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Close to home: Family-centered spatial analysis of access to early care and education

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ABSTRACT

This study addresses the issue of equitable access to early care and education (ECE) taking the state of Hawai'i as an example. We used spatially-based measures of demand-adjusted slots, cost burden relative to family income, and quality that quantified the supply of ECE services within a five-mile drive, a ten-mile drive, and a 30-min public transit commute from a family's home. Multivariate spatial modeling techniques were used to predict ECE access at the community level, with median income, county of location, population density, and community ethnic composition as predictors. Results revealed some disparities, such as better slot capacity in areas that were densely populated or had a high share of persons of East Asian heritage. We also found promising results relating to slots and quality in low-income communities. The strategic location of Head Start, public preK, and classrooms sponsored by a local philanthropy created conditions where some low-income communities had very favorable access to ECE slots and high-quality programs, relative to the state overall. The spatial methods used in this study are flexible and can be adapted to answer any number of questions about access to community resources for young children and families at different levels of geographic granularity.

1. Introduction

Despite notable advances, such as the expansion of public pre-kindergarten (pre-K) and revised Head Start Program Performance Standards (Friedman-Krauss et al., 2022, 2023), the U.S. has yet to realize the goal of having high-quality, affordable early care and education (ECE) options for all families that want it. Equity is also a key concern, given the evidence that persistent disparities in ECE access are associated with family income, race and ethnicity, immigration status, and residential area (Harding & Paulsell, 2018; Hardy et al., 2021; Malik et al., 2018). Most families use ECE services located within several miles of their home (Hardy et al., 2021). Access constraints such as cost, distance, and the availability of slots vary widely across neighborhoods, even within the same municipality (Fantuzzo et al., 2021). As a result, some neighborhoods are rich in ECE choices while others have few or even no options. From a policy perspective, the ability to identify community hot spots of highest unmet need could lead to a more strategic and effective allocation of ECE resources as the nation works towards the establishment of a strong and sufficient ECE system.

Policymakers need accurate and granular data in order to evaluate needs, set goals, and monitor progress. ECE access is a complex construct, so measurement strategies should be sufficiently nuanced to reflect that complexity. A rich approach to measurement would be multidimensional, localized, and spatially family-centered (Azuma et al., 2023; Davis et al., 2019; Friese et al., 2017; Lin & Madill, 2019; Paschall et al., 2021). In this study, we created measures of ECE access level that met the abovementioned criteria. Our measures of nearby slots, cost burden, and quality adjust for the number of nearby children potentially competing for these same slots, providing an accurate metric of the likelihood that a family can obtain desirable ECE services within a reasonable proximity of their home. Using one state as a case study, we sought to determine whether ECE access at the community level was equitably distributed, i.e., associated with community location, population density, income, and the ethnic make-up, taking into account possible spatial autocorrelation between communities.

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1.1. Conceptualizing access

The ECE Access Expert Panel proposed that “Access to early care and education means that parents, with reasonable effort and affordability, can enroll their child in an arrangement that supports the child’s development and meets the parents’ needs” (Friese et al., 2017, p. 6). According to this framework, access comprises four dimensions. The first dimension, reasonable effort, relates to having an adequate supply of nearby ECE slots relative to family demand, as well as ease of accessing information about ECE options. Affordability includes fees, the family’s ability to pay based on income and adjustments such as child care subsidies, and the costs of providing care. Support for child development encompasses overall program quality and providers’ ability to address children’s diverse needs, such as dual language instruction or behavioral support. Meeting parents’ needs includes logistic aspects, such as hours of operation, and preferential aspects, such as desired program type. A later expansion of the original access framework added a fifth dimension of equity (Thomson et al., 2020). Equity includes disparities in ECE supply, affordability, quality, and choice, as well as efforts taken to reach and retain underserved groups in ECE programs.

1.2. Disparities in ECE access

Systemic inequalities and structural racism limit children’s access to the conditions and resources they need to thrive, including ECE services (Hardy et al., 2021; Meek et al., 2020). Underserved groups include low-income children, children of color, and those living in rural areas or places with concentrated poverty (Hardy et al., 2021; Malik et al., 2018). Taking strong actions to reduce access disparities is a necessary but insufficient first step to ensuring that children also have equitable positive experiences once enrolled and equitable developmental outcomes (Meek et al., 2020).

1.2.1. Enrollment

Results of the 2019 Early Childhood Program Participation Survey showed that 32 % of children under age 6 were in center-based care and another 8 % in home-based care not provided by a relative; however, older children were much more likely to be in centers (53 %) compared to infants (12 %) and toddlers (22 %) (National Center for Education Statistics [NCES], 2021); . Socioeconomic status (SES) was the factor next most strongly associated with the use of formal ECE, and to a lesser degree, maternal age, employment status, and household size. Rural families and Whites were most likely to use non-relative home-based care (i.e., family child care homes). Center use was lowest in small towns, and Whites were more likely to use center care than Hispanics. (Comparisons based on the authors’ construction and interpretation of confidence intervals). These patterns are largely consistent with American Community Survey data on preschool enrollment among 3- and 4-year-olds (NCES, 2023a, 2023b) SES differences in the use of formal ECE were much larger for infants and toddlers than for older children (Flood et al., 2022). Enrollment in preschool centers was more uniform, