Demographic, Clinical, and Geographic Predictors of Placement Disruption among Foster Care Youth Receiving Wraparound Services

Dana A. Weiner, Scott C. Leon, & Michael J. Stiehl

Abstract

The effective delivery of wraparound depends upon the availability of a wide range of community-based services. This study seeks to determine the impact of proximity to resources on the effectiveness of a wraparound program for stabilizing foster care placements among a sample of youth. We present a methodology for deriving proximity scores for individual clients using Geographic Information Systems technology, and incorporate this score into a model for predicting placement disruption among youth in foster care receiving services within a wraparound model aimed at preventing placement disruptions. Cox Regression is used to predict length of time until placement disruption using clinical, demographic, and service proximity measures. Risk of placement disruption is predicted by trauma experiences, risk behaviors, and age, and is reduced by the presence of child strengths and proximity to resources. The impact of proximity to resources on placement disruption varies by land use type, suggesting that proximity exerts a greater impact on youth in rural and suburban areas than in urban areas where wraparound service delivery models may be able to overcome distance and other barriers. Implications for the implementation of wraparound programs as well as service system planning are discussed.

Introduction

Historically, children served in the foster care system experience less favorable mental health outcomes than those in the general population (Anctil et al. 2007; Burns et al. 2004; Garland et al. 2001; Zima et al. 2000) and are up to eight times more likely to have a diagnosis of mental illness (Burns et al. 2004; Landsverk and Garland 1999). These figures are not surprising considering the traumatic experiences that lead youth to enter the child welfare system, such as severe abuse, neglect, and instability. Unfortunately, once in the foster care system, many children continue to be exposed to stressors, such as separation from familiar people and surroundings, disruption of mental health and educational services, and possibly ongoing abuse (Benedict et al. 1996; Newton et al. 2000; Roberts 1993; Skarbo et al. 2004). However, arguably the most prevalent stressor youth experience in foster care is chronic placement disruption, and research has demonstrated that chronic placement instability has a deleterious long-term impact on youth in the child welfare system (Newton et al. 2000; Rubin et al. 2007; Simmel 2007; Unrau et al. 2008).

The literature suggests that the following variables predict placement disruption: (a) youth characteristics, most notably emotional and behavioral problems; (b) number of prior placements; and (c) quality of relationship with foster and biological families (Smith et al. 2001; Zinn et al. 2006). A much smaller body of research suggests that community interventions such as those using a wraparound model can improve the placement outcomes of youth in the foster care system by increasing the breadth, flexibility, and coordination of service provision (e.g., Clark et al. 1996). Wraparound approaches have been shown to be successful in the mental health, child welfare, and juvenile justice systems (Burchard et al. 2002; Suter and Bruns 2009). Using existing community services and natural supports, the wraparound system is a family-centered and child-focused intervention that capitalizes on youth strengths, creating an individualized, community-based treatment program that is interagency-coordinated and culturally competent (Walker et al. 2004; Burchard et al. 2002; Walker and Bruns 2008).

Within a wraparound model, many of the traditional barriers to receiving services can be ameliorated—flexible funding can provide hard goods in addition to services so that a wide range of needs can be met as determined by the team and the family. Without financial or administrative obstacles, the degree to which providers can employ varied strategies to address child and family needs are limited only by the availability of a wide range of services.

While the last 10 years has seen an increase in research addressing geospatial factors that impact health care and outcomes, to date this research has not examined the impact of access or proximity to needed resources on the effectiveness of wraparound for improving foster care outcomes and stabilizing placements. The current study examines the role of proximity to community services on the primary outcome of placement stability among youth in the Illinois foster care system receiving services within a wraparound model.

Wraparound Implementation in the Illinois Child Welfare System

In 2002, the State of Illinois responded to the national call to serve youth in their communities by developing a state-wide community-based program designed to provide multi-modal services to at-risk youth in substitute care (Stroul and Friedman 1994). The program was designed by the Illinois Department of Children and Family Services (IDCFS) to address the needs of children and adolescents who were capable of community functioning but were either at risk for stepping up to a higher level of placement (specialized foster or residential care) or were stepping down from these higher level placements and required special attention to ensure the success of the less restrictive placement. All clients who are admitted to the IDCFS community-based program reside in relative or traditional foster care homes. The Illinois model, called System of Care (SOC), implements wraparound planning principles to develop Child and Family Teams, identify strengths during the assessment process, and develop individualized plans of care that reflect the needs and strengths of the child and family (IDCFS 2005). Not only does the SOC Program Plan incorporate wraparound principles, but ongoing data and evaluation reinforce these principles by providing feedback to providers on their success in addressing client needs; this outcomes monitoring process is also a key feature of wraparound implementations (Bruns et al. 2008).

To implement the SOC program, IDCFS contracts with 28 agencies (e.g., Community Mental Health Centers, Foster Care Agencies) to serve eligible youth in circumscribed catchment areas known as Local Area Networks (LANS) across the state (State of Illinois DCFS 2009). These contracts are "capitated" service agreements; providers agree to serve any eligible youth in the LAN who was referred by a caseworker. If a client is accepted into the program, the provider is responsible for planning, organizing, staffing, and administering an array of community-based positive youth development and therapeutic services. The agency may deliver the services and interventions directly or may secure needed services through subcontracts or other formal arrangements. A variety of services can be provided, ranging from traditional psychotherapy to more positive youth development activities (e.g., boys and girls club memberships, music lessons, etc.) as well as hard goods (professional clothing for job interview, class rings, yearbooks, beds, etc.).

On the whole, the Illinois SOC program has been successful in stabilizing community placements for the majority of enrolled youth. Youth referred for SOC services experience a mean placement change rate of 1.58 per year before referral; entry to services reduces placement change by more than 50%, to a low of .73 among youth who stay in the program between 30 and 150 days. The rate of placement change in the 6 months following SOC services is 0.26 placement changes per year of custody, a reduction of 35%, which is now lower than that of foster care youth overall (.35 placement changes per year of custody; McClelland and Schneider 2009).

Community Based Services and Geographic Information Systems

Recent research has incorporated Geographic Information Systems (GIS) technology into strategies for understanding the relationship between service needs and outcomes. Generally speaking, these studies seek to validate several key assumptions: (1) receipt of community-based services can alleviate the need for more costly, inpatient treatment; (2) individuals will use those services they can more readily access; and (3) the receipt of services results in better outcomes than when needs remain untreated (Allard et al. 2003; Kirby and Kaneda 2005; Laditka et al. 2009; Mansfield et al. 1999).

Some of these assumptions have been supported by the research. Studies suggest that costs and disease burden increase as distance from providers increases (Billi et al. 2007; Fortney et al. 1999). Distance from providers can mean that patients wait longer to receive needed care, or resort to more costly emergency services because they are without access to less expensive community care as problems arise and begin to worsen. However, findings on whether the utilization of community-based services can reduce the utilization of more costly inpatient mental health services are conflicting (Curtis et al. 2009; Mobley et al. 2006).

Despite disagreement about the impact of service proximity on the use of costly emergency care, proximity to community services does seem to increase the likelihood that residents in need will use community services (Allard et al. 2003). However, this depends on whether the providers in high need areas have the capacity to meet the high level of need among residents (Hipp et al. 2009). In addition, residents' ability to access community-based services depends upon a variety of "non-spatial" factors (Guagliardo 2004). These barriers include attitudes, cultural norms, perceptions of service availability, mode of transportation and driving ability/license (Arcury et al. 2005; Han and Stone 2007).

