial Surfaces

In some instances, it is useful to generalize a (synthetic) space of sociality as "socio-spatial surfaces." While sociality is not necessarily continuous in space and time, the *potential* for sociality over space and time can be useful in exploring people's social interactions and their engagement with their surroundings. This may be particularly useful in studying children's sociality in preschool, where spaces of play, learning, problem solving, regulation, and so forth may be actively considered as significant inputs to their perception, their social formation, and how they learn to be social.

In essence, here, we try to statistically estimate the potential substrate for social activity. We achieve this using spatial interpolation by kriging (Oliver & Webster, 1990). Kriging is a geostatistic that may be used to estimate a

statistically robust (significant) surface from point data. A spatial-statistical model is applied to the data, weighting the variable value of the data per point (in our case, the frequency of a given activity in 1 m² spatial “bins”) before those data are statistically “massaged” into a surface using a moving filter. The statistical model is based on spatial variation in the data; this spatial relationship is then summarized as a function (specific to the input data) that is used to build interpolation weights. Kernel smoothing (Cressie, 1991) is then used to interpolate the data by those weights. The spatial variation in the data is characterized by a semivariogram, which describes the structure between point-pairs in terms of the difference in their variable values, the distance between them, and an applied distance-decay factor that is derived from an initial summary of the data (see Online Appendix [Appendix 1] at <http://eab.sagepub.com/>).

Spatial Activity Composition

Examination of spatial composition could supply insight into the heterogeneity of social activity, interaction, and events, yielding formal measurements of segregation, inclusion, and dissonance. The spatial composition of activity is tied to children’s spatial behavioral propensities: It relates to spatio-cognitive mechanisms that they use to create places and spaces of play, from imagination (e.g., role-play), through team-building (e.g., playing sports), or through contesting (e.g., arguing over territory; Cosco et al., 2010). We captured these and similar components of social behavior in our study, with consideration of three aspects of activity: Dominance, Intermixing, and Diversity.

Dominance. To assess relative dominance, we evaluated the coded data for the presence of contagion (Riitters, O’Neill, Wickham, & Jones, 1996) among social activities (from a 29-activity array; see section on “Observational Measures” for a discussion of these activities). We used contagion, essentially, to evaluate the dominance of social activities over the landscape. A value of contagion approaches zero when the spatial distribution of social activities is maximally disaggregated and equals 100% when they are maximally aggregated (i.e., when the landscape is dominated by large patches of social activity). The value is calculated by examining the likelihood of finding one activity (as coded by point-pattern in our observations) next to another in space (Li & Reynolds, 1993; see Online Appendix [Appendix 2] at <http://eab.sagepub.com/>).

In essence, contagion describes “clumpiness” in a space (McGarigal & Marks, 1995). Activities that are observed as collocating in few large clumps will yield higher contagion because they have relatively high contiguity. This

is useful in relating those activities to particular areas of space (and time) as coincidence of “clumps” in specific areas, among diverse activities, or between different sexes or cohorts could be useful in associating those things with each other. There is a methodological distinction in calculating contagion: Contiguity is judged on a cell-by-cell geography (i.e., at the most local “atom” of spatial analysis). It is, therefore, resolution sensitive.

Intermixing. We also tested the level of intermixing among social activities, using the interspersion and juxtaposition index. The metrics are related but yield distinct results. The contagion index measures dominance by calculating interspersion and dispersion, but the interspersion and juxtaposition index focuses only on interspersion. The contagion index evaluates the geography of adjacencies between raster cells, whereas the interspersion and juxtaposition index compares the geography of patches (i.e., coarser “clumps” of similar rasters). A value of interspersion and juxtaposition approaches zero when patches of social activity are uneven in the spatial distribution of their adjacency; it reaches a value of 100% when social activity types are equally adjacent to all other types (i.e., fully interspersed and juxtaposed). Derivation of the interspersion and juxtaposition index (McGarigal & Marks, 1995) is shown in see Online Appendix (Appendix 3) at <http://eab.sagepub.com/>.

The interspersion and juxtaposition index evaluates the adjacency of patches of activity (i.e., already-identified-as-contiguous swaths of activity). This is useful because it essentially tests adjacency at a different scale than contagion, and it is not necessarily sensitive to local-level discrepancies.

Diversity. Last, to capture socioenvironmental indices, we calculated metrics for the level of diversity of social activity in the landscape, using Shannon’s evenness index. This index assesses the proportional abundance of social activity types in the landscape. If the area covered by social activities is evenly distributed across space, a value of the index reaches 1. A value reaches 0 when the landscape lacks diversity (i.e., when the landscape contains only one patch). The calculation is based on information entropy (Shannon, 1948) and uses the formulation found in McGarigal and Marks (1995; see Online Appendix [Appendix 4] at <http://eab.sagepub.com/>).

Evenness is concerned with spatial distribution (rather than interspersion), and it is thus a complement to dominance (McGarigal & Marks, 1995). A high value of evenness for an activity implies diversity of that activity over space. In other words, it is a test of mixing rather than clumping. This is useful, because we may also wish to test when diverse activities or behaviors coincide over space, groups, tasks, cohorts, and so on.

Spatial Clustering

Moran's *I* (Global) Test for Spatial Autocorrelation. We used measures of spatial clustering, based on tests of spatial autocorrelation (Moran, 1950) in the data, to evaluate the spatial configuration (structure) of social activity. Tests for spatial autocorrelation evaluate the propensity for variables (in our case, the frequency of social activities observed in the space) to correlate with themselves over space. This is significant for social analysis, as social connections are often catalyzed by affinities (or dissonance) in behavior. We evaluated clustering in two phases: testing for global and local spatial autocorrelation (see Online Appendices 5 and 6, respectively at <http://eab.sagepub.com/>) by calculating scaled versions of Moran's (1950) *I* index. The index ranges between values of -1 and $+1$ (see Table 1; Online Appendix [Appendix 5] at <http://eab.sagepub.com/>).

A (statistically significant) value of 0 for the index indicates that no spatial autocorrelation was present in a landscape: In this case, a given social activity would tend to be randomly distributed over space, with no clustering effects. Negative values indicate negative spatial autocorrelation, that is, social activities that tend to "repel" themselves in space. When a value of the index nears -1 , almost perfect negative spatial autocorrelation is diagnosed; this would manifest, structurally, in a checkerboard pattern, for example, whereby children who play with toys never do so next to each other.

