Abstract

We describe an analytic methodology useful for recording and interpreting dynamic micro-processes that occur during social interaction, making use of space-time data collection techniques, spatial-statistical analysis, and visualization. The proposed scheme has three investigative foci: Structure, Activity Composition, and Clustering; each being associated with either acquiring resources or using socio-environmental features to influence social intercourse. For each point of focus we 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. Our 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 geographical factors (location, space, place, spatial structure, spatial composition, landmarks, site) have on the evolving reciprocal inter-play between individuals and groups.

1   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). And we know even less about how these interactions translate into to group-scale phenomena. Calls for additional attention to these issues have come, in particular, from study of children's geographies, which, it has been argued, have been relatively overlooked (Ansell, 2009; Barker & Weller, 2003; Skelton, 2009) and 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 areas, 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, social phenomena are complex evolving structures generated by many-to-many interactions among- and between- people and their environments. These interactions, characterized by inconsistency in form and often unpredictable outcomes, epitomize one of the major conundrums for contemporary social science: how we might reliably and efficiently investigate the micro-scale of sociality and catalyze that insight, from the bottom-up,

to meso- and macro-scale social phenomena (Butts, 2009; Lazer et al., 2009). Second, geography often 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 (Longley, Goodchild, Maguire, & Rhind, 2001); spatial and spatial-statistical analysis (Wong & Lee, 2005); and qualitative geo-visualization (Dykes, MacEachran, & Kraak, 2005).

This coupling of data and related "dataware" allows us to explore inter-related indices of social interaction: affect, group formation, place and space, the geography of activity, and their combined influence upon 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: 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.

As we noted above, the data used to verify our analytic approach were drawn from an observational study of pre-school children forming playgroups (See Methods 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, e.g., Santos, *et al*., (2008)), but we extend the notion of ecological validity to include physical structures that have facilitator or inhibitory effects on socialization and networks. To investigate this, we applied a series of spatial analyses, using the data that we acquired, to capture these dimensions. Specifically, we explored socio-environmental factors using point-pair distances, contagion, interspersion and juxtaposition, and Shannon Evenness; we also examined the influence of resources using global and local spatial autocorrelation. A general overview of the scheme is

shown in Table 1; which summarizes the tie between the spatial construct and its method, its index, and its range along with a simple interpretation.

[Table 1 goes here]

Table 1. An overview of the analytic scheme by construct, method, index, with a brief interpretation.

2 Methods

In order to capture the dynamics of sociality in play, peer group formation, and the evolving nature of children's social behavior, we performed a three-year observational study of children in a pre-school. This was focused on coding children's social (or non-social) interactions, as well as tracking their movement and the locations of their activities.

2.1 Participants

Each participant had a maximum opportunity to be in the study for five semesters, though 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=.90) who attended a university preschool in a Southwestern metropolitan area. Written informed parental consent was obtained before the onset of children's participation in the study. 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 $116,000, and 50% were female.

2.2   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 five-and-a-half hours each day of the nine 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).

Approximately 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 aclimated 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.

[Figure 1 goes here]

Figure 1. Observational data were entered on a Tablet PC by coders and the data were immediately registered to an integrated database management system and Geographic Information System that was developed for the project.

2.3   Observational Measures

After initial training, inter-rater 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

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the second author). The coding procedure was designed to be intuitive: using the GUI interface shown in Figure 1, a drop-down box identified a target child, randomly selected, who was observed for ten seconds; 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. During the ten-second period, the target child was coded for behavior, peers (up to five, if applicable), activity, affect, and physical location. More specifically, coders indicated if 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 allow 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 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.

[Figure 2 goes here]

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).

As briefly mentioned above, the child's primary activity (i.e., their activity for five or more seconds) was observed and recorded in each ten-second 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 inter-rater reliability; it also allowed ample opportunity to observe each participant.

Activities (i.e., coded behaviors) encompassed all developmentally appropriate behaviors including several gross motor (e.g., Walking, Physical Games), 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 is provided in Table 2 along with the developmental construct associated with the activity. Also note that, based on one of four criteria, six tasks were removed before commencing data analyses. Two tasks not included in all semesters (Animal Observation, Non-Directed 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. One task (Circle Time) was 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 provide no information about task selection. The fourth exclusion criteria pertained to Other and Unoccupied. These tasks were invoked while coding if the activity could not be classified into any of the other 28 tasks or if the child was completely uninvolved with activities or people in the preschool. Other and Unoccupied provides no information about an interaction. Additionally, 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). Lastly, 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 ten second 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 Geographic Information System 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.

2.4   Data

This study concluded in June, 2009; it generated 178,565 codeable 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 paper.

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In sum, while watching a randomly chosen child for ten-seconds, 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.

[Table 2 goes here]

Table 2. Listed in the second column are the major observational codes (n=29) used to generate the data. Column 1 gives a general construct associated with the coded behaviors; some codes are found in multiple constructs.

3   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.

3.1   Socio-spatial 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 $1m^2$ 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 Appendix 1).

3.2   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, Inter-Mixing, and Diversity.

3.2.1   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 Appendix 2).

3.2.2   Inter-mixing

We also tested the level of inter-mixing among social activities, using the Interspersion and Juxtaposition Index. The metrics are related but yield distinct results. The Contagion Index

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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, while 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 Appendix 3.

3.2.3   Diversity

Lastly, to capture socio-environmental 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 zero 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 & Marks (1995), see Appendix 4.

3.3   Spatial Clustering

3.3.1   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

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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 Appendices 5 and 6, respectively) by calculating scaled versions of Moran's (1950) I index. The Index ranges between values of –1 and +1 (see Table 1; Appendix 5).

A (statistically significant) value of zero 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, i.e., 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 that play with toys never do so next to each other.

Positive values suggest positive spatial autocorrelation, i.e., 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, while 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, i.e., 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, Brunsdon, & Charlton, 2004); See Appendix 5).

3.3.2   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 Appendix 6). 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 "coolspots" ("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).

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4   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.

4.1   Socio-environmental geography

4.1.1   Indoor vs. 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 interspersion and juxtaposition (~73%), and very high evenness (~91%) (see Appendix 7 for more details); 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 interspersion and juxtaposition (~65%), and lower evenness (~61%): social activity was more homogeneous outside. Moreover, sex did not make a difference: indoor/outdoor heterogeneity manifested in almost identical proportions [indoor contagion was ~24% for boys and ~22% for girls (averaged across all times)], while outdoor contagion values were ~45% and ~43% respectively; values of indoor interspersion and juxtaposition were ~75% for boys and ~77% for girls, while outdoors the values were ~60% and ~62% respectively; the average value of indoor evenness was ~88% for boys and ~89% for girls, while 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 Appendix 7, a visual, and more importantly, interpretable representation of the general trends is evident as a

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

[Figure 3 goes here]

Figure 3. Spatial indices by sex, location, and behavior type across time periods.

4.1.2   Spatial Autocorrelation

The results for the *global* Moran's I test revealed strong positive spatial autocorrelation for indoor socialization (~ +0.39, averaged over the entire study period), but weakly positive spatial autocorrelation for the outdoor area (~ +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.

4.2   Resource geography

4.2.1   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 classrooms; and the sand-pit, play-houses, slide, tires, and wood stumps in the playground (Figure 4).

[Figure 4 goes here]

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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.

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 7). Although why this occurs 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.

[Figures 5 and 6 go here]

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

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

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 play-house and the climbing structure supported similar dichotomous behaviors.

The outdoors belonged to the sand-pit—it formed the main hub of social interaction (Figures 4, 6, and 8) and presented as a statistically significant hot-spot across all social interactions. The sand-pit 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 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 sand-pit 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.)

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 play-house 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 play-houses, suggesting that these structures are another major hub for social activity in the playground.

Besides the climbing structure (which was a hotspot 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-spots 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 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.

4.3   Sex differences

Analyses indicated that socio-spatial 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' hot-spots for teacher interaction (Figure 7). 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 too 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).)

[Figures 7 and 8 go here]

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

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

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 7). 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.

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Differences in the patterning of social behavior between and within the sexes were less distinct outdoors. Girls and boys both 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. Both boys and girls frequented the sand-pit as a hot-spot for solitude (Figures 4 and 6).

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, 7, and 8). Indeed, large spaces of separation form between the two sexes in these cases. The pattern of socio-spatial 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 *socio-spatial 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 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.

[Figure 9 goes here]

Figure 9. Logged ratio of Boy/Girl Contagion scores. Darker shading indicates higher Girl scores. Values from upper and lower 2 deciles are embedded within relevant cells.