GIS technology has been used to quantify accessibility to services for adults needing psychiatric care, pregnant and parenting teens, older adults, parolees, and the general population's use of primary care and emergency services at broad geographic levels like zip codes and census tracts (Almog et al. 2004; Han and Stone 2007; Mobley et al. 2006; Nemet and Bailey 2000; Wang and Luo 2005). While GIS has been used to study geospatial patterns of entry into foster care, it has not been used to understand access to resources at a client level among youth in child welfare, where access is mediated by caseworkers, foster care agencies, or wraparound programs. Studies predicting entry into care identify socioeconomic factors that are confounded with neighborhood or region (Coulton et al. 2007). Inconclusive geospatial findings from studies examining outcomes have been attributed to a lack of precise location data, as there is insufficient variability in the zipcodes that are relied upon to index client locations (Eggertsen 2008).

With the expansion of research on service accessibility has come the refinement of approaches for understanding accessibility from a geographic perspective. In order to add geographic data into predictive models that traditionally have included clinical, demographic, and other individual characteristics, it is necessary to simplify and quantify each individual's access to resources. Of numerous approaches, two in particular address some of the key problems associated with calculating client service access. Both present appealing approaches to analyzing the geographic variables that may contribute to success in the implementation and outcomes of services delivered within a wraparound model.

Wang and Luo's (2005) "two-step floating catchment area" (FCA) measure of spatial accessibility uses a process which results in a spatial accessibility score, reported as a provider-to-population ratio for each census tract in a given study area. The provider-to-population ratio is derived using zip code-level provider populations distributed over 30-min drive-time areas and aggregated to population centroids, (e.g., census tracts). This method has been demonstrated mathematically to be a gravity model sensitive to geopolitical border-crossing (Wang and Luo 2005).

Alternatively, Guagliardo (2004) presents the "Kernal Density" model (Guagliardo 2004). This approach uses the ArcGIS Spatial Analyst software to create two continuous layers of data: one based on population and the other on the number of providers. Data from defined geographic areas (e.g., census tracts, zip codes, etc.) are used to calculate the density of the observed data over a given area or map extent. Each calculation uses the same search parameters (e.g., a 3-mile radius) and creates a density layer of identically sized grid cells over the same map extent. This provider-to-population density surface is then used to compute a mean cell ratio for each census tract in the study area. This method also addresses previous challenges to calculating spatial accessibility, including patient border crossing. Additionally, it is a relatively easy calculation to undertake in ArcGIS and one that provides an elegant output that is easily understood.

The volume and specificity of the data used in this study allow us to examine the relationship between clients and providers at an individual level. Examination of service accessibility in the child welfare population at the individual level presents several additional challenges, including residential instability, transportation, and related demand for providers. As a result, this study will use an enhanced gravity model approach that incorporates variation in travel impedance by land use type as well as individually-derived proximity scores (rather than those computed generally for an area and applied to all individuals within that area). Additionally, this study will examine the impact of proximity and other predictors on placement stability among youth engaged in the wraparound process. Individual-level data on client and provider locations allow us to calculate more accurately the spatial relationship between clients and providers and to avoid some of the problems inherent in using aggregated data that presumes demand in a predefined geographic area.

We hypothesize that, along with other variables, proximity to services will predict placement stability. To test this hypothesis we will employ two unique data sources in addition to traditional administrative records of child welfare cases and residential moves: (1) a geocoded database of contracted and non-contracted community providers of a broad array of clinical and non-clinical services, and (2) a large database of clinical assessments quantifying clinical functioning upon entry into SOC.

Method

Sample

This study utilizes data from youth who entered the SOC program between January 2007 and September 2009. We obtained SOC intake assessments from 1,448 cases meeting this criterion, and then obtained start dates for the placement of the child at the time of their SOC intake, and end dates for cases in which placements had "disrupted." Because the primary goal of the SOC program is to stabilize placements and avoid disruptions, for the purpose of this research placement disruption refers to the termination of a placement for any reason other than reunification with birth parents or adoption. Of the 1,448 cases in our sample, 10 youth were adopted during the study period and 2 were reunified. These cases were not counted as "disruptions" but maintained in the survival analysis as stable placements. Interruptions in placement (e.g., runaway, brief hospitalization, brief detention) after which the youth returned to the same foster home were not counted as placement disruptions. If any of these interruptions were followed by a different placement, they were counted as placement disruptions.

Forty-eight percent (n = 699) of the study participants were female, and the ages of participants ranged from 2 to 20 with an average age of 10.2 (SD = 4.6) years. The sample included 830 African-American youth (57.4%), 468 White youth (32.3%), 124 Hispanic youth (8.6%), 2 Asian youth (.1%) and 1 Native American youth (.1%).

Measures

Clinical Functioning. Clinical functioning of the youth in our sample was measured using the Child and Adolescent Needs and Strengths tool (CANS; Lyons 2004), an inventory of problems, issues, and strengths that is used universally within IDCFS to evaluate child needs for treatment and strengths on which to build. The CANS tool does not yield diagnoses, but rather identifies areas on which treatment should focus and provides composite scores for various domains, including Traumatic Stress Symptoms, Strengths, Emotional/Behavioral Needs, Life Domain Functioning, Acculturation, Risk Behaviors, and Trauma Experiences.

Proximity to Resources. Calculating proximity scores requires data on the geographical distribution of youth and providers. Youth information was obtained using the Child and Youth Case Information System (CYCIS) maintained by the IDCFS. CYCIS tracks youth moves and allowed us to determine start and end dates for placements overlapping with SOC intake assessments. Provider information was obtained using the Statewide Provider Database (SPD; Weiner 2009), a comprehensive, searchable database of community-based providers of mental health and other types of services. Both CYCIS and SPD are live databases, in use daily by thousands of staff and maintained by units responsible for their upkeep and accuracy. Because of this regular use and ongoing maintenance, inaccuracies are rapidly detected and corrected as information is continuously refreshed. For the purposes of these analyses, we used Mental Health and Non-Clinical services from the SPD. The 28 SOC agencies themselves were only included in these analyses if they offered Mental Health or Non-Clinical services, thus serving as a "community provider" in addition to an SOC agency. Mental Health provider locations offering family, individual, and group counseling as well as other related therapeutic services comprised 64.4% (n = 797) of the provider locations used, and non-clinical provider locations offering nontraditional services including mentoring, tutoring, recreational programs, and other types of assistance comprised 29.7% (n = 366) of the locations used. Seventy-one provider locations (5.8%) offered both Mental Health and Non-Clinical Programs.

We calculated a score to capture proximity to community providers for each child who began receiving SOC services between July 2007 and September 2009. This score was derived using a modified gravity model, an indicator of both proximity and likely influence based on Newton's Law of Gravitation (Guagliardo 2004). Gravity models represent the potential interaction between any population point and all service points within a reasonable distance, discounting the value of providers with increasing distance modified by travel impedance (Guagliardo 2004).