Positive values suggest positive spatial autocorrelation, that is, social activities that tend to cluster in space, and values that tend toward $+1$ are indicative of strongly positive spatial autocorrelation, say, when children get together in a large group to play a game like "pass the parcel," for example. More substantively, positive spatial autocorrelation suggests group formation, whereas negative spatial autocorrelation is indicative of relative solitude; moreover, these structures can be evaluated per social activity to compare clustering in one type of social behavior to others. Testing for these configurations locally also allows for relative clustering within a landscape to be evaluated. Because the units of observation and analysis in our study were so fine in resolution, we were able to test for clustering on the order of a square meter, that is, the footprint and arm extension of a small child.

Global measures of spatial autocorrelation using Moran's *I* index diagnose the presence of spatial autocorrelation in an entire space. To evaluate the statistical significance of the index, we evaluated a null hypothesis that no underlying pattern was present by testing against a random spatial pattern, perturbed 999 times (Fotheringham, Brunson, & Charlton, 2004; see Online Appendix [Appendix 5] at <http://eab.sagepub.com/>).

Local Calculations of Moran's I Test for Spatial Autocorrelation. We also tested for local spatial autocorrelation (Getis & Ord, 1992) by sweeping through the data, point-by-point (where points are observed activity locations) and testing for autocorrelation around each point (see Online Appendix [Appendix 6] at <http://eab.sagepub.com/>). This yielded measures of spatial autocorrelation per point, and it allowed us to examine the presence of “hot spots” (“high–high” relationships in which high frequencies of a variable were found to be situated next to other strongly high-frequency points in a statistically [and spatially] significant relationship) and “cool spots” (“low–low” relationships in low-frequency points situated next to other low-frequency points) in the data. We also looked for intermediate cases in which there was “high–low” and “low–high” clustering. “Low–high” relationships present when low values of a variable are correlated with high values of the variable in space. Significant “high–low” values are found when high values of a variable are correlated with low variables of the same variable over space. In some instances, these could be indicative of relative activity isolation within a space (statistically significant clustering of low frequency around high-frequency observation of a particular social activity), or even of “acting-out” (a high frequency that is spatially coincident with low-frequency observation of an activity).

Results

Our data collection and analyses scheme proved to be particularly useful in exploring the patterns of social interaction among the observed children and points to several insightful conclusions regarding likely underlying drivers of that behavior.

Socioenvironmental Geography

Indoor Versus Outdoor Patterns. Considering the space globally (i.e., “looking from the top, down”), we found a crisp distinction between the socio-spatial composition of indoor and outdoor landscapes. The classroom area was characterized by low contagion (~26%, averaged for all activities, sexes, and times), high interspersed and juxtaposition (~73%), and very high evenness (~91%; see Online Appendix [Appendix 7], for more details, at <http://eab.sagepub.com/>); that is, social activity—using spatial composition as an index—was relatively heterogeneous in the classroom. Conversely, the play area outside was characterized by higher levels of contagion (~39%), lower interspersed and juxtaposition (~65%), and lower evenness (~61%): Social activity was more homogeneous outside. Moreover, sex did not make

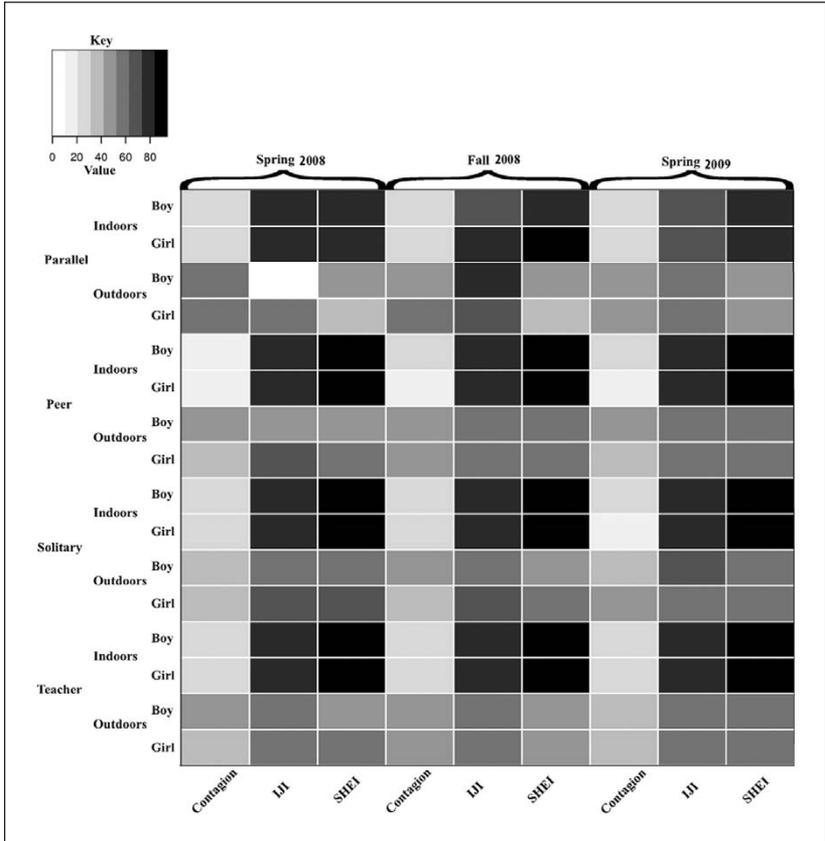


Figure 3. Spatial indices by sex, location, and behavior type across time periods
 Note: IJI = interspersion and juxtaposition index; SHEI = Shannon’s evenness index.

a difference: Indoor/outdoor heterogeneity manifested in almost identical proportions (indoor contagion was ~24% for boys and ~22% for girls [averaged across all times], whereas outdoor contagion values were ~45% and ~43% respectively; values of indoor interspersion and juxtaposition were ~75% for boys and ~77% for girls, whereas for outdoors, the values were ~60% and ~62%, respectively; the average value of indoor evenness was ~88% for boys and ~89% for girls, whereas the outdoor values were ~53% and ~55% for boys and girls, respectively).

While the abundance of numerical data generated by these analyses is apparent in see Online Appendix (Appendix 7) at <http://cab.sagepub.com/>, a visual and, more importantly, interpretable representation of the general trends

is evident as a heatmap in Figure 3. It shows the similarities and dissimilarities evident in behavior type, sex, spatial index, and location across each time period.

Spatial Autocorrelation. The results for the *global* Moran's *I* test revealed strong positive spatial autocorrelation for indoor socialization ($\sim +0.39$, averaged over the entire study period), but weakly positive spatial autocorrelation for the outdoor area ($\sim +0.17$). Social activities of all types were more likely to be found next to other social activities indoors than they were in the outdoor environment: Children formed groups (whether formally or informally) with greater propensity indoors than they did outdoors. Once again, this effect remained when the data were parsed by sex.

Resource Geography

Indoor Versus Outdoor Patterns. The primary method used to explore the fine-scale geographical connections between resource use and sociality is *local* spatial autocorrelation, and in our preschool environment, distinct geographic patterns emerged as clear descriptors of social behavior. Specifically, only a small portion of the preschool was used for social activity, and most of it was concentrated in a few distinct areas: tables and the loft areas in the two classroom, and the sandpit, playhouses, slide, tires, and wood stumps in the playground (Figure 4).

Interstitial sites, away from furniture and activity stations in the classroom environment, produced significant low–low cool spots for each form of social interaction; what distinguishes those spaces is that they are devoid of resources that the children might use for socialization. Cool spots indicate a statistically significant clustering of low-frequency activity; these were clearly evident in corridors and corner areas. Conversely, free spaces that conveyed meaning or were associated with specific types of interaction were socialization hot spots; for example, interaction with teachers was clustered in hot spots around book shelves. When teachers and children assembled to read, it was in these locations.

Note that these instances were impromptu, occurring outside formal instruction. For example, we eliminated observations of story-time assembly from our cluster analysis because it is a formal “clustering” task that the children are instructed to engage in, rather than an emergent socialization pattern. Interestingly, the table(s), an obvious candidate for clustering, showed minimal social peer interaction; instead, it was mostly teacher interaction, parallel play, or solitary behavior (see Figures 5 and 6). Although why this occurs

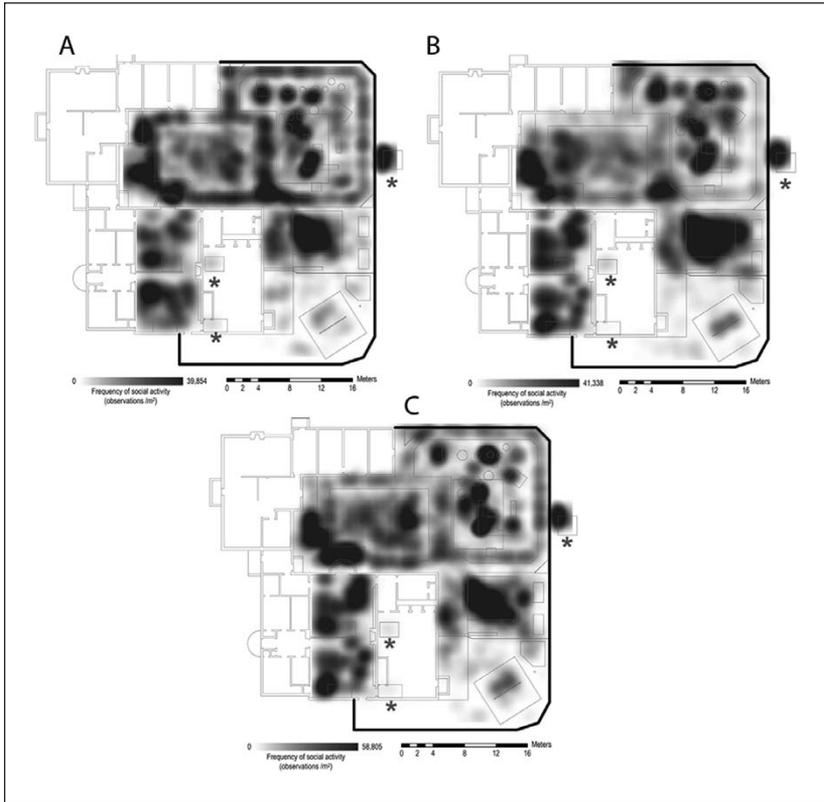


Figure 4. (a) A kernel density map of all observed social activity for spring 2008 (the boxes underscored by an asterisk represent the second-story of lofted areas); (b) fall 2008; (c) spring 2009.

would require additional study, it is possible that around tables, the teacher is busily instructing the child or the child is busily working on projects.

Finally, some dual function sites were found: The lofted area in one (the upper) classroom was a hot spot of frequent direct (peer) interaction between children but also a hot spot for solitary behavior. Likewise, outdoors, the playhouse and the climbing structure supported similar dichotomous behaviors.

The outdoors belonged to the sandpit—It formed the main hub of social interaction (Figures 4, 7, and 8) and presented as a statistically significant hot spot across all social interactions. The sandpit seemed to function almost like an oasis (or water cooler; Fayard & Weeks, 2007): a spatial anchor for social visits of all kinds. Despite its focus for social behavior it also had a

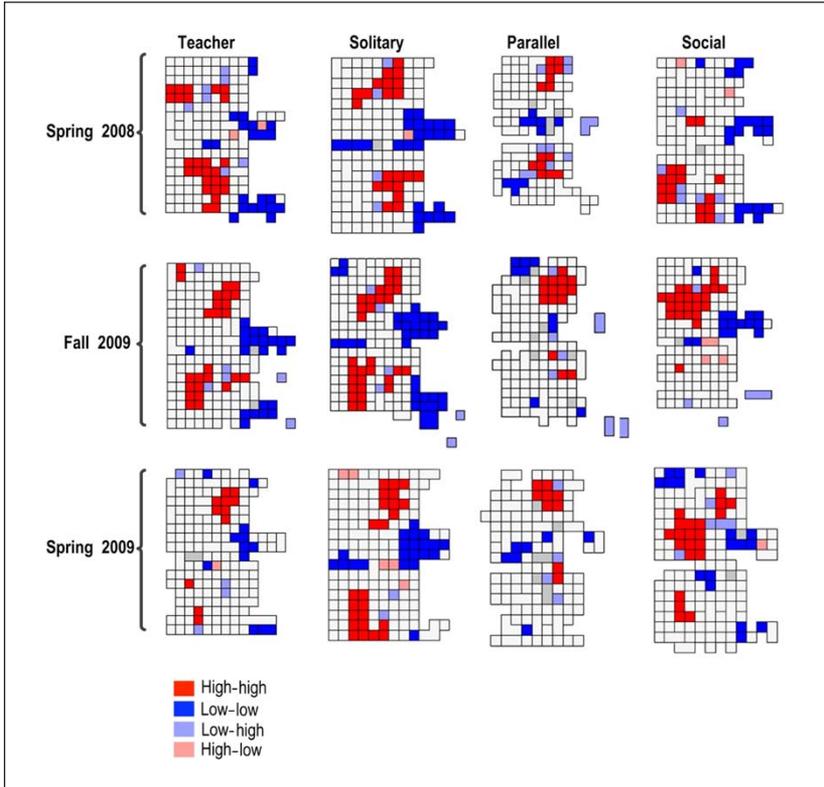


Figure 5. Local spatial autocorrelation by type of sociality and date, for all children, indoors.

Note: Each square in the graphic represents 1 m on the ground; white cells have no statistically significant autocorrelation; empty spaces have no observations for a given variable.

significant positive spatial autocorrelation for solitary behavior; in fact, it was the main hub for solitary behavior in the entire preschool.

Children may simply migrate to the sandpit to be alone. Recall that we did code for parallel behavior, so if the children were intensively focused on fine motor skills at the pit (building towers or pushing cars) to the point of excluding bids for social interaction from other children, we would have seen those behaviors in the data. Another factor in the attraction of the sandpit for solitary behavior may be its size: It is the largest play “station” in the outdoor area, and, as such, it offers the greatest chances for solitude. (It was covered by a large umbrella structure that protects the children from rain and sun, but most of the play equipment has these coverings.)

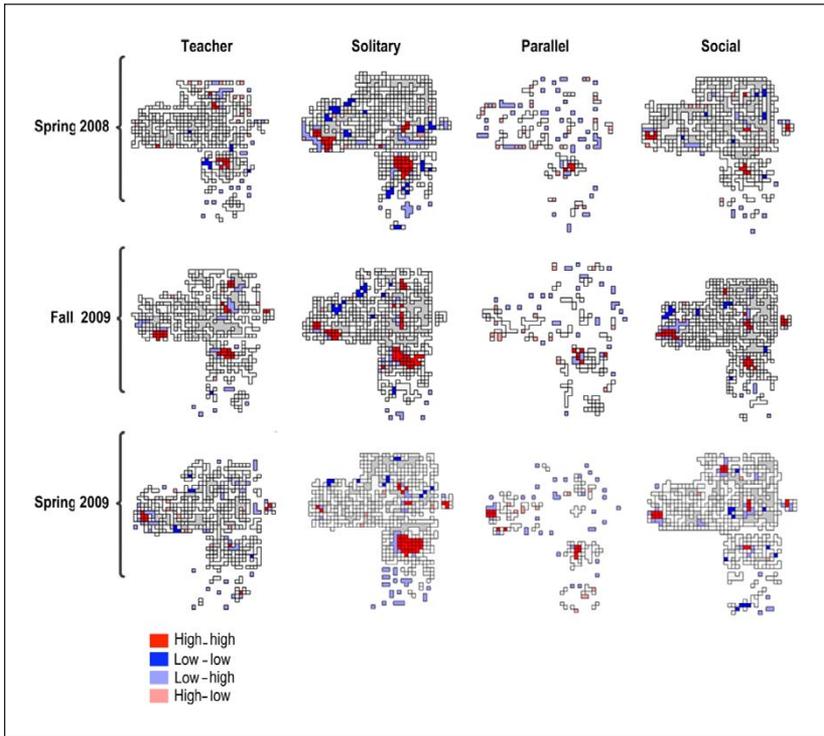


Figure 6. Local spatial autocorrelation by type of sociality and date, for all boys, outdoors.

Note: Each square in the graphic represents 1 m on the ground; white cells have no statistically significant autocorrelation; empty spaces have no observations for a given variable.

As we noted, the loft structures in the classroom presented mixed results for spatial autocorrelation, with mostly minor hot spots of direct social interaction and some hot spots of solitary behavior. However, outdoors, the playhouse structures (two huts and a platform climbing structure) hosted very distinct hot spots of social behavior and solitary behavior; hot spots for teacher interaction also clustered around playhouses, suggesting that these structures are another major hub for social activity in the playground.

Besides the climbing structure (which was a hot spot for direct social interaction), the tires, tree stumps, and steps are the only elevated areas in the playground. Tires and tree stumps generated distinct cool pots of social behavior: Children went to them frequently, not to be solitary, but *to not be social*. The steps between classroom and playground were cool spots

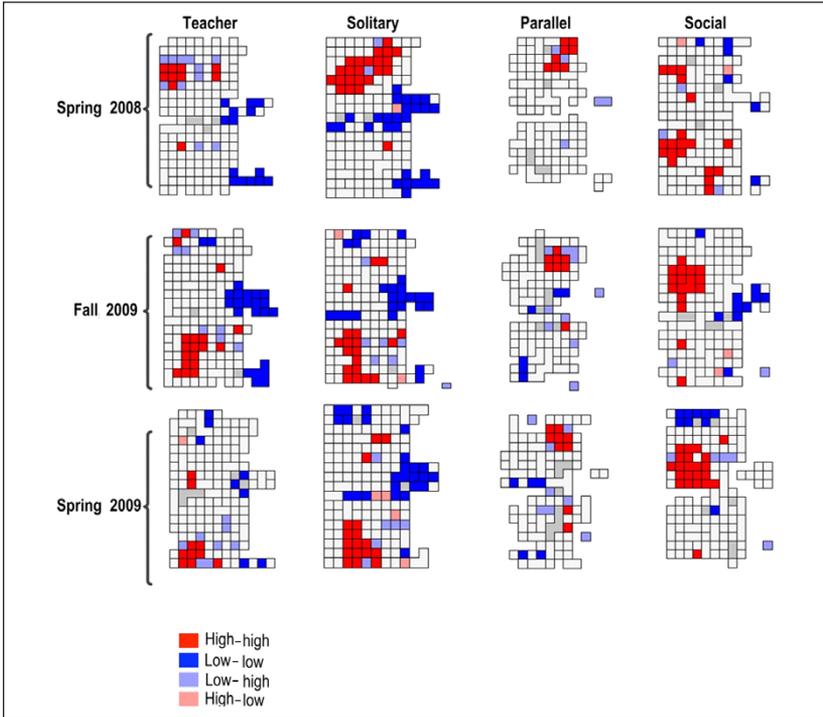


Figure 7. Local spatial autocorrelation by type of sociality and date, for all children, indoors.

Note: Each square in the graphic represents 1 m on the ground; white cells have no statistically significant autocorrelation; empty spaces have no observations for a given variable.

for solitary behavior, but they also hosted significant low–high clusters for parallel behavior (i.e., a statistically significant cluster of low-frequency parallel socialization, surrounded by high-frequency parallel socialization). These elevated areas perhaps serve as landmarks, which children use as a zone of transition between behaviors.

Sex Differences

Analyses indicated that sociospatial interaction patterns differed substantially between and within sex. Indoors, a large and distinct hot spot of solitary behavior presented for boys, mostly occupying an area of free space, but with some overlap into the tabled areas of the classroom and coincident with boys'

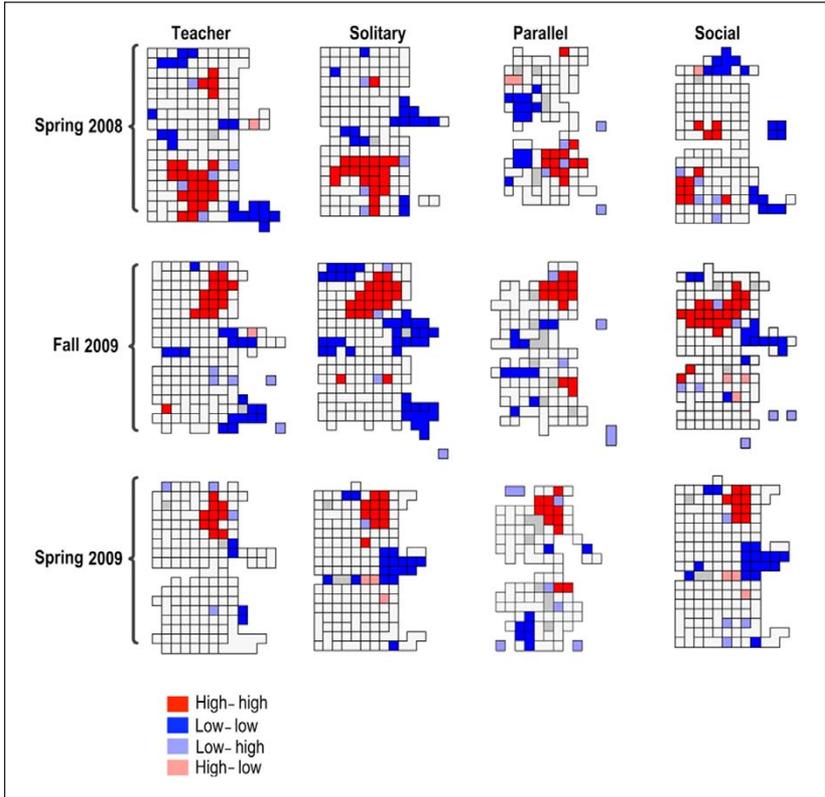


Figure 8. Local spatial autocorrelation by type of sociality and date, for all girls, indoors.

Note: Each square in the graphic represents one meter on the ground; white cells have no statistically significant autocorrelation; empty spaces have no observations for a given variable.

hot spots for teacher interaction (Figure 6). This location switched to the opposite side of the classroom structure between semesters, as we will discuss in the next section, also to a hot spot for teacher interaction. The hot spot for solitary behavior for girls was located at the polar opposite end of the classroom building, with a large buffer of separation from the boys' cluster of frequent solitary behavior; moreover, when the boys' hot spot for solitude moved between semesters, so did the girls', again to a polar opposite location (Figure 8). The same pattern of separation between boys and girls was observed for direct peer interaction. (It is important to note that these behaviors may have been boy–boy or boy–girl interactions, or vice versa.)

For boys, a clear distinction between spaces for solitude and spaces for direct peer interaction was evident. Boys were frequently social on one side of the classroom building in significant clusters, and frequently solitary on an opposite side (Figure 6). When the location of these clusters shifted between semesters, the mirror separation persisted. The girls' most-frequented locations for social and solitary behavior actually overlapped, however (Figure 8). As with the case of the boys, these locations coincided with hot spots for teacher interaction for the girls.

Differences in the patterning of social behavior between and within the sexes were less distinct outdoors. Girls and boys chose playhouses as sites for solitude and direct peer interaction. Some exclusivity was evident (one or two houses were favored by boys or girls in any given semester), but the pattern was more apparent than was seen indoors. Boys and girls frequented the sandpit as a hot spot for solitude (Figures 4 and 7).

Boys appear to favor very specific (and separate) areas of the classroom for very specific social behaviors, but girls favor almost mirror locations (Figures 5, 6, and 8). Indeed, large spaces of separation form between the two sexes in these cases. The pattern of sociospatial separation based on activity persists within the boy population, but girls' social activities overlap with each other. Teachers in the preschool do not actively encourage sex-specific games and toys, so the pattern cannot be explained by instruction.

Both sexes also used spaces for social behavior and solitude that they frequented for social interaction with teachers, so the effect is not a by-product of ignoring or shadowing teachers. This leaves us to assume that there are clear and distinct spatial differences in the ways that boys and girls socialize over space, and these differences manifest most clearly in the classroom environment. The topic of sex differences in *spatial abilities* of children is hotly contested in the geographical sciences (Kerns & Berenbaum, 1991), and authors have speculated that many of these differences can be better understood if *sociospatial behaviors* are considered (Torrens, 2001) alongside the usual psychological and psychometric approaches (Kitchin, Blades, & Golledge, 1997).

It is worth emphasizing that our geography-based analytic structures permit extensive and detailed examination of local patterns within the data; for example, should the investigator need to either affirm or disconfirm working hypotheses about sex and location differences, existing metrics can easily be constructed to provide the answer. To illustrate, Figure 9 shows a uniquely defined interpretation of contagion across sex, behavior type, location, and time. Specifically, the shading of each cell represents the ratio value of \log_e (boy contagion/girl contagion) for each behavior type and location across each time period. Assuming no sex differences, cell shadings should be a

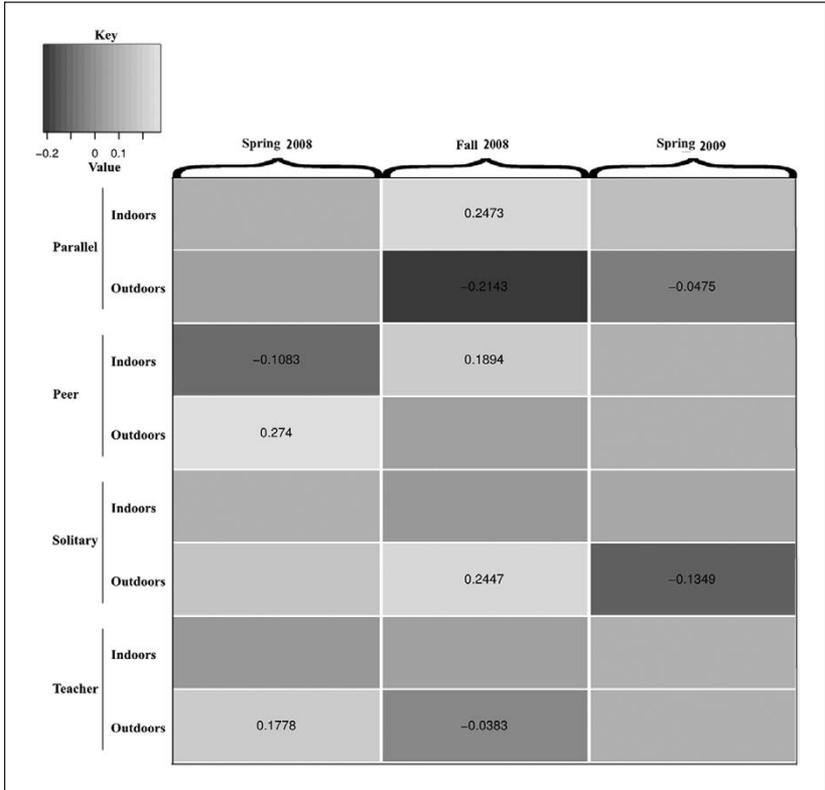


Figure 9. Logged ratio of boy/girl contagion scores. Darker shading indicates higher girl scores.

Note: Values from upper and lower 2 deciles are embedded within relevant cells.

middle-level gray, reflecting a value of zero (ln 1). To better visualize where, and by how much, contagion sex differences exist, we show the value of the top and bottom 2 deciles (upper and lower 20%) in the distributed scores; relevant values are shown within the cells. Darker shaded cells reflect ratio values, indicating girls with substantially higher contagion values than boys; lighter shading indicates the converse. Notice that in the spring 2008 data, boys showed much higher levels of contagion while engaged in outdoor Peer behavior and yet the converse occurred indoors; likewise, in the fall 2008 data, Parallel behavior showed an inverse relationship by sex, and at a more

macro level, each shows some change over time. These simple illustrations show that it is possible, using a (descriptive) spatial measure such as contagion, to drill down into the data to uncover diagnostic patterns.

Space–Time Dynamics

The spatial patterning in socialization observed in the study did not hold constant over time. Indeed, although the physical environment of the preschool changed little over the study period (see Figure 2), marked differences in sociospatial behavior were noticed. In the fall of 2008, the study population underwent some change: An influx of students joined the population, although typically about one-half of the students remained from the previous year. The spatial pattern of behavior changed markedly during this transition, settling into a new spatial equilibrium for the remainder of the study period (Figure 4).

This was especially apparent in the classroom environment (Figures 5, 6, and 8). Hot spots of direct peer interaction and solitary behavior shifted, wholesale, from one classroom to another. This is entirely a by-product of the social interactions within the group; it cannot be explained through any shifts in instruction. Indeed, each cohort develops its own unique pattern of spatial interaction (reaction) in light of the changes.

Conclusion

Using traditional GIS tools along with contemporary observation methods, we demonstrated that socialization in young children is, indeed, heavily reliant on coupled sociospatial mechanisms. More specifically, we identified four clear signatures of geographical behavior that were associated with sociality.

First, children use the geography of their environment to differentiate their social activities in unique ways—Distinct spatial patterns of behavior were observed for indoor and outdoor socialization. There are many possible reasons why these patterns may have manifested. The classroom provided an environment that supported an array of social behaviors by providing the substrate for varying social skills. To a certain degree, the availability of social tasks was also more constrained indoors, as children followed a given day's lesson plan and the instructional staff introduced a variety of activities in the classroom, with a greater opportunity for diversification in socialization. But one of the main rationales has to be geography: Many tasks are structured in

lesson-type fashion in the playground, yet marked differences still persist between outdoor and indoor spatial composition.

Second, children also factored the geography of the resources (i.e., affordances, see Cosco et al., 2010) that they used—objects, infrastructure, landmarks, and space—while socializing; access to affordances significantly altered both the propensity and type of observed interactions, as well as with whom children played. These results suggest that children are quite adept at leveraging the resources around them to create “imagined spaces” to supplement the tangible spaces that they encounter; in turn, this leads to the use of incorporating these socializing spaces in an interchangeable and malleable manner. Children clustered social activity of varying types in resource-rich locations in the built environment. Some resources were clearly targeted for particular behaviors (huts for solitary behavior and peer interaction, the sandpit for solitude). This was also the case in the classrooms; however, in the outdoors, many of the locations (the sandpit, the playhouses, steps) were used for multiple types of socialization. This may have occurred because the children were relatively free from instructor-supervised activity, but the children might also be creating their own “imagined spaces” at these sites. This is certainly the case for the playhouse areas, where the children create elaborate games involving imaginary monsters, “playing house,” or hiding.

Third, there were marked differences between the sexes in the geography of their social behavior. Boys, in particular, used space and spatial separation to distinguish between different types of social activities; girls did not.

Finally, the geography of sociospatial interaction was malleable over space and time. Distinct changes in the sociospatial landscape were observed over the study period when the population was subject to change. As shifts in the makeup of the social cohorts took place, different social groups were formed, and they generated different social geographies than their predecessors did.

In summary, the clustering of activity around classroom resources was classically appropriate. Distinct clusters of local spatial autocorrelation appeared in the classroom space as cool spots and hot spots of socialization, but mostly for expected activities. The approach that we have described in this article suffers some limitations that require further work before its application can reach a fuller potential. Because much of our data is categorical in nature (coded social transactions and affects), the range of spatial analysis techniques that we could apply was limited to those that could operate on frequency data and that could be meaningfully referenced against null hypotheses of complete spatial randomness. The latter, in particular, is appropriate for the population and environments considered in this study (a base condition of “random” is often quite appropriate for toddler behavior). The

result, however, is that our inferences are necessarily qualitative in nature, and we were unable to look more closely at the strength of some of the relationships that we observed, using techniques such as spatially adjusted or geographically weighted regression. Discussion of social *networks*, although implied, is obviously absent from our analysis, as is its integration with socio-metrics; combining these is well established in the human development literature (see, for example, Santos et al., 2008), but current work in that area has not utilized the tools described herein. Relative to our work, we have collected network relationship data in this preschool population, but we have not yet completed the necessary work to integrate those analyses with our spatial approaches. Those data can, however, be “docked” with the data that we described in this article, and we suspect that merging the two approaches would be of considerable value in teasing out the intricacies of social dynamics that we observed. Indeed, existing inroads made by scholars to fuse Geographic Information Science and social network analysis are already leading the way in proving the value of such connections (Dibble & Feldman, 2004; Eubank et al., 2004; Faust, Entwistle, Rindfuss, Walsh, & Sawangdee, 2000). Finally, much of the insight generated in this study related socialization and spatial behavior through *patterns* of activity, but we could offer relatively little empirical insight into the spatial *processes* generating those patterns and in elucidating the relationship between social activity and spatial behavior. To advance those abilities, we are currently developing dynamic agent-based models using the data collected in this study to experiment with what-if scenarios in simulation, using the knowledge that we have gleaned from the work discussed in this article.

Acknowledgments

We would also like to thank Casey Sechler, Jillian Smith, Atsushi Nara, Shana Schmidt, Xun Li, and Jennifer Fewell for their advice and their assistance in data collection and analysis. We are particularly thankful to the children, teachers, and parents who allowed us to share so much time with them while doing this work.

Declaration of Conflicting Interests

The authors declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding

The authors disclosed receipt of the following financial support for the research, authorship, and/or publication of this article: This work was supported in part by grants from the National Science Foundation (0624208, 0643322, and 1002517).

References

- Andrews, H. F. (1977). The spatial context of the small-world problem. *Environment and Planning A*, 9, 1253-1258.
- Ansell, N. (2009). Childhood and the politics of scale: Descaling children's geographies? *Progress in Human Geography*, 33, 190-209.
- Atladóttir, H. Ó., Parner, E. T., Schendel, D., Dalsgaard, S., Thomsen, P. H., & Thoresen, P. (2007). Time trends in reported diagnoses of childhood neuropsychiatric disorders. *Archives of Pediatrics & Adolescent Medicine*, 161, 193-198.
- Barker, J., & Weller, S. (2003). "Is it fun?" Developing child-centered research methods. *International Journal of Sociology and Social Policy*, 23, 33-58.
- Butts, C. T. (2009). Revisiting the foundations of network analysis. *Science*, 325, 414-416.
- Cosco, N. G., Moore, R. C., & Islam, M. Z. (2010). Behavior mapping: A method for linking preschool physical activity and outdoor design. *Medicine and Science in Sports and Exercise*, 42, 513-519.
- Cressie, N. A. C. (1991). *Statistics for spatial data*. New York, NY: John Wiley.
- Dibble, C., & Feldman, P. G. (2004). The GeoGraph 3D computational laboratory: Network and terrain landscapes for RePast. *Journal of Artificial Societies and Social Simulation*, 7. Retrieved from <http://jasss.soc.surrey.ac.uk/7/1/7.html>
- Dykes, J., MacEachran, A. M., & Kraak, M.-J. (2005). *Exploring geovisualization*. London, England: Elsevier.
- Epstein, J. M. (2007). *Generative social science: Studies in agent-based computational modeling*. Princeton, NJ: Princeton University Press.
- Eubank, S., Guclu, H., Kumar, A., Marathe, M. V., Srinivasan, A., Toroczkai, Z., and Wang, N. (2004). Modelling disease outbreaks in realistic urban social networks. *Nature*, 429 (6988):180-184.
- Fagot, B. I., & Hagan, R. (1991). Observation of parent reactions to sex-stereotyped behaviors: Age and sex effects. *Child Development*, 62, 617-628.
- Faust, K., Entwistle, B., Rindfuss, R. R., Walsh, S. J., & Sawangdee, Y. (2000). Spatial arrangement of social and economic networks among villages in Nang Rong District, Thailand. *Social Networks*, 21, 311-337. doi:10.1016/S0378-8733(99)00014-3
- Fayard, A.-L., & Weeks, J. (2007). Photocopiers and water-coolers: The affordances of informal interaction. *Organization Studies*, 28, 605-634. doi:10.1177/0170840606068310
- Fotheringham, A. S., Brunson, C., & Charlton, M. (2004). *Geographically weighted regression: The analysis of spatially varying relationships*. Chichester, UK: Wiley.
- Gallacher, L., & Gallagher, M. (2008). Methodological immaturity in childhood research? Thinking through "participatory methods." *Childhood*, 15, 499-516.

- Getis, A., & Ord, J. K. (1992). The analysis of spatial association by use of distance statistics. *Geographical Analysis, 24*, 189-207.
- Griffin, W. A., Greene, S. M., & Decker-Haas, A. (2004). The MICSEASE: An observational coding system for capturing social processes. In P. K. Kerig & D. Baucom (Eds.), *Couple observational coding systems*. Mahwah, NJ: Lawrence Erlbaum.
- Hägerstrand, T. (1975). Space-time and human conditions. In A. Karlqvist, L. Lundqvist, & F. Snickars (Eds.), *Dynamic allocation of urban space* (pp. 3-12). Farnborough, UK: Saxon House.
- Hartup, W. W., & Laursen, B. (1999). Relationships as developmental contexts: Retrospective themes and contemporary issues. In W. A. Collins & B. Laursen (Eds.), *Relationships as developmental contexts: The Minnesota symposia on child psychology* (Vol. 30, pp. 13-35). Mahwah, NJ: Lawrence Erlbaum.
- James, S. (1990). Is there a "place" for children in geography? *Area, 22*, 278-283.
- Kerns, K. A., & Berenbaum, S. A. (1991). Sex differences in spatial ability in children. *Behavior Genetics, 21*, 383-396. doi:10.1007/BF01065974
- Kinderman, T. (1998). Children's development within peer groups: Using composite social maps to identify peer networks and to study their influences. *New Directions in Child Development, 81*, 55-82.
- Kitchin, R. M., Blades, M., & Gollidge, R. A. (1997). Relations between psychology and geography. *Environment and Behavior, 29*, 554-573. doi:10.1177/001391659702900406
- Ladd, G. W., Kochenderfer, B. J., & Coleman, C. C. (1997). Classroom peer acceptance, friendship, and victimization: Distinct relational systems that contribute uniquely to children's school adjustment? *Child Development, 68*, 1181-1197.
- Latner, J. D., & Stunkard, A. J. (2003). Getting worse: The stigmatization of obese children. *Obesity Research, 11*, 452-456.
- Lazer, D., Pentland, A., Adamic, L., Aral, S., Barabási, A.-L., Brewer, D. et al. (2009). Computational social science. *Science, 323*, 721-723.
- Legendrea, A., & Munchenbach, D. (2011). Two-to-three-year-old children's interactions with peers in child-care centres: Effects of spatial distance to caregivers. *Infant Behavior and Development, 34*, 111-125.
- Li, H., & Reynolds, J. F. (1993). A new contagion index to quantify spatial patterns of landscapes. *Landscape Ecology, 8*, 155-162.
- Longley, P. A., Goodchild, M. F., Maguire, D. J., & Rhind, D. W. (2001). *Geographic information systems and science*. Chichester, UK: Wiley.
- Martin, C. L., & Fabes, R. A. (2001). The stability and consequences of young children's same-sex peer interactions. *Developmental Psychology, 37*, 431-446.
- Martin, P., & Bateson, P. (1996). *Measuring behaviour: An introductory guide* (2nd ed.). Cambridge, UK: Cambridge University Press.

- McGarigal, K., & Marks, B. (1995). *FRAGSTATS: Spatial pattern analysis program for quantifying landscape structure*. Portland, OR: Pacific Northwest Research Station, USDA Forest Service.
- Mize, J., & Ladd, G. W. (1988). Predicting preschoolers' peer behavior and status from their interpersonal strategies: A comparison of verbal and enactive responses to hypothetical social dilemmas. *Developmental Psychology, 24*, 782-788.
- Moore, G. T. (1986). Effects of the spatial definition of behavior settings on children's behavior: A quasi-experimental field study. *Journal of Environmental Psychology, 6*, 205-231.
- Moran, P. A. P. (1950). Notes on continuous stochastic phenomena. *Biometrika, 37*, 17-23.
- Oliver, M. A., & Webster, R. (1990). Kriging: A method of interpolation for geographical information systems. *International Journal of Geographic Information Systems, 4*, 313-332.
- Pate, R. R., Davis, M. G., Robinson, T. N., Stone, E. J., McKenzie, T. L., & Young, J. C. (2006). Promoting physical activity in children and youth: A leadership role for schools. *Circulation, 114*, 1214-1224.
- Pellegrini, A. D. (1996). *Observing children in their natural worlds: A methodological primer*. Mahwah, NJ: Lawrence Erlbaum.
- Riitters, K. H., O'Neill, R. V., Wickham, J. D., & Jones, K. B. (1996). A note on contagion indices for landscape analysis. *Landscape Ecology, 11*, 197-202.
- Rusby, J., Estes, A., & Dishion, T. (1991). The interpersonal process code. Unpublished coding manual. (Available from Oregon Social Learning Center, 207 East 5th Avenue, Ste. 202, Eugene, OR).
- Santos, A. J., Vaughn, B. E., & Bost, K. K. (2008). Specifying social structures in preschool classrooms: Descriptive and functional distinctions between affiliative subgroups. *Acta Ethologica, 11*, 101-113. doi:10.1007/s10211-008-0047-0
- Schwartz, M. S., & Schwartz, C. G. (1955). Problems in participant observation. *American Journal of Sociology, 60*, 343-353.
- Shannon, C. E. (1948). A mathematical theory of communication. *Bell System Technical Journal, 27*, 379-423, 623-656.
- Skelton, T. (2009). Children's geographies/geographies of children: Play, work, mobilities and migration. *Geography Compass, 3*, 1430-1448.
- Thomson, S. (2005). "Territorialising" the primary school playground: Deconstructing the geography of playtime. *Children's Geographies, 3*, 63-78.
- Torrens, P. M. (2001). Where in the world? Exploring the factors driving place location knowledge among secondary level students in Dublin, Ireland. *Journal of Geography, 100*, 49-61.
- Walker, H. M., & Severson, H. H. (1991). *Systematic screening for behavior disorders*. Longmont, CO: Sopris West.

- Walker, H. M., Severson, H. H., Nicholson, F., Kehle, T., Jenson, W. R., & Clark, E. (1994). Replication of the Systematic Screening for Behavior Disorders procedure for the identification of children. *Journal of Emotional and Behavioral Disorders*, 2, 66-77.
- Willis, A., Gjersoe, N., Havard, C., Kerridge, J., & Kukla, R. (2004). Human movement behaviour in urban spaces: Implications for the design and modelling of effective pedestrian environments. *Environment and Planning B*, 31, 805-828. doi:10.1068/b3060
- Wong, D. W. S., & Lee, J. (2005). *Statistical analysis of geographic information*. Hoboken, NJ: John Wiley.

Author Biographies

Paul M. Torrens is an associate professor in the Department of Geographical Sciences at the University of Maryland, College Park. He is also director of the Geosimulation Research Laboratory. His work is focused on Geographic Information Science and geocomputing, applied to human and behavioral geography.

William A. Griffin is a professor in the School of Social and Family Dynamics and the Center for Social Dynamics and Complexity at Arizona State University. His research revolves around the identification, the quantification, and the subsequent computational modeling of the behavioral dynamics observed during complex social processes.