4.4 Space-time dynamics

The spatial patterning in socialization observed in the study did not hold constant over time. Indeed, while the physical environment of the preschool changed little over the study period (see Figure 2) marked differences in socio-spatial 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, 7, 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.

5   Conclusions

Using traditional Geographic Information System tools along with contemporary observation methods, we demonstrated that socialization in young children is, indeed, heavily reliant upon coupled socio-spatial 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

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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 sand-pit for solitude). This was also the case in the classrooms; however, in the outdoors many of the locations (the sand-pit, the play-houses, 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 play-house 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 socio-spatial interaction was malleable over space and time. Distinct changes in the socio-spatial landscape were observed over the study period when the population

was subject to change. As shifts in the make-up 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 both cool-spots and hot-spots of socialization, but mostly for expected activities. The approach that we have described in this paper 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 sociometrics; combining these is well established in the human development literature (see, e.g., 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 paper 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 in-roads made by scholars to fuse Geographic

Information Science and social network analysis is 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 paper.

Acknowledgements

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Table 1. Overview of the metrics used to analyze the data.

Geography Type	Social Spatial Construct	Method	Appendix	Index	Range	Interpretation
Socio-environmental	Structure	Semivariogram, variogram	2	Point-pair distance	≥ 0, $\leq$ max	0 at origin (lack dependence), increases until max is reached
Socio-environmental	Activity	Dominance	3	Contagion	≥ 0, ≤ 1	0: maximal disaggregation; degree of clumping of attributes
Socio-environmental	Activity	Inter-Mixing	4	Interspersion - Juxtaposition	≥ 0, ≤ 100	0: extreme variability 100: uniform activity
Socio-environmental	Activity	Diversity	5	Shannon Evenness	≥ 0, ≤ 1	0: no diversity 1: uniform
Resource	Clustering	Moran's I (global)	6	Global Spatial Autocorrelation	≥ -1, ≤ 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	≥ -1, ≤ 1	$0 < I \leq 1$: Clustered $I = 0$: Random $-1 \leq I < 0$: Dispersed

Table 2. Observed activities.

Construct	Activity (tasks)
Planning and Organization	Manipulatives, Art, Board Games Language Arts, Math/Science Board Games, Physical Games
Self-Management	Affection, Conflict, Problem Solve Circle Time, Clean-up, Instruction Onlooking, Unoccupied, Non-dir. Phys.
Accommodation Strategies	Pretend Play, Talk
Higher Cognition	Math/Science, Language Arts Pretend Play, Molding, Sensory Play
Language	Problem Solve, Talk, Conflict
Fine motor	Figure Play, Manipulatives
Gross Motor	Large Motor, Physical Games Walking, Digging

Figures
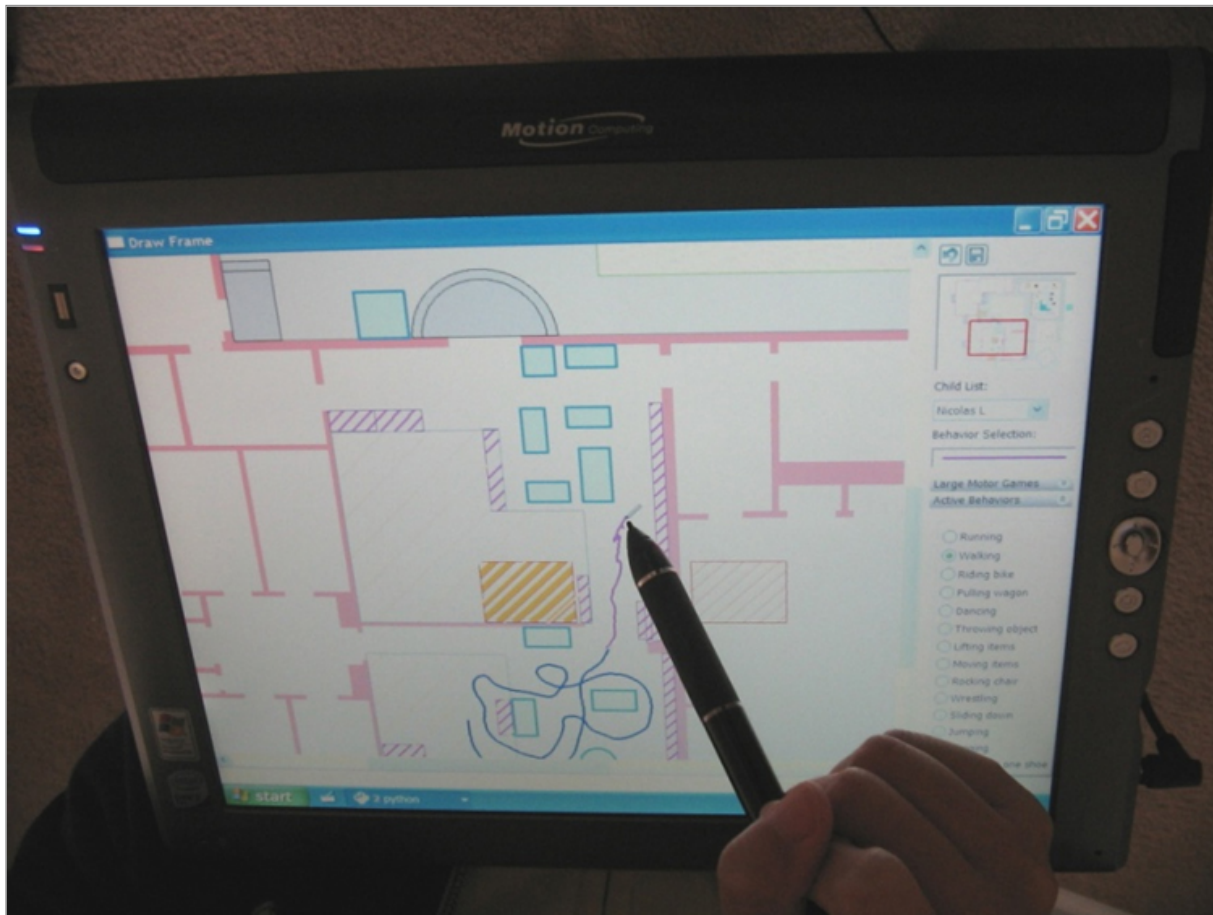
Figure 1. Observational data are entered on a Tablet PC by coders and the data are immediately registered to an integrated database management system and Geographic Information System that was developed for the project.
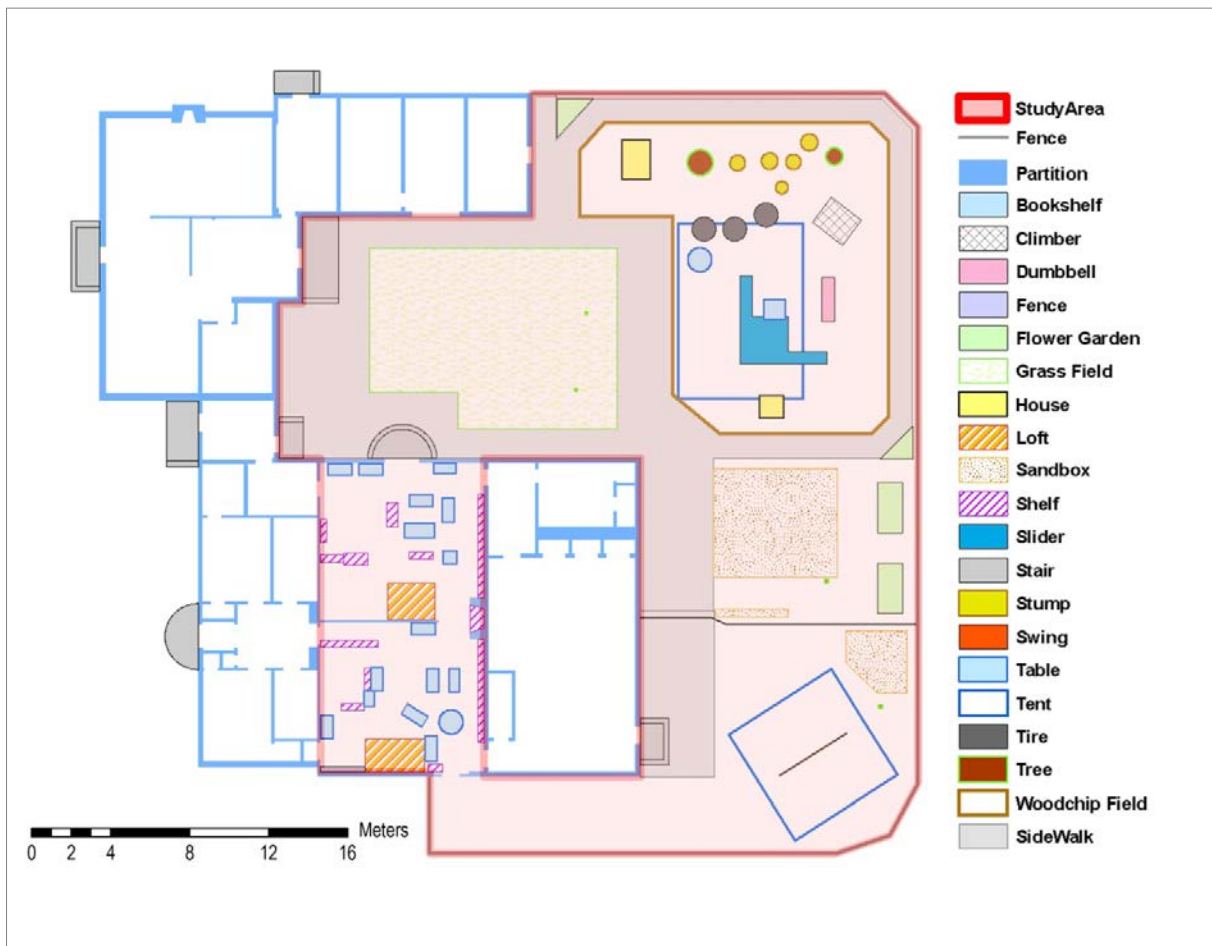
Figure 2. A map of the preschool structure (some of the furniture in the classrooms was rearranged over the study period; the map reflects the locations in which the furniture remained for the longest period of time).
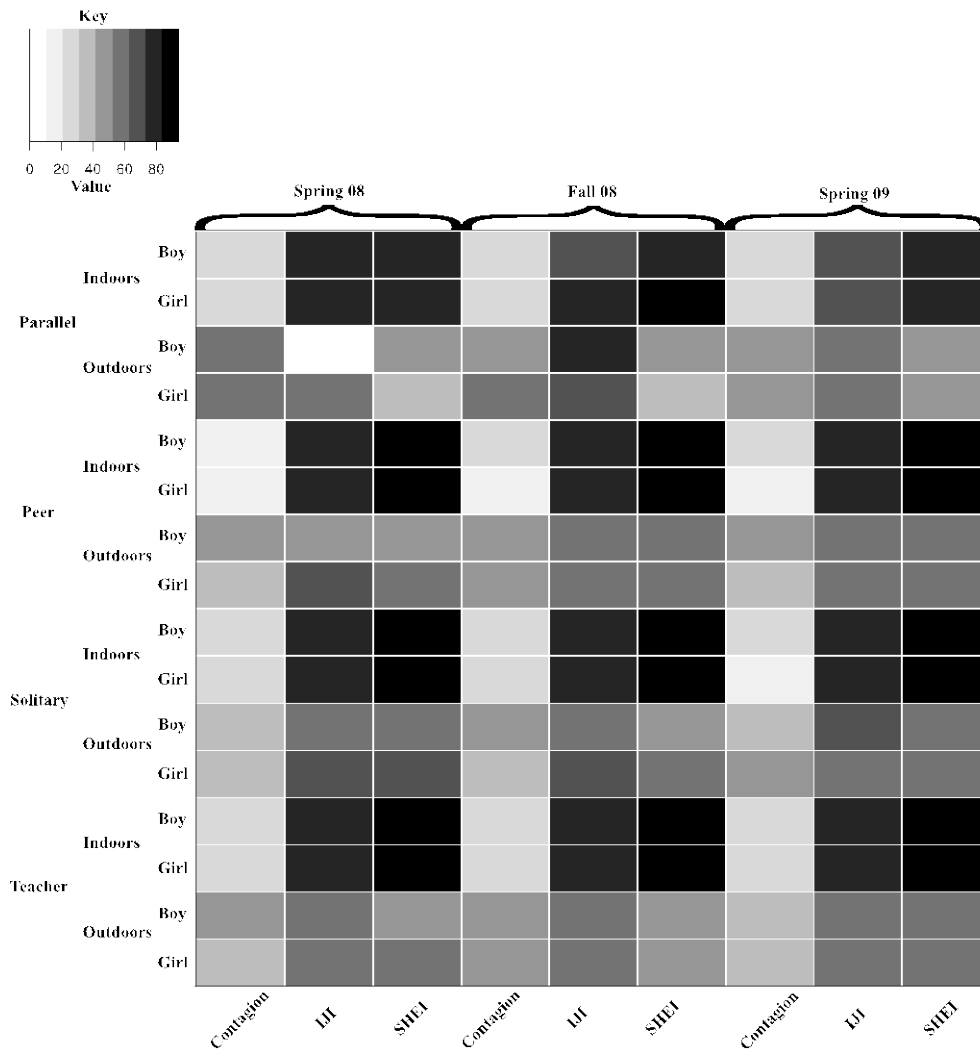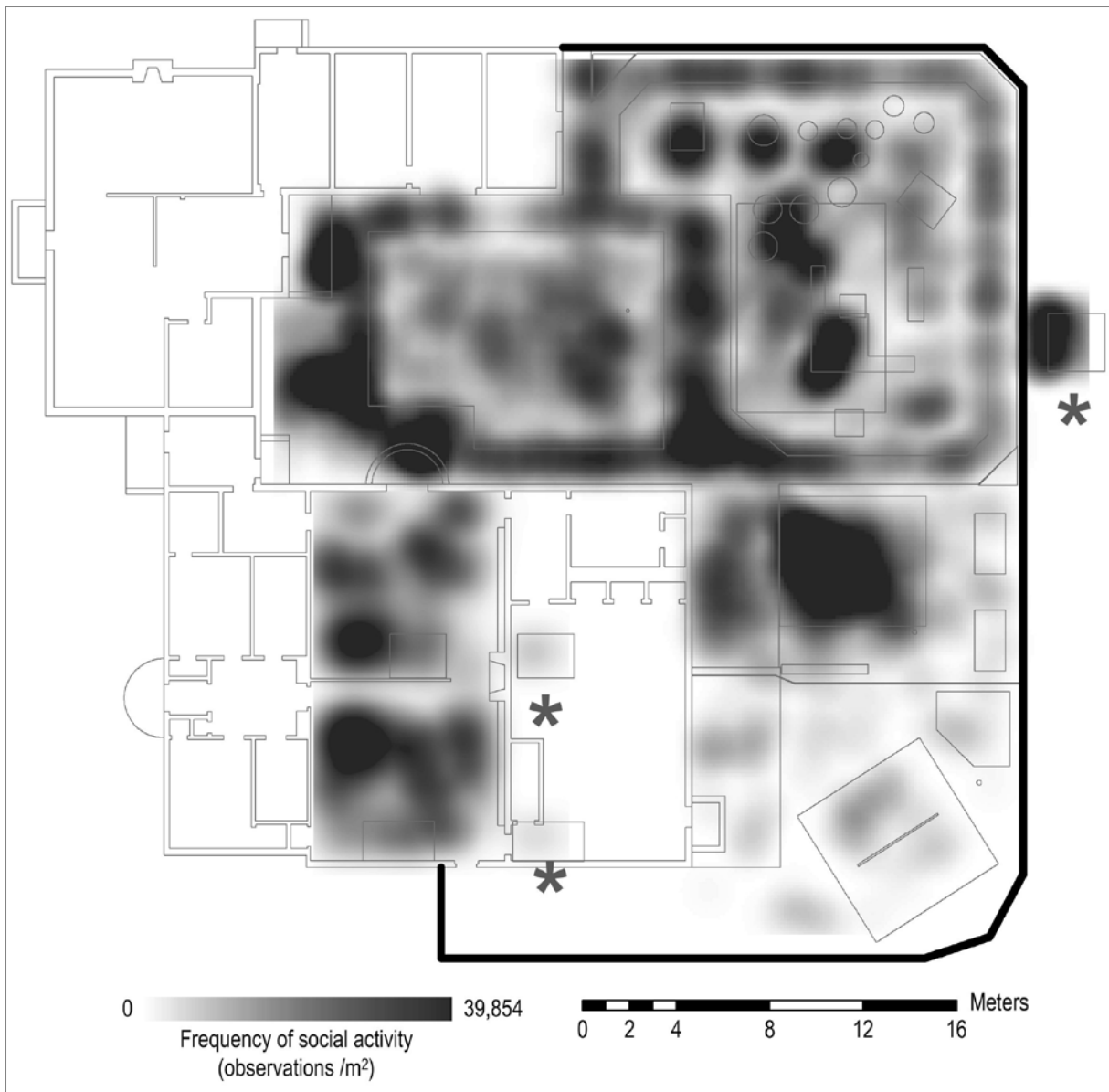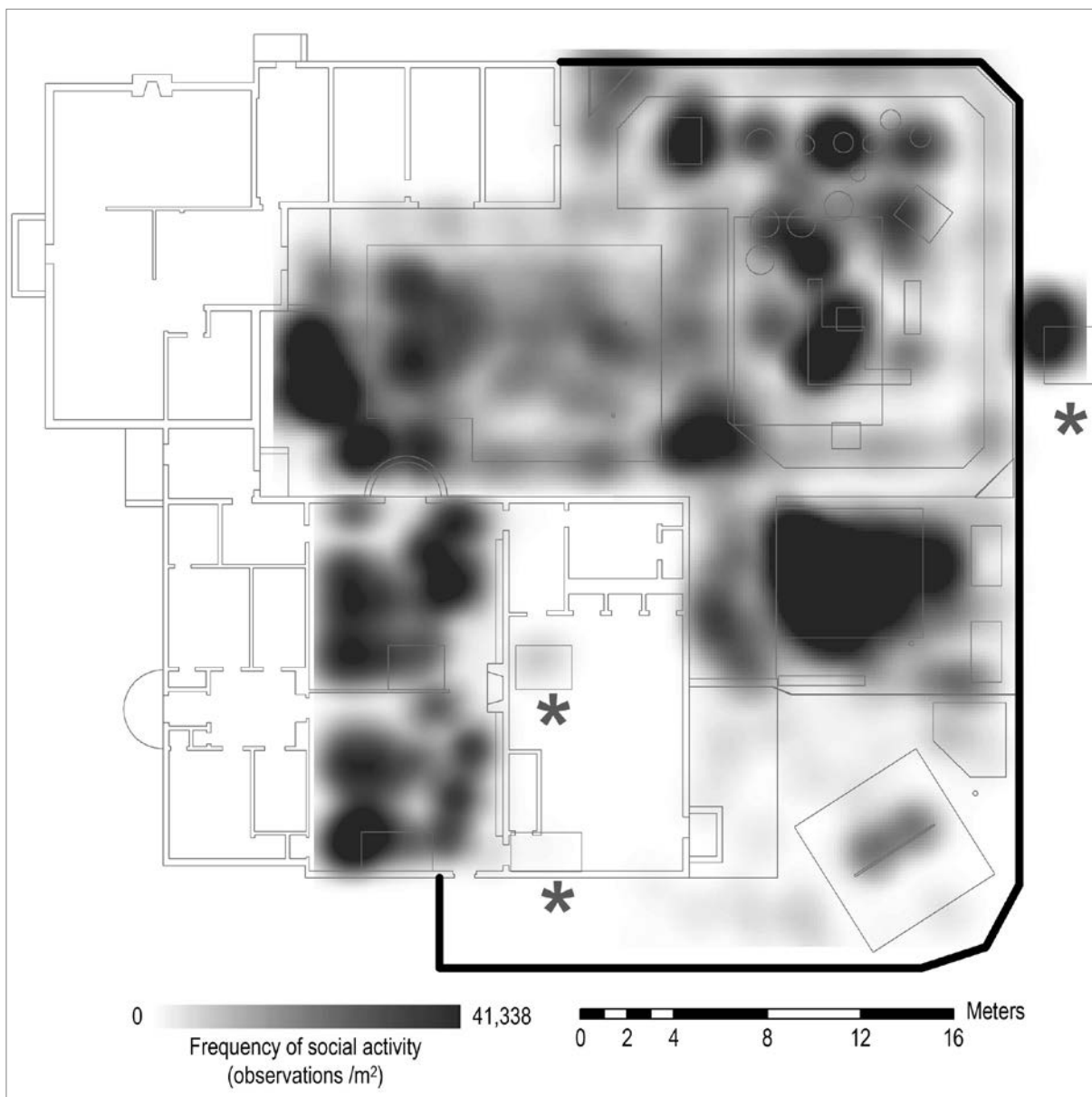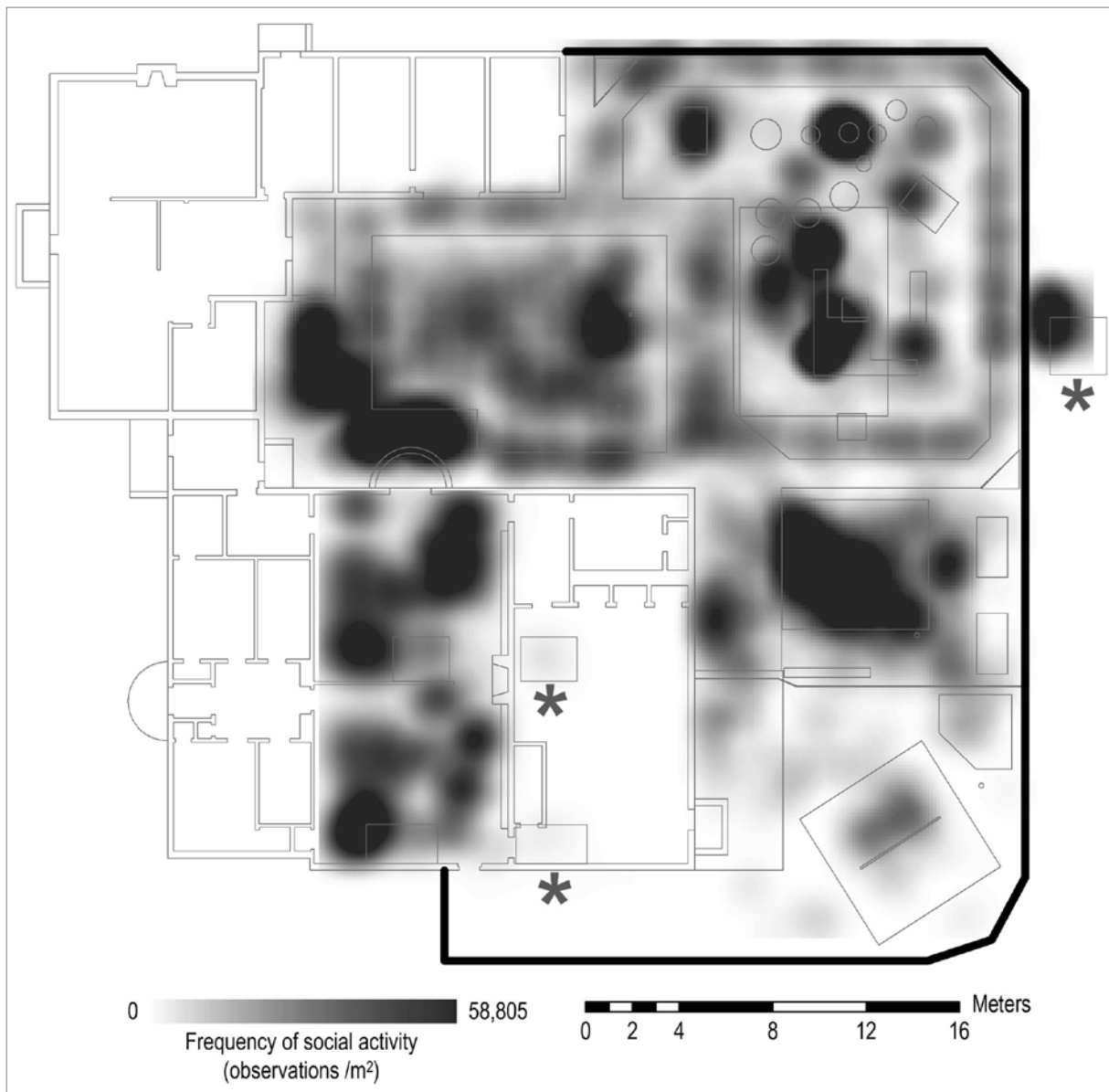
Figure 3. Spatial indices by sex, location, and behavior type across time periods.

0 ▓ 39,854

Frequency of social activity
(observations /m²)

0 2 4 8 12 16 Meters

(a)

4

0 �— 41,338

Frequency of social activity
(observations /m²)

0   2   4   8   12   16   Meters

(b)

5

(c)

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.
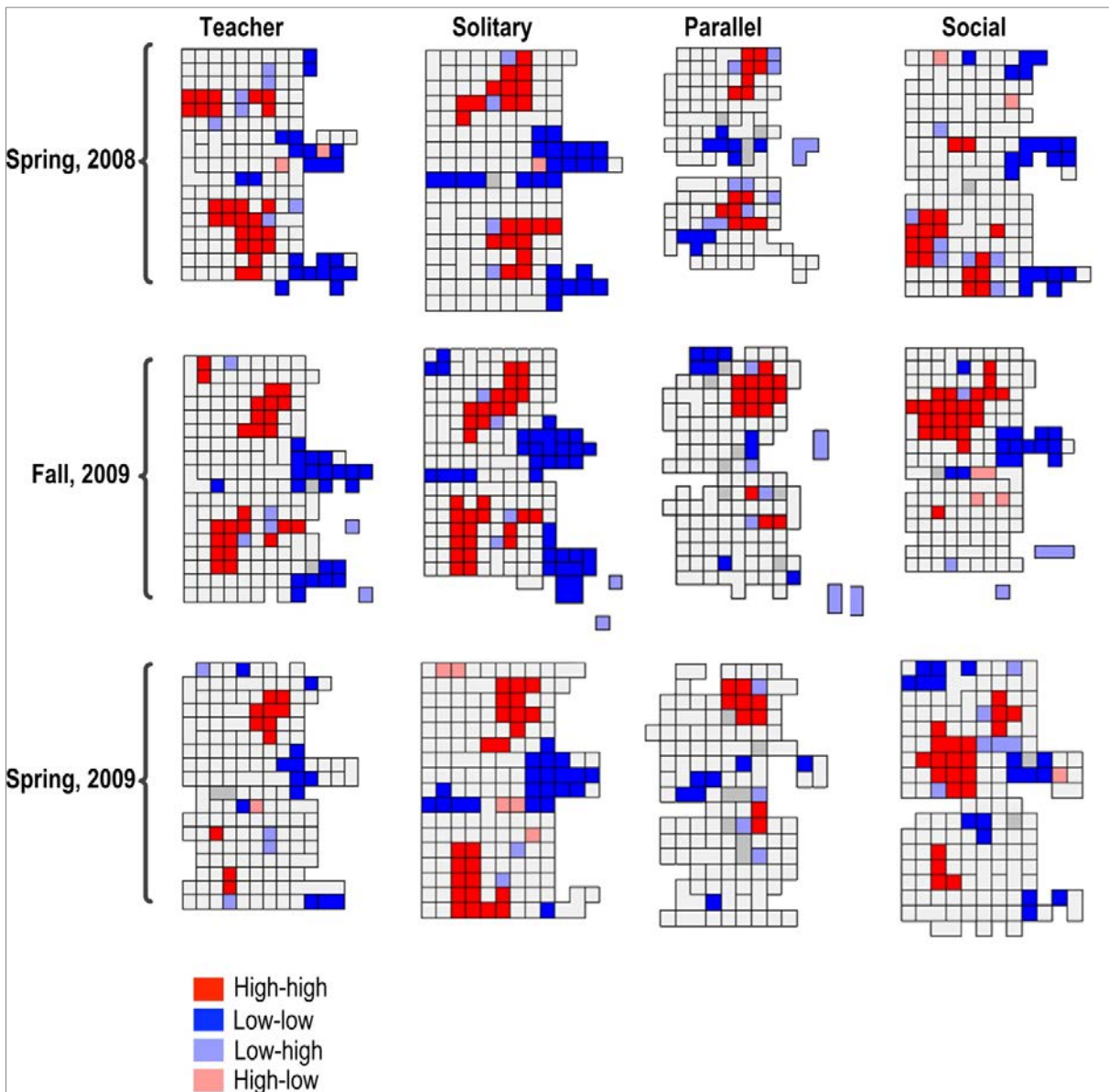
Figure 5. Local spatial autocorrelation by type of sociality and date, for all children, indoors. (Each square in the graphic represents one meter on the ground; white cells have no statistically significant autocorrelation; empty spaces have no observations for a given variable.)
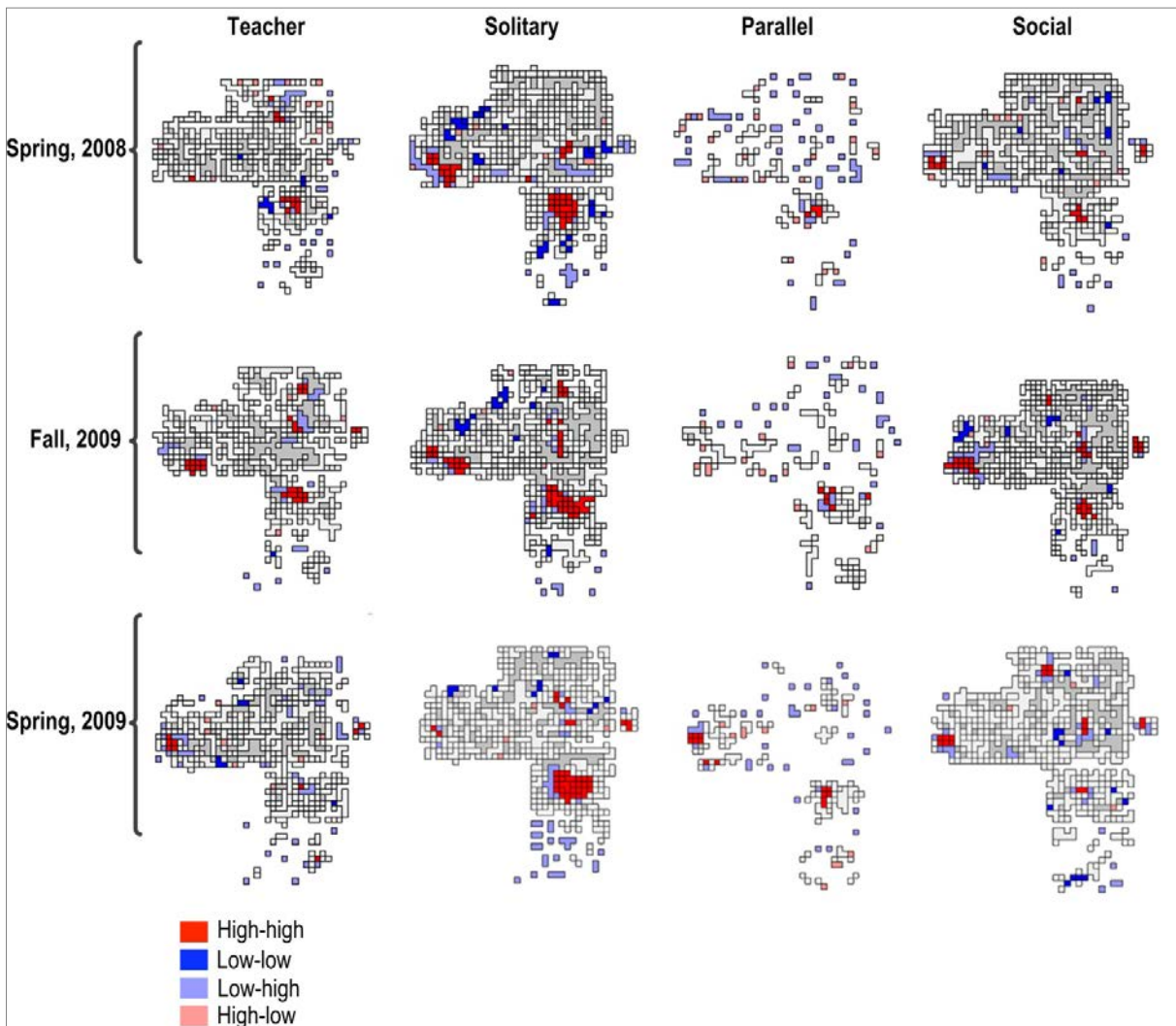
Figure 6. Local spatial autocorrelation by type of sociality and date, for all children, outdoors. (Each square in the graphic represents one meter on the ground; white cells have no statistically significant autocorrelation; empty spaces have no observations for a given variable.)
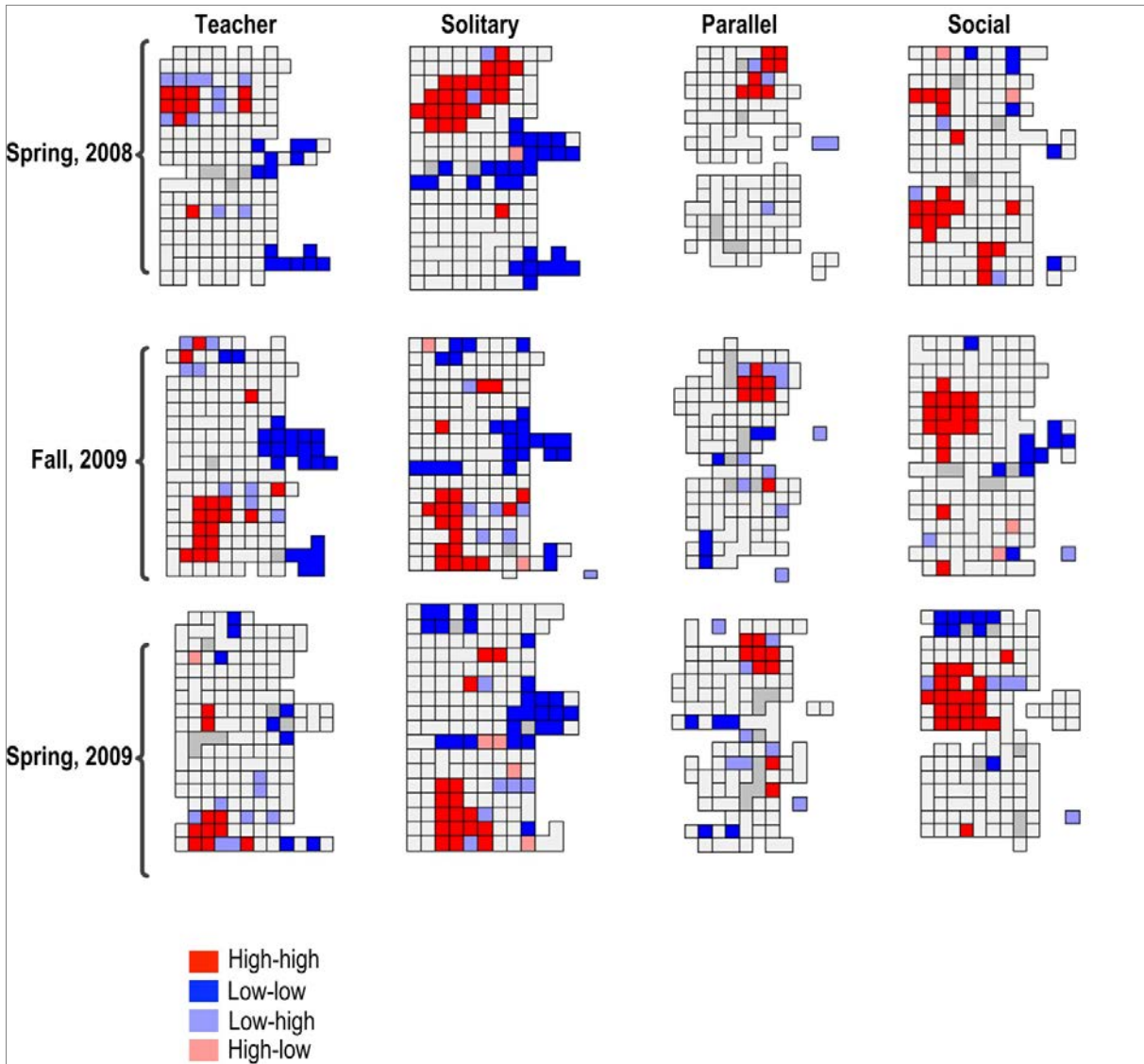
Figure 7. Local spatial autocorrelation by type of sociality and date, for all boys, indoors. (Each square in the graphic represents one meter on the ground; white cells have no statistically significant autocorrelation; empty spaces have no observations for a given variable.)
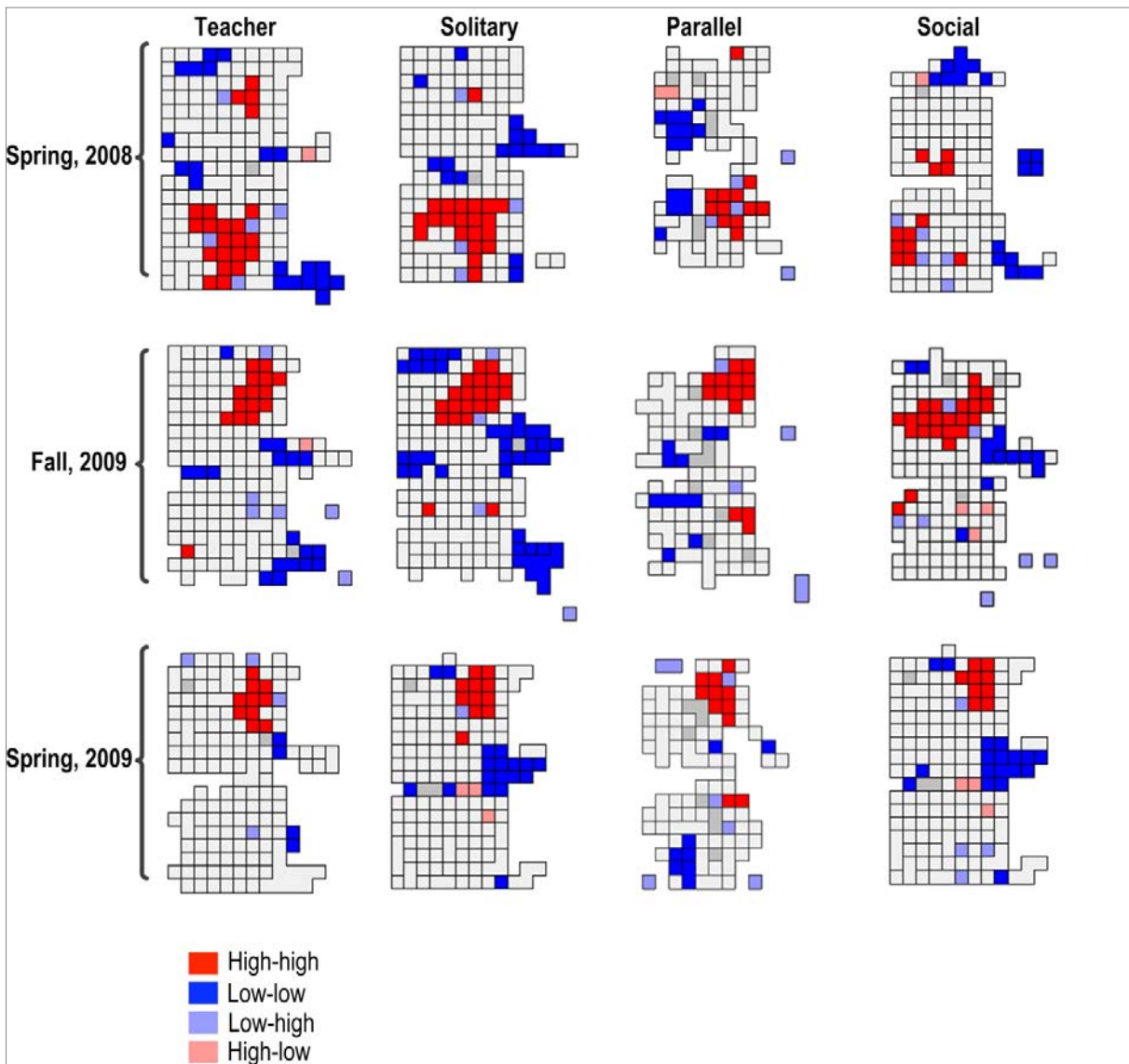
Figure 8. Local spatial autocorrelation by type of sociality and date, for all girls, indoors. (Each square in the graphic represents one meter on the ground; white cells have no statistically significant autocorrelation; empty spaces have no observations for a given variable.)
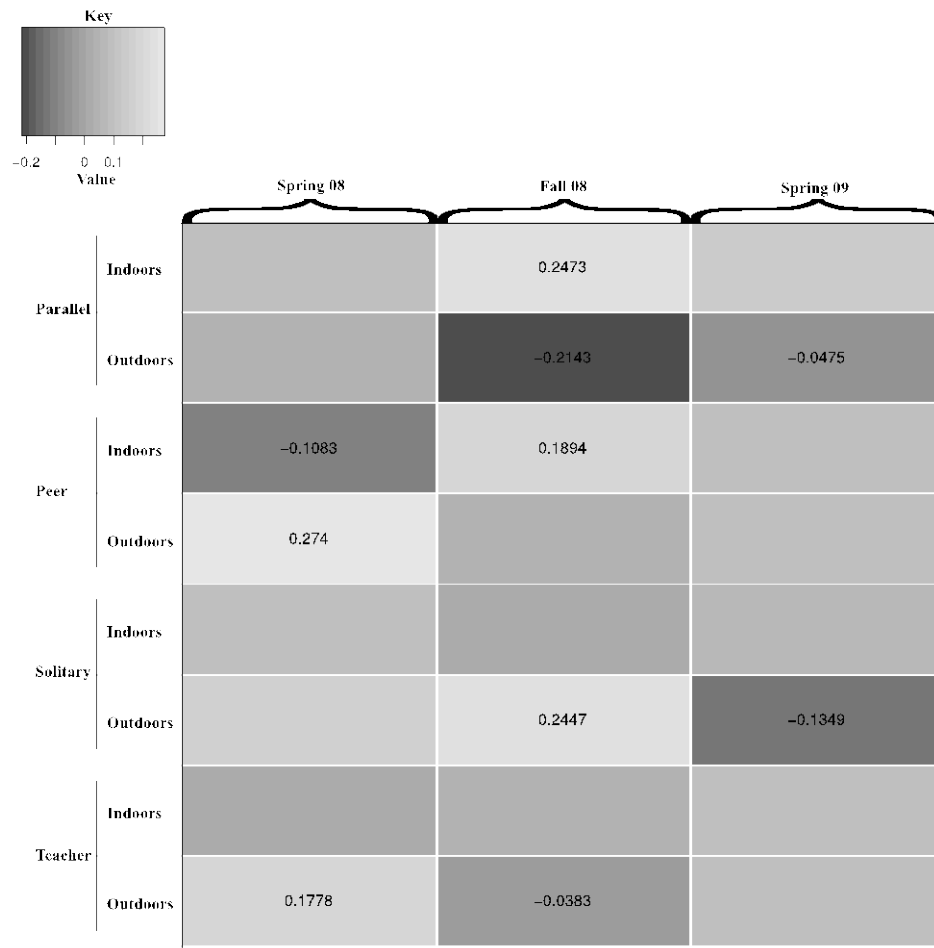
10

Figure 9. Logged ratio of Boy/Girl Contagion scores. Darker shading indicates higher Girl scores. Values from upper and lower 2 deciles are embedded within relevant cells.

Appendix1. Results of tests for dominance (Contagion), interspersion (the Interspersion and Juxtaposition Index, IJI) and evenness (Shannon's Evenness Index, SHEI)

Population ↓	Spring08			Fall 08			Spring 09		
Metric →	Contagion	IJI	SHEI	Contagion	IJI	SHEI	Contagion	IJI	SHEI
Boys: parallel interaction	38.8106	74.4721	0.6364	44.1702	69.4755	0.6264	45.805	60.3045	0.5913
Boys: peer interaction	44.2363	65.2394	0.6005	44.4056	64.5825	0.6044	43.4067	64.8595	0.5911
Boys: solitary behavior	46.3179	62.2697	0.6166	48.6425	60.8713	0.5794	43.3187	63.1587	0.6203
Boys: teacher interaction	47.31	63.915	0.5956	48.8521	61.3011	0.5865	47.4858	61.8179	0.595
Girls: parallel interaction	39.7917	73.4277	0.6106	39.1462	72.2341	0.6307	37.3041	70.0639	0.6445
Girls: peer interaction	39.5401	67.2056	0.6453	44.0262	63.3539	0.597	42.5841	64.249	0.6054
Girls: solitary behavior	42.2677	61.5177	0.6392	46.5181	62.3798	0.6047	44.1044	62.4399	0.609
Girls: teacher interaction	47.6695	59.0805	0.5872	50.2214	61.9228	0.5805	47.865	57.0454	0.5823
All: parallel interaction	44.2995	69.0769	0.591	45.9252	67.9319	0.5962	41.6404	66.0061	0.6273
All: social interaction	41.9233	61.7156	0.6435	43.2866	59.2858	0.6228	44.5955	57.7934	0.605
All: solitary behavior	43.3559	57.6199	0.6458	47.1353	55.7041	0.6068	42.7658	59.3226	0.6437
All: teacher interaction	46.6245	56.6537	0.6102	47.921	58.3076	0.6003	45.2939	57.6583	0.6194

1

Population ↓	Spring08			Fall 08			Spring 09		
Metric →	Contagion	IJI	SHEI	Contagion	IJI	SHEI	Contagion	IJI	SHEI
Boys: parallel interaction (indoors)	26.1607	74.7137	0.8236	30.8435	68.5854	0.7947	31.0593	67.4176	0.8007
Boys: peer interaction (outdoors)	56.9977	N/A	0.4638	44.5607	75.1901	0.5067	45.0914	59.9107	0.4939
Boys: peer interaction (indoors)	17.8325	81.1803	0.9036	23.1048	77.1572	0.8866	22.2805	77.9168	0.8727
Boys: peer interaction (outdoors)	48.7897	50.5729	0.4921	44.5989	61.0465	0.5485	44.7705	57.3198	0.537
Boys: solitary behavior (indoors)	23.7537	74.9355	0.9092	24.1175	75.0473	0.9074	21.972	76.8896	0.9204
Boys: solitary behavior (outdoors)	41.7586	58.0523	0.5632	48.3072	55.4609	0.5175	36.6957	67.2617	0.6193
Boys: teacher interaction (indoors)	21.8408	76.9291	0.8996	24.7978	74.0227	0.9037	23.9008	76.4652	0.8959
Boys: teacher interaction (outdoors)	45.1921	58.6415	0.5139	45.6167	58.8502	0.5204	41.3723	61.4024	0.5658
Girls: parallel interaction (indoors)	23.6485	77.8364	0.8174	24.0848	75.7499	0.8396	27.2238	71.9035	0.8092
Girls: parallel interaction (outdoors)	55.3003	53.2776	0.4176	55.2113	67.9864	0.4	47.2887	57.5698	0.4944
Girls: peer interaction (indoors)	19.8726	79.0129	0.9128	19.1167	80.4753	0.9079	20.1936	78.9463	0.8855
Girls: peer interaction (outdoors)	37.0957	64.3214	0.6188	43.1891	58.4831	0.5607	41.17	60.5576	0.5788
Girls: solitary behavior (indoors)	21.7565	76.3678	0.9406	23.7769	75.0783	0.9151	20.7874	77.8864	0.9267

2

Girls: solitary behavior (outdoors)	35.2615	64.3036	0.6351	37.8215	68.3133	0.6068	41.9954	60.3553	0.5798
Girls: teacher interaction (indoors)	21.7086	76.9986	0.9148	24.0297	75.307	0.9092	22.0042	77.0995	0.9119
Girls: teacher interaction (outdoors)	37.8274	62.6143	0.6009	47.3992	60.8999	0.5179	37.467	62.0176	0.6126
All: parallel interaction (indoors)	25.3195	75.8187	0.8341	28.4552	71.2501	0.846	29.3217	69.9712	0.8306
All: parallel interaction (outdoors)	53.611	54.8346	0.4469	51.447	71.5928	0.475	40.7968	72.4849	0.5575
All: peer interaction (indoors)	22.8588	75.6747	0.9361	24.7794	74.9836	0.9231	23.8851	75.0889	0.9159
All: peer interaction (outdoors)	35.442	65.7266	0.6474	36.8806	63.7113	0.6375	37.8664	61.3212	0.6268
All: solitary behavior (indoors)	26.7524	71.3158	0.9461	27.6223	70.9391	0.9377	26.0576	72.1215	0.9442
All: peer interaction (outdoors)	30.6163	68.4431	0.7016	40.9282	59.2709	0.6004	36.3675	64.4551	0.6513
All: teacher interaction (indoors)	24.1982	74.0448	0.9472	27.9208	70.5007	0.9306	27.8454	70.7781	0.9079
All: teacher interaction (outdoors)	35.6936	64.1407	0.6362	37.592	67.0051	0.6174	32.001	69.2512	0.679

Table 2. Results of tests for global spatial autocorrelation using Moran's *I* statistic

	Solitary behavior					
	Indoor			Outdoor		
	Moran's I	P-value	Z-value	Moran's I	P-value	Z-value
2008 Spring (all)	0.3509	0.001	8.174312	0.2797	0.001	8.524242
2008 Fall (all)	0.4199	0.001	10.34867	0.2723	0.001	7.916667
2009 Spring (all)	0.2514	0.001	5.894977	0.3331	0.001	10.58044
2008 Spring Boy	0.3212	0.001	6.880503	-0.0193	N/A	N/A
2008 Spring Girl	0.3758	0.001	8.626697	0.1644	0.001	4.265985
2008 Fall Boy	0.4098	0.001	9.634884	0.223	0.001	4.424184
2008 Fall Girl	0.3096	0.001	7.085393	0.1895	0.001	3.835341
2009 Spring Boy	0.1964	0.001	4.568539	0.1884	0.001	3.995825
2009 Spring Girl	0.2544	0.001	5.759382	0.2336	0.001	5.331818

	Parallel interaction					
	Indoor			Outdoor		
	Moran's I	P-value	Z-value	Moran's I	P-value	Z-value
2008 Spring (all)	0.2968	0.001	5.268966	-0.1082	0.1	N/A
2008 Fall (all)	0.3818	0.001	7.5	0.1784	0.025	2.42487
2009 Spring (all)	0.2557	0.001	4.585366	0.2383	0.008	3.304465
2008 Spring Boy	0.4332	0.001	6.131148	-0.0844	N/A	N/A
2008 Spring Girl	0.3531	0.001	5.658842	-0.0044	N/A	N/A
2008 Fall Boy	0.4477	0.001	6.945619	0.1966	0.024	2.362251
2008 Fall Girl	0.2828	0.001	4.874791	0.2126	0.037	2.360465
2009 Spring Boy	0.312	0.001	4.863429	0.0092	0.3	N/A
2009 Spring Girl	0.1706	0.013	2.72549	0.0424	0.2	N/A

	Peer interaction					
	Indoor			Outdoor		
	Moran's I	P-value	Z-value	Moran's I	P-value	Z-value
2008 Spring (all)	0.3591	0.001	7.4651	0.0993	0.008	2.62
2008 Fall (all)	0.3476	0.001	8.077626	0.2704	0.001	8.140299
2009 Spring (all)	0.2948	0.001	6.532328	0.2107	0.001	5.703504
2008 Spring Boy	0.2922	0.001	5.882813	0.0559	0.13	N/A
2008 Spring Girl	0.2642	0.001	5.155598	0.0557	0.1	N/A
2008 Fall Boy	0.2982	0.001	6.23374	0.1957	0.001	3.916996
2008 Fall Girl	0.2934	0.001	5.91068	0.1226	0.007	2.727273
2009 Spring Boy	0.1964	0.001	4.476718	0.103	0.028	2.075728
2009 Spring Girl	0.3708	0.001	6.829401	0.099	0.032	1.984466

	Teacher interaction					
	Indoor			Outdoor		
	Moran's I	P-value	Z-value	Moran's I	P-value	Z-value
2008 Spring (all)	0.4993	0.001	11.0655	0.153	0.002	3.886305
2008 Fall (all)	0.3766	0.001	8.794457	0.2446	0.001	6.136476
2009 Spring (all)	0.2989	0.001	6.997701	0.1128	0.001	2.982005
2008 Spring Boy	0.4875	0.001	10.86842	0.3261	0.001	5.551261
2008 Spring Girl	0.4442	0.001	10.25455	0.0096	0.362	N/A
2008 Fall Boy	0.3834	0.001	9.140515	0.077	0.07	N/A
2008 Fall Girl	0.3821	0.001	9.027842	0.1067	0.04	1.908766
2009 Spring Boy	0.4456	0.001	9.171079	-0.0217	N/A	N/A
2009 Spring Girl	0.3827	0.001	8.974713	0.0567	0.113	N/A

Appendix 2. Variogram.

$$\text{Variogram} = 2\hat{\gamma}(d) = \frac{1}{n}\sum_{d_{ij}=d-\frac{\Delta}{2}}^{d+\frac{\Delta}{2}}(z_i - z_j)^2$$

(i)

Where $2\hat{\gamma}$ is the estimated variogram; d is the distance between sample points i and j; n is the

number of sample point-pairs (i,j); $(z_i - z_j)$ is the difference in the variable value of sample

point-pairs; and Δ is the size of a lag band used to poll locations around a given point.

Appendix 3. Contagion.

The value of contagion is calculated as follows (Li & Reynolds, 1993):

$$\text{Contagion Index} = \left[1 + \frac{\sum_{i=1}^{m} \sum_{k=1}^{m} \left[(P_i) \left(\frac{g_{ik}}{\sum_{k=1}^{m} g_{ik}} \right) \right] \left[ln(P_i) \left(\frac{g_{ik}}{\sum_{k=1}^{m} g_{ik}} \right) \right]}{2ln(m)} \right] (100) \qquad (ii)$$

Where, P_i is the proportion of the landscape covered by a social activity i (i.e., the total number

of rasters in the landscape, divided by the number of rasters of type i) ; g_{ik} is a count of the

number of adjacencies between rasters denoting activities i and k; and m is the number of social

activity types.

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Appendix 4: Interspersion and Juxtaposition Index.

The Interspersion and Juxtaposition Index is calculated as follows (McGarigal & Marks, 1995):

$$\text{Interspersion and Juxtaposition Index} = \frac{-\sum_{k=1}^{m}\left[\left(\frac{e_{ik}}{\sum_{k=1}^{m}e_{ik}}\right)ln\left(\frac{e_{ik}}{\sum_{k=1}^{m}e_{ik}}\right)\right]}{ln(m-1)}(100) \qquad \text{(iii)}$$

Where, i and k reference social activity types that are being compared; e_{ik} is the total amount of

edge shared between patches of i and k; and m is the number of social activity types.

Appendix 5. Shannon's Evenness Index.

Shannon's Evenness Index is formulated as follows (McGarigal & Marks, 1995):

$$\text{Shannon's Evenness Index} = \frac{-\sum_{i=1}^{m} (P_i \ln P_i)}{\ln(m)} \qquad \text{(iv)}$$

Where P_i is the proportion of the space that is occupied by social activity i and m is the number

of social activity types.

Appendix 6. Global Moran Index.

The global Moran index is calculated as follows (Fotheringham, Brunsdon, & Charlton, 2000):

$$\text{Global Moran's } I \text{ index} = \left(\frac{n}{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}}\right)\left(\frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(x_i-\bar{x})(x_j-\bar{x})}{\sum_{i=1}^{n}(x_i-\bar{x})^2}\right),$$

and the expected value of $I = E[I] = \frac{-1}{n-1}$,

and the variance of $I = var[I] = \frac{n^2 S_1 - n S_2 + 3\left(\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}\right)^2}{\left(\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}\right)^2 (n^2-1)}$ when we assume that

(v)

the process producing the observed pattern is random,

and where

$$S_1 = \sum_{i=1}^{n}\sum_{j=1}^{n}(w_{ij}+w_{ji})^2$$
$$S_2 = \sum_{i=1}^{n}\left(\sum_{j=1}^{n} w_{ij} + \sum_{j=1}^{n} w_{ji}\right)^2$$
$$S_3 = \frac{n^{-1}\sum_{i=1}^{n}(x_i-\bar{x})^4}{\left(n^{-1}\sum_{i=1}^{n}(x_i-\bar{x})^2\right)^2}$$
$$S_4 = (n^2 - 3n + 3)S_1 - nS_2 + 3\left(\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}\right)^2$$
$$S_5 = S_1 - 2nS_1 + 6\left(\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}\right)^2$$

Where, n is the number of observations (locations) considered in the analysis; w_{ij} registers

adjacency between observations i and j (this can be expressed in many ways; for this analysis we

rasterized the data into frequencies per $1m^2$ units and tested adjacency using first-order queen

contiguity); and x is the valuable of a variable (frequency of observed social activity, by activity type). (Note that we are "overloading" the notation in this formula because the autocorrelation metrics are calculated per activity-type; for landscape metrics, i and j referenced social activity types, but here they are used to denote locations.)

Appendix 7. Local Moran Index.

A local version of the Moran's I statistic is calculated as follows (Anselin, 1995; Wong & Lee, 2005):

Local Moran's $I = I_i = z_i \sum_{j=1 \in J_i}^{n} w_{ij} z_j$, where $z_i = \frac{x_i - \bar{x}}{\delta}$ and $z_j = \frac{x_j - \bar{x}}{\delta}$,

The expected value is $E[I_i] = \frac{-w_i}{n-1}$,

and the variance is $V[I_i] = w_{i(2)} \frac{\left(n - \frac{m_4}{m_2^2}\right)}{(n-1)} + 2w_{i(kh)} \frac{\left(2\frac{m_4}{m_2^2} - n\right)}{(n-1)(n-2)} - \frac{w_i^2}{(n-1)^2}$,

where $w_i^2 = \left(\sum_{j=1}^{n} w_{ij}\right)^2$,

$$(vi)$$

and where $w_{i(2)} = \sum_{j=1}^{n} w_{ij}^2, i \neq j$,

and where $m_2 = \frac{\sum_{i=1}^{n} x_i^2}{n}$,

and where $m_4 = \frac{\sum_{i=1}^{n} x_i^4}{n}$,

and where $2w_{i(kh)} = \sum_{k \neq i} \sum_{h \neq i} w_{ik} w_{ij}, k \neq h, j \neq i$

Where i, j, k, h are point locations; x_i is the value of a variable (the frequency of a given social activity) at a location i; δ is the standard deviation of the variable x; $j \in J_i$ indicates that only adjacent locations are used; and w_i is the sum of row elements in an adjacency matrix w_{ij} (and w_{ii} was assumed to equal zero).