Because Illinois encompasses both rural and dense urban settings, our modified gravity model divided children into "land use groups" based upon the density of development and the travel impedance of the area in which they lived. These types were assigned using a combination of posted road speeds and the intensity of developed land provided by the Illinois Department of Transportation (IDOT) and the Illinois Department of Natural Resources. These settings also determined the rate at which provider value was discounted over space and the maximum distance at which a provider could be included in an individual child's total proximity score.

Census block groups within Illinois were divided into three different zones (rural, suburban, and urban) based on the combination of travel impedance and development density within those zones. Census block groups are the ideal geographic level of analysis as they are typically about one-third the size of census tracts both in terms of area and population. When determining land use type census block groups enabled a more granular differentiation of urban neighborhoods from each other and of mid- to small-sized cities from the surrounding countryside in rural areas.

Figure 1 displays the locations of the study participants across the state, along with the locations of the 28 SOC agencies. We used ArcGIS Spatial Analyst (ESRI 2007) to interpolate from Census block groups a surface of combined travel impedance and development density for the entire state. This eliminated artificial boundaries and smoothed the scores more evenly throughout Illinois. Using the Inverse Distance Weighted interpolation function in Spatial Analyst, individual block group scores were used to create a 100 meter grid of combined travel impedance and development density for the entire study area (ESRI 2007). This grid was then reclassified into three zones, urban, suburban, and rural; Fig. 2 displays the zones. We then classified each child in the study into one of these three land use types based on the location of their living arrangement during the study period.

Figure 1. IDCFS wards receiving SOC services

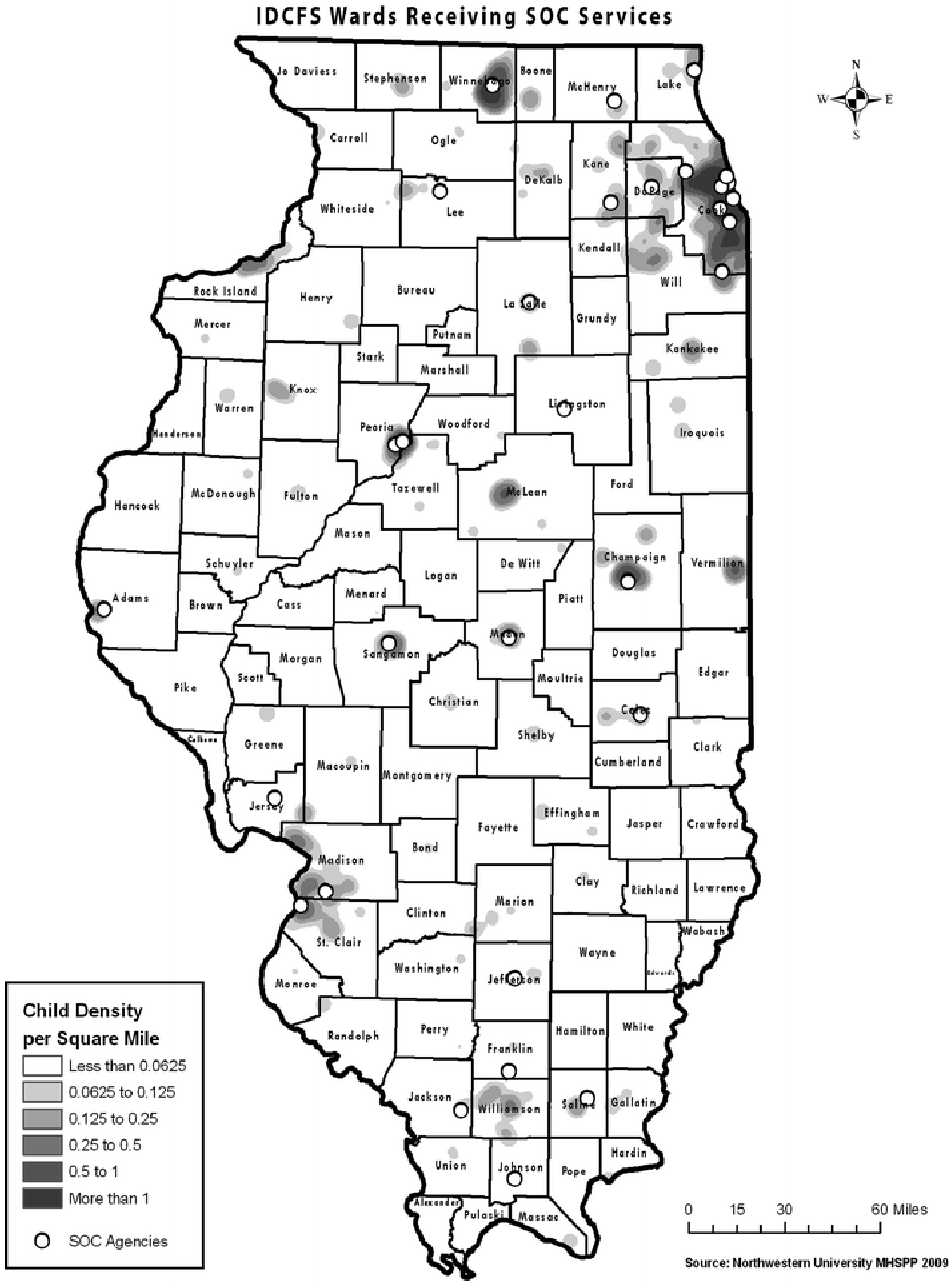
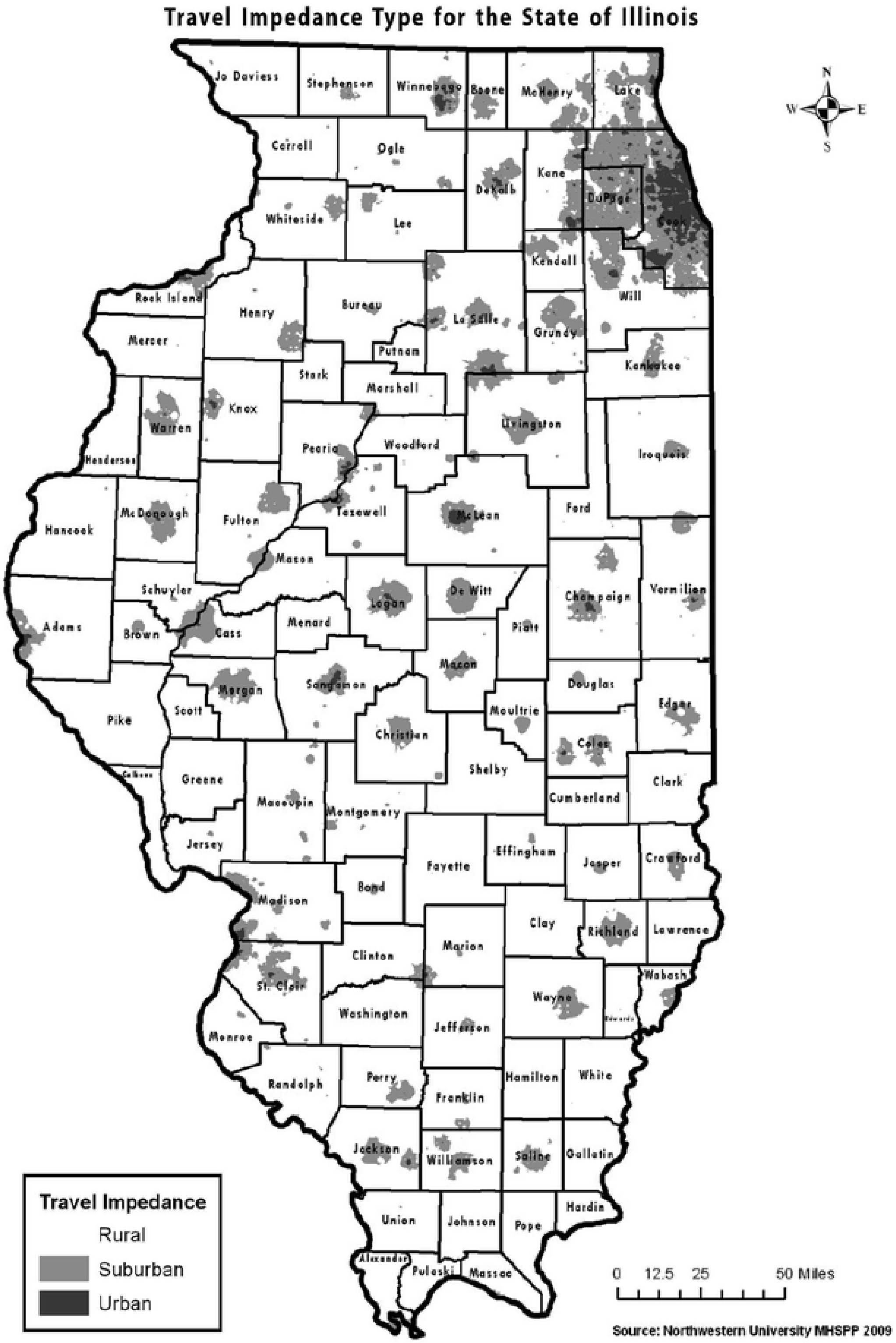


Figure 2. Travel impedance zones



Each child's land use type determined two functions within the gravity model: the size of the catchment area for each child used to calculate proximity and the rate at which distance decayed the value of a provider, or the "*p* value." Catchment areas were defined as the maximum space in which a provider had any value to the child. These limits were determined within land use types using two standard deviations above the mean distance between each child and the ten providers nearest that child. For example, the average distance between all children in the suburban land use type and their ten nearest providers is 6.82 miles with a standard deviation of 8.16 miles. Therefore, the catchment area for children in this land use type has a 23.14 mile radius (urban = 10.02, rural = 37.28). This provided us with catchment areas, differentiated by land use, that capture roughly 95% of the providers surrounding a given child with providers beyond these limits being seen as outliers and unlikely to be utilized. While it is possible that rural youth could be served by providers further than two standard deviations from the mean distance between these providers and youth, long travel times/distances are not desirable for financial and logistic reasons. Traditionally, the child welfare system has applied a "20 miles/20 min" rule that has been applied as the ideal maximum travel distance to services. In this study, any provider outside of a child's catchment area was not included in the calculation of their proximity score.

In addition to catchment area size, land use type also determined the rate at which distance diminished the value of providers over space. In general, the value of providers to children decays faster in urban areas, where distance takes longer to travel and density is greater. The more urban the land use type, the faster the value of a provider to a child decreases. Thus, a provider two miles away from a child in an urban area would have less value to that child than a provider two miles away from a child in a rural area. In our model, all providers start with a value of one and that value is reduced at a different rate within each land use type as distance increases, so that by 2 miles the value of that provider is 0.005 in urban areas, 0.013 in suburban areas, and 0.031 in rural areas. All of the discounted provider values within a child's catchment area are then summed to arrive at each child's proximity score.

Finally, we modified the gravity model so that no provider's value to a given child could exceed one; 44 of the 105,988 provider-child distances required this adjustment. To do this, we measured the distance from a provider to a child using one hundred meter increments (blocks). Therefore, any provider who was less than one city block from a child counted as one and if they were more than one city block from a child they counted as some number between one and zero.

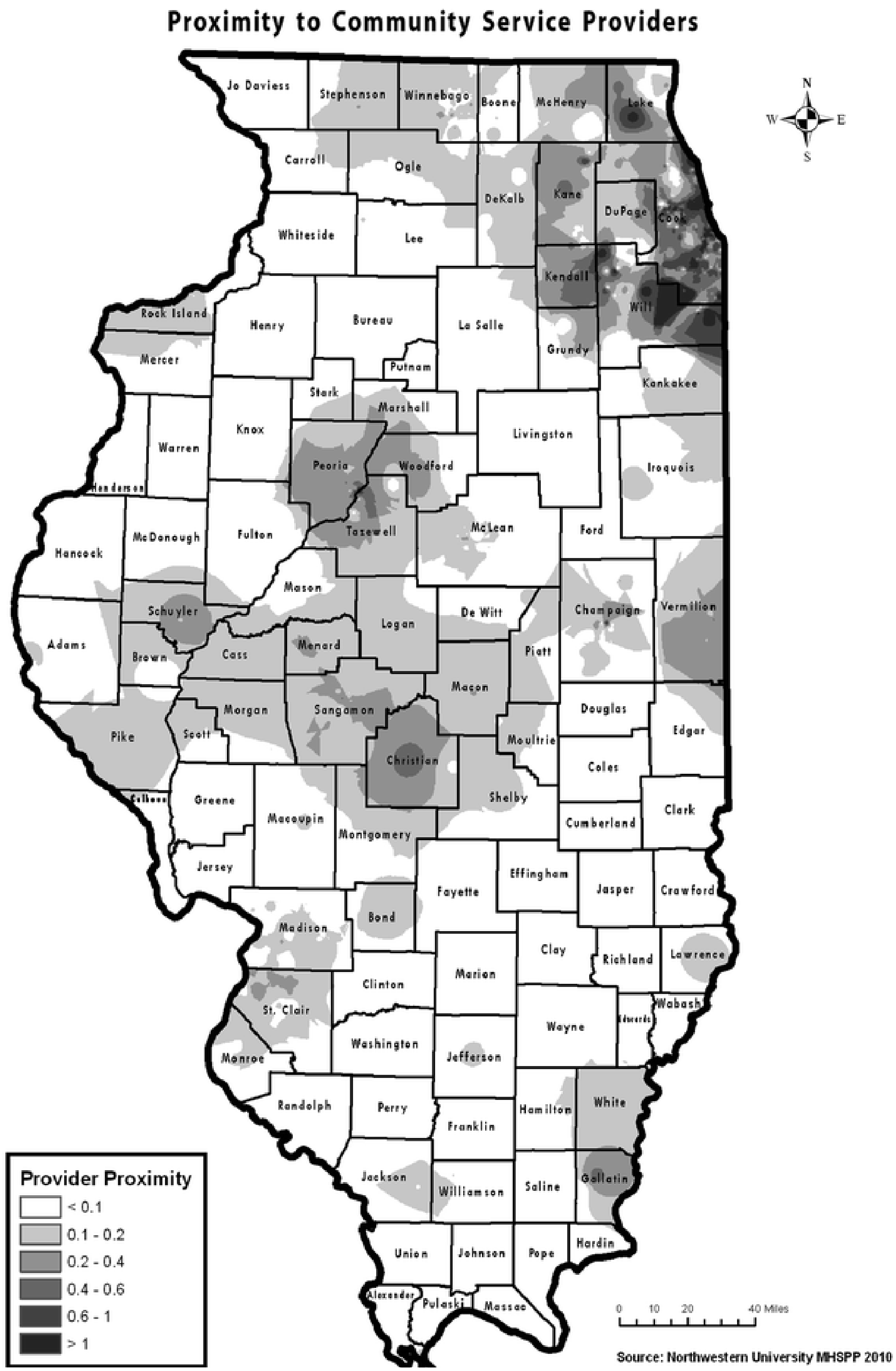
Once catchment areas were assigned to each child the ArcGIS Network Analyst extension was used to create an origin–destination (OD) cost matrix. For each child the OD cost matrix contained the road network impedance, both miles along the network and travel times, from that child to all service providers. The number of service providers included in the OD cost matrix was limited by the catchment area for a particular land use type so, for example, a child in the urban land use type would have an OD cost matrix calculated for all of the service providers within 10.02 miles of their location. Providers further than that on the network would be excluded from this sample. Proximity scores were then derived by discounting provider values for each of the 105,988 pairs of interactions (child & provider) with the resulting values summed for each individual child.

This method of measuring distance is more accurate than a straight line measurement as it accounts for distortions in the road network than can cause total travel distance to exceed the catchment cut off even though the geographic distance does not. For example, in communities where there are limited river or train track crossings travel to a provider may require going significantly out of the way to locate a bridge. These kinds of distortions can add significantly to the total travel distance in an OD cost matrix but will not appear at all in a traditional straight line measurement.

Data Analysis

We used Cox Regression to model the relationship between baseline clinical characteristics, age, proximity, and placement stability, first for the over-

Figure 3. Proximity to community service providers among Illinois youth receiving SOC services



all sample and then within Land Use types. The Cox approach was chosen because the outcome variable is right-censored (may not have occurred for all subjects by the end of the study period) and the predictors are continuous rather than categorical.

Results

Proximity

Figure 3 displays a map of community provider proximity for 1,448 children included in the sample. Darker shading on the map represents areas in which children have greater proximity to community resources, and lighter areas represent lower mean proximity scores. The higher the proximity score, the greater proximity a child has to community providers. Proximity scores ranged from 0 to 3.76. The mean proximity score for this sample was .37 (*SD* = .47), with approximately 74% falling between 0 and .5 and 92% falling between 0 and 1. Nonetheless, if accurate, the estimate provided from this survey would mean that wraparound is being employed far more often than other prominent community-based treatment models for youth with serious and complex needs. This includes five times as many youth as multisystemic therapy (MST; Henggeler et al. 1998), which is estimated to serve 19,000 youths (Evidence-Based Associates 2008a, b, c); over three times more youth than Functional Family Therapy (FFT; Alexander et al. 2000), which is estimated to serve 30,000 youth annually (Evidence-Based Associates 2008a, b, c); and many times more youth than Multidimensional Treatment Foster Care (MTFC; Chamberlin and Reid 1998), which is estimated to serve 1,200 youth annually (Evidence-Based Associates 2008a, b, c).

Overall Predictors of Placement Disruption

Cox proportional hazards regression models (Cox 1972) were used to study the effects of demographics, baseline CANS domain scores, provider proximity, and land use types on days of placement stability. Days of placement stability was calculated as the number of days from referral to the SOC program until the placement disrupted or until the study sample enrollment end date of September 25th, 2009. We used the proportional hazards regression procedure from the SPSS software package to estimate the Cox regression models. Of the original 1,448 cases, 131 (9.1%) had missing data and were not used in the regressions, leaving 1,316 cases. Of these, 307 (21.2%) were right censored (i.e., did not experience a placement disruption in the study period), and 1,009 experienced placement disruption during the study period.

The covariates were entered into models in two blocks. In the first block, all main effects (demographics, CANS composite scores, provider proximity, and land use) were entered into the analysis using the forward selection technique; forward selection was used to develop the most parsimonious regression model possible. In the second block, interactions between proximity and the CANS and land use variables were entered, again using the forward selection technique. All variables were first centered before the interactions were generated. None of the covariates in the model had zero order correlations higher than .40, indicating that multicolinearity was not a concern in the regression analyses.

Kaplan–Meier analysis was conducted to test the proportional hazards assumption. Since proximity is a continuous variable, we categorized proximity scores into thirds (lower, middle, and upper). Kaplan–Meier survival analysis for the impact of the categorical predictor variable (high, medium, and low proximity) on placement disruption confirmed a proportional relationship between proximity and days in placement (Length of Stay), indicating that the assumption of proportional hazards was not violated. The mean number of days to placement disruption (Length of Stay) for the three proximity groups also supported the assumption of proportionality. The mean days to disruption for the three groups were 486.88 (*SD* = 343.97) for youth in the lower third of proximity scores, 496.01 (*SD* = 512.03) for youth in the middle third of proximity scores, and 663.01 (*SD* = 614.94) for youth in the upper third of proximity scores. The difference between these means was significant, F (2, 1444) = 37.40, $p < .001$.

Table 1 displays the results of the variables that were statistically significant covariates of placement stability for the overall model; Table 2 displays results for the models conducted for each land use type. While several statistics are presented, our description of the results focuses on the relative risk statistics. Relative Risk refers to the hazard ratio or the proportional increase or decrease in risk of placement disruption associated with each unit increase in the independent variable (Exp (B) column). Of the 19 covariates tested in the overall model, five emerged as statistically significant predictors of placement stability. The predictors were: Age, the CANS module scales Traumatic Experiences, Child Strengths, and Risk Behaviors, and Proximity.

Increasing Age, Traumatic Experiences, and Risk Behaviors were associated with higher likelihood of placement disruption, while greater Proximity and Child Strengths were associated with lower likelihood of placement disruption. With each increase of one year in the child's age, the risk of placement disruption increased by 3%. The risk of placement disruption also increased by 3% for each increase of one unit on the CANS Traumatic Experiences scale and 7% for each increase of one unit on the CANS Risk Behaviors scale.

The newly developed provider proximity scale can be understood in terms of the "provider value within the child's proximity". If a provider that is footsteps away from a child's home is worth 100% of it's value (1), as providers are located further and further from the child their value "decays" to something less than 100% (<1). While a "1" on the provider scale has no absolute value (100% of 1 provider), it is twice as much provider value as a .5 on the provider scale. Of course the value of providers is moderated by many other factors, including the clinical appropriateness of the services they offer and the eligibility of the child to receive those services. The provider proximity scale can also be understood in light of its relationships to other variables. While there is no precise definition for a 1-unit increase in provider terms, the risk of placement disruption decreased by 21% for every increase of one unit on the provider proximity variable. Further, none of the Proximity interactions (e.g., Proximity × Risk Behaviors) were significant, suggesting that the effect of provider proximity is not moderated by other variables. For every one unit increase on the CANS Strengths scale, youth on average were 4% less likely to experience placement disruption.

Predictors of Placement Disruption by Land Use Type

Next, we used Cox regression models to estimate risk of placement disruption for each of the three land use types: rural, suburban, and urban. Interestingly, each of the three final land use models produced a unique set of significant covariates. For the rural land use analysis, provider proximity and the Risk Behaviors scale of the CANS significantly predicted placement disruption. Proximity was

Table 1. Overall predictors of placement disruption

Covariates	Beta	SE	Wald	*p* value	Exp (B)	Exp (B) 95% CI
Age	.03	.01	14.14	<.001	1.03	1.01–1.04
Trauma experiences	.03	.01	9.58	<.01	1.03	1.01–1.04
Strengths	-.04	.01	19.34	<.001	.96	.95–.98
Risk behaviors	.07	.01	29.81	<.001	1.07	1.04–1.09
Proximity	-.31	.04	14.16	<.001	.74	.63–.87

Overall model $\chi 2$ (5) = 156.10, $p < .001$. The following variables were not significant predictors of placement disruption: Gender, Trauma Symptoms, Functioning, Emotional and Behavioral Needs, Caregiver Needs and Strengths, or any of the interactions involving provider access and CANS scale scores

Table 2. Predictors of placement disruption for each land use type (Rural, Suburban, Urban)

Covariates	Beta	SE	Wald	*p* value	Exp (B)	Exp (B) 95% CI
Land use: rural						
Risk behaviors	.14	.03	25.64	<.001	1.15	1.10–1.22
Proximity	-.63	.23	7.63	<.01	.54	.39–.89
Land use: suburban						
Trauma experiences	.04	.01	11.29	<.01	1.04	1.02–1.07
Functioning	.06	.02	16.29	<.001	1.06	1.05–1.11
Proximity	-.30	.12	5.98	<.05	.74	.59–.94
Land use: urban						
Age	.04	.01	8.84	<.01	1.04	1.01–1.06
Strengths	-.03	.01	7.14	<.01	.97	.95–.99
Risk behaviors	.06	.02	8.76	<.01	1.06	1.02–1.11

Overall model (rural) $\chi 2$ (2) = 36.11, $p < .001$; Overall model (Suburban) $\chi 2$ (3) = 82.61, $p < .001$; Overall model (urban) $\chi 2$ (3) = 36.93, $p < .001$. The following variables were not significant predictors of placement disruption in any of the land use analyses: Gender, Trauma Symptoms, Emotional and Behavioral Needs, Caregiver Needs and Strengths, or any of the interactions involving provider access and CANS scale scores

associated with a decreased risk of placement disruption; for each increase of one unit on the Proximity scale, youth were a mean of 46% less likely to experience placement disruption. Risk behaviors were associated with more placement disruption; the relative risk statistic suggests that for each increase of one unit on the Risk Behaviors scale of the CANS, youth experience a 15% increase in risk of placement disruption.

For youth in suburban land use areas, three covariates were significantly associated with placement disruption: Proximity, CANS Trauma Experiences, and CANS Functioning. The Relative Risk statistic for Proximity among youth in the suburban land use area was .74, suggesting that for every one unit increase on the provider proximity scale, youth were 26% less likely to experience placement disruption. The relative risk statistic for both Trauma Experiences and Functioning among youth in the suburban land use area was 1.04, suggesting that for every one unit increase on these CANS scale scores, youth were 4% more likely to experience placement disruption. Both of these CANS scales were significant predictors of placement disruption in only the suburban land use area.

For youth in the urban land use area, three covariates were significant predictors of placement stability: Age, Strengths, and Risk Behaviors. With each increase of one year in the child's age, the risk of placement disruption increased by 4%; age appeared as a significant predictor of placement disruption in only the urban land use analyses. The risk of placement disruption decreased by 3% for each increase of one unit on the CANS Strengths scale and increased 6% for each increase of one unit on the CANS Risk Behaviors scale.

The Proximity variable was the only variable that appeared to evidence a distinct pattern across the land use analyses. Proximity had the largest effect in rural areas, followed by suburban, and was not significant in the urban land use analysis. It is important to note that proximity varied by land use type. An ANOVA comparing the three land use types on proximity was statistically significant, *F* (3,

1443) = 15.27, $p < .001$; the proximity means across land use were .26 ($SD = .52$), .35 ($SD = .49$), and .46 ($SD = .41$) for the rural, suburban, and urban land use types, respectively. However, it does not appear that proximity had its relatively larger effect in the rural land use type due to greater variability in proximity, since the proximity standard deviation was the lowest in the rural land use type.

Discussion

This study sought to predict the likelihood of placement disruption in a sample of at-risk youth in foster care. Prior research has found that placement disruption is a prominent stressor for youth in foster care, and a primary aim of the SOC intervention is to keep foster care youth in stable, community-based placements. The hypothesis of this study was that youth proximity to community-based services would be protective against placement disruption. This study represents the first effort to explore the role of proximity to both mental health and non-clinical (e.g., boys and girls clubs, etc.) resources in predicting placement disruption after controlling for youth demographic and clinical variables.

In the overall analysis, the hypothesis that provider proximity would predict placement stability was supported. Age, Trauma Experiences, and Risk Behaviors also predicted placement disruption. However, when separate analyses were conducted for each Land Use type, the results demonstrated that the impact of demographic and clinical variables is somewhat contingent on the type of area in which a child resides. For example, Risk Behaviors were associated with greater likelihood of placement disruption in rural and urban areas but not in suburban areas. Child Strengths predicted greater stability (longer duration of time until disruption), and age predicted shorter duration of time until disruption only in urban areas.

The provider proximity results illuminate some of the issues inherent in implementing wraparound. Namely, that implementation depends not only on factors internal to an agency's delivery of services, but external to that program in the surrounding community or region. The fifth principle of wraparound processes stresses that family members receiving wraparound should have access to services *within their communities* (Bruns et al. 2006). A measure of proximity to service providers is a useful tool for evaluating adherence to this principle. Results suggesting that proximity matters more when implementing wraparound programs in rural and suburban areas than in urban areas confirm the results of previous studies examining the effectiveness of services in rural areas: accessibility of providers to clients and clients to community resources may hinder the delivery of services that are flexible and unlimited in every other respect.

That proximity to resources is predictive of placement stability in rural and suburban areas but not in urban areas underscores the differential impact of community factors. Threats to target outcomes may vary depending on the environment in which the program is implemented, and the role of Risk Behaviors, Strengths, and Trauma Experiences may vary according to environmental and community factors that can protect or impede children and families. These differences also call into question the capacity of wraparound to help compensate for resource deficits among children by assisting with transportation and other facilitative efforts. It appears that in less densely populated areas where these resources are simply nonexistent, there is little SOC can do to ameliorate the effects of poor proximity. This can be understood in light of the SOC program's charge to "contract for, develop, or provide" needed services (Hastings et al. 2009). In urban areas the potential exists to overcome a lack of neighborhood resources with transportation to other local but previously inaccessible areas, whereas transportation assistance cannot overcome a total lack of resources and/or expertise in an entire region.

Implications for Policy and Planning

Given the role that the availability of resources in the community may play in predicting outcomes for children receiving care within a wraparound model, what are the implications for system planning? Several approaches are implied by these findings. First, funders/contractors for wraparound should take into account the additional expense of delivering services within in a community with scarce resources, or in which residents must travel long distances to receive needed services. Any performance-based contracting strategy should adjust for the additional barriers to achieving positive outcomes in resource-poor areas. In Illinois, SOC agencies help families to access a combination of home-based and outpatient services. A strategic approach to designing wraparound implementation might call for rural SOC agencies to increase the number of home-based services provided and to factor transportation into clinical planning.

Second, by reversing the direction of the calculations presented here, we can derive a proximity score for each community provider. That is, we can determine which providers are more easily reached by more children and which providers are harder to access because they are further away from the children they intend to serve. This awareness can facilitate contracting approaches that either (1) direct funds for programs to providers that are more easily reached, or (2) require providers to offer more extensive home-based and transportation services in areas in which children with low proximity scores are located.

These results undermine some of the assumptions about system planning that may perpetuate the inequities experienced by individuals in resource-poor areas: namely, that equitable distribution of resources can be accomplished by distributing providers evenly over a service area, and that broadening a provider's coverage area means that individuals within that area are "covered" (Holley 1998). These data suggest that proximity exerts a powerful effect on outcomes among individuals residing in resource-poor areas, and that for these individuals provider locations may be more important than a provider's willingness to work with a youth who is willing to travel to their office.

These data also underscore the importance of having a provider catalogue that can inform both wraparound program staff as well as system planners about the landscape of service providers in every community. The Statewide Provider Database, developed by IDCFS in collaboration with Northwestern University, utilizes strategies to engage the community in maintaining up-to-date information that can facilitate access to and utilization of resources by improving awareness and providing an empirical basis for system planning decisions (Weiner 2002). This system enables a granular analysis of child-to-provider distances that enables the calculation of proximity scores for individuals. In addition, the system tracks the locations of many non-traditional service types sought by wraparound providers. Because these services and activities may be offered by park districts, churches, local community centers, or private providers, they are hard to capture using traditional sources of provider data (e.g., state agency contract databases, Medicaid billing data) and may require a data collection approach that is more "word-of-mouth" or "door-to-door" (Weiner 2009).

Limitations

Of course, any examination of the availability of resources depends upon a comprehensive dataset of existing community providers. Because the Statewide Provider Database is a dynamic tool that is always being modified in response to information from the community, it may at times lack information about a particular resource in a particular area. While this method for gauging actual community capacity is still preferable to one that uses prior utilization (billing data) or intended capacity (contract data) to define availability, provider catalogues are time-consuming to build and maintain and require ongoing collaboration with system users and providers to ensure their accuracy.

The generalizability of this study to wraparound implementation more broadly is also limited by the lack of empirical documentation of the SOC program's fidelity to the wraparound model. While the SOC program plan clearly articulates wraparound principles (and fidelity to the program plan has been documented), no standardized measure has been applied to ensure that the SOC program does in fact constitute a true wraparound implementation.

Third, at this preliminary phase of research on the geospatial value of community resources, we are not yet able to prioritize resources in a child's catchment area based on child need or provider capacity. This would be an essential step in improving our understanding of the relationship between proximity and outcomes, which is unlikely to be linear as each successive provider leads to an incrementally lesser impact on outcomes. Any transformation of the relationship (e.g., loglinear) would require us to prioritize some providers over others in determining which add incrementally less value. To do so, we might apply additional CANS data to document need for specific services, along with data on provider capacity.

While the focus of this study has been to develop a measure of proximity that could be used to answer questions about the impact of proximity on outcomes, there are other measures of outcomes and predictors that could enhance the model. First, these analyses could be repeated with other clinical outcomes to determine if these outcomes are similarly impacted by proximity and the other predictors. Second, additional data collection is now underway that will allow us to enhance the predictive model for placement disruption by incorporating caregiver factors. It is possible that there are other caregiver factors that co-vary with land use type, (e.g., isolation and social support) that impact a caregiver's ability to maintain a child in placement. Third, including the SOC provider as another level of analyses could inform us about how well each SOC provider is able to mediate the effects of poor proximity on outcomes. These findings suggest they may be better able to do this in urban areas, but future research could apply additional data to answering this question.

From a methodological standpoint, future research should build upon this work to determine if there is a threshold proximity score below which outcomes are certain to be affected, so that funders and policy makers can target service development in areas where youth proximity to resources is below the critical level. The examination of the survival function in this study suggests that there may be three meaningful designations of proximity (low, medium, and high) but future work may clarify and quantify clinically meaningful proximity thresholds.

There are undoubtedly many factors that predict placement disruption, and not all placement changes are negative. Understanding and predicting the outcomes of children, families, and the systems that serve them require that many complex variables are taken into account. Using a wraparound model, the IDCFS SOC program has greatly improved placement stability by facilitating access to needed services using a strengths-based approach. This research broadens traditional approaches to studying the predictors of negative outcomes for youth in foster care, by providing a measure of community access to traditional and non-traditional resources, and by demonstrating that this proximity plays a key role in predicting outcomes among youth in foster care.

References

Allard, S. W., Tolman, R. M., & Rosen, D. (2003). Proximity to service providers and service utilization among welfare recipients: The interaction of place and race. *Journal of Policy Analysis and Management, 22,* 599–613.

Almog, M., Curtis, S., Copeland, A., & Congdon, P. (2004). Geographic variation in acute psychiatric admissions within New York city 1990–2000: Growing inequalities in service use? *Social Science and Medicine, 59,* 361–376.

Anctil, T. M., McCubbin, L. D., O'Brien, K., & Pecora, P. (2007). An evaluation of recovery factors for foster care alumni with physical or psychiatric impairments: Predictors of psychological outcomes. *Children and Youth Services Review, 29,* 1021–1034.

Arcury, T. A., Gesler, W. M., Preisser, J. S., Sherman, J., Spencer, J., & Perin, J. (2005). The effects of geography and spatial behavior on health care utilization among the residents of a rural region. *Health Services Research, 40,* 135–155.

Benedict, M. I., Zuravin, S., Somerfield, M., & Brandt, D. (1996). The reported health and functioning of children maltreated while in family foster care. *Child Abuse and Neglect, 20,* 561–571.

Billi, J. E., Pai, C. -W., & Spahlinger, D. A. (2007). The effect of distance to primary care physician on health care utilization and disease burden. *Health Care Management Review, 32,* 22–29.

Bruns, E. J., Suter, J. C., & Leverentz-Brady, K. M. (2006). Relations between program and system variables and fidelity to the wraparound process for children and families. *Psychiatric Services, 57,* 1586–1593.

Bruns, E. J., Walker, J. S., & The National Wraparound Initiative Advisory Group. (2008). Ten principles of the wraparound process. In E. J. Bruns & J. S. Walker (Eds.), *The resource guide to wraparound.* Portland, OR: National

Wraparound Initiative, Research and Training Center for Family Support and Children's Mental Health.

Burchard, J. D., Bruns, E. J., & Burchard, S. N. (2002). The wraparound approach. In B. J. Burns & K. Hoagwood (Eds.), *Community treatment for youth* (pp. 69–90). New York: Oxford University Press.

Burns, B. J., Phillips, S., Wagner, H., Barth, R., Kolko, D., Campbell, Y., et al. (2004). Mental health need and access to mental health services by youths involved with child welfare: A national survey. *Journal of the American Academy of Child and Adolescent Psychiatry, 43,* 960–970.

Clark, H. B., Lee, B., Prange, M. E., & McDonald, B. A. (1996). Children lost within the foster care system: Can wraparound service strategies improve placement outcomes? *Journal of Child and Family Studies, 5,* 39–54.

Coulton, C. J., Crampton, D. S., Irwin, M., Spilsbury, J. C., & Korbin, J. E. (2007). How neighborhoods influence child maltreatment: A review of the literature and alternative pathways. *Child Abuse and Neglect, 31,* 1117–1142.

Cox, D. R. (1972). Regression models and life tables (with discussion). *Journal of the Royal Statistical Society: Series B, 34,* 187–220.

Curtis, S., Congdon, P., Almog, M., & Ellermann, R. (2009). County variation in use of inpatient and ambulatory psychiatric care in New York State 1999–2001: Need and supply influences in a structural model. *Health and Place, 15,* 568–577.

Eggertsen, L. (2008). Primary factors related to multiple placements for children in out-of-home care. *Child Welfare, 6,* 71–90.

Environmental Systems Research Institute (ESRI). (2007). ArcIMS (Internet Map Server), ArcView (computer software), Redlands: CA.

Fortney, J. C., Owen, R., & Clothier, J. (1999). Impact of travel distance on the disposition of patients presenting for emergency psychiatric care. *Journal of Behavioral Health Services and Research, 26,* 104–109.

Garland, A. F., Hough, R. L., McCabe, K. M., Yeh, M., Wood, P. A., & Aarons, G. A. (2001). Prevalence of psychiatric diagnoses in youth across five sectors of care. *Journal of the American Academy of Child and Adolescent Psychiatry, 40,* 409–418.

Guagliardo, M. F. (2004). Spatial accessibility of primary care: Concepts, methods and challenges. *International Journal of Health Geographics, 3,* 1–13.

Han, M., & Stone, S. (2007). Access to psycho-social services among pregnant and parenting teens: Generating questions using youth reports and GIS mapping techniques. *Child and Youth Care Forum, 36,* 213–224.

Hastings, J. (2009). IDCFS SOC Program Director; personal communication.

Hipp, J. R., Jannetta, J., Shah, R., & Turner, S. (2009). Parolees physical closeness to health service providers: A study of California parolees. *Health and Place, 15,* 679–688.

Holley, H. L. (1998). Geography and mental health: A review. *Society for Psychiatry and Psychiatric Epidemiology, 33,* 535–542.

Illinois Department of Children and Family Services (IDCFS). (2005). System of care (SOC) program plan, CFS968-54, www.state.il.us/dcfs.

Kirby, J. B., & Kaneda, T. (2005). Neighborhood socioeconomic disadvantage and access to health care. *Journal of Health and Social Behavior, 46,* 15–31.

Laditka, J. N., Laditka, S. B., & Probst, J. C. (2009). Health care in rural areas: Evidence that hospitalization for ambulatory care-sensitive conditions in the United States may increase with the level of rurality. *Health and Place, 15,* 761–770.

Landsverk, J., & Garland, A. F. (1999). Foster care and pathways to mental health services. In P. A. Curtis, G. Dale, & J. C. Kendall (Eds.), *The foster care crisis: Translating research into policy and practice* (pp. 193–210). Lincoln, NE: University of Nebraska Press.

Lyons, J. (2004). *Redressing the emperor: Improving our children's public mental health system.* Westport, CT: Praeger.

Mansfield, C. J., Wilson, J. L., Kobrinski, E. J., & Mitchell, J. (1999). Premature mortality in the United States: The roles of geographic area, socioeconomic status, household type, and availability of medical care. *American Journal of Public Health, 89,* 893–898.

McClelland, G. M. & Schneider, A. (2009). *Annual report of performance of SOC program.* (Report to IDCFS) Chicago, IL.

Mobley, L. R., Root, E., Anselin, L., Lozano-Gracia, N., & Koschinsky, J. (2006). Spatial analysis of elderly access to primary care services. *International Journal of Health Geographics, 5,* 1–19.

Nemet, G. F., & Bailey, A. J. (2000). Distance and health care utilization among rural elderly. *Social Science and Medicine, 50,* 1197–1208.

Newton, R. R., Litrownik, A. J., & Landsverk, J. A. (2000). Children and youth in foster care: Disentangling the relationship between problem behaviors and number of placements. *Child Abuse and Neglect, 24,* 1363–1374.

Roberts, J. (1993). Abused children and foster care—the need for specialist resources. *Child Abuse Review, 2*(1), 3–14.

Rubin, D. M., O'Reilly, A. L. R., Luan, X., & Localio, A. R. (2007). The impact of placement stability on behavioral well-being for children in foster care. *Pediatrics, 119,* 336–344.

Simmel, C. (2007). Risk and protective factors contributing to the longitudinal psychosocial well-being of adopted foster children. *Journal of Emotional and Behavioral Disorders, 15,* 237–249.

Skarbo, T., Rosenvinge, J. H., & Holte, A. (2004). Adolescent life events and adult mental health 5–9 years after referral for acute psychiatric outpatient treatment. *Clinical Psychology and Psychotherapy, 11,* 401–413.

Smith, D., Stormshak, E., Chamberlain, P., & Whaley, R. (2001). Placement disruption in treatment foster care. *Journal of Emotional and Behavioral Disorders, 9,* 200–210.

State of Illinois Department of Child and Family Services. (2009). *Procedures 301: Placement and visitation services.* Retrieved October 24, 2009 from http://dcfswebresource.dcfs.illinois.gov/procedures/procedures_301/homepage.phtml?page=2#P10_85.

Stroul, B. A., & Friedman, R. M. (1994). *A system of care for children and youth with severe emotional disturbances. (Revised edition).* Washington, D.C.: Georgetown University Child Development Center, CASSP Technical Assistance Center.

Suter, J. C., & Bruns, E. J. (2009). Effectiveness of the wraparound process for children with emotional and behavioral disorders: A meta-analysis. *Clinical Child and Family Psychology Review, 12,* 336–351.

Unrau, Y. A., Seita, J. R., & Putney, K. S. (2008). Former foster youth remember multiple placement moves: A journey of loss and hope. *Children and Youth Services Review, 30,* 1256–1266.

Walker, J. S., & Bruns, E. J. (2008). *Phases and activities of the wraparound process: Building agreement about a practice model.* Portland, OR: National Wraparound Initiative, Research and Training Center on Family Support and Children's Mental Health, Portland State University.

Walker, J. S., Bruns, E. J., VanDenBerg, J. D., Rast, J., Osher, T. W., Miles, P., et al. (2004). *Phases and activities of the wraparound process.* Portland, OR: National Wraparound Initiative, Research and Training Center on Family Support and Children's Mental Health, Portland State University.

Wang, F., & Luo, F. (2005). Assessing spatial and non-spatial factors for healthcare access: Towards an integrated approach to defining health professional shortage areas. *Health and Place, 11,* 131–146.

Weiner, D. (2002). Statewide provider database (Computer Software) Chicago, IL.

Weiner, D. (2009). Planning and managing service system investments using provider profiles and clinical assessments. In J. S. Lyons & D. Weiner (Eds.), *Strategies in behavioral health care.* Kingston, NJ: Civic Research Institute.

Zima, B. T., Bussing, R., Yang, X., & Belin, T. R. (2000). Help-seeking steps and service use for children in foster care. *Journal of Behavioral Health Services and Research, 27,* 271–285.

Zinn, A., DeCoursey, J., Goerge, R., & Courtney, M. (2006). *A study of placement stability in Illinois.* (Chapin Hall Working Paper) Chicago, IL.

This manuscript was published in the *Journal of Child and Family Studies, 20,* 758-770, in 2011. The original publication is available at www.springerlink.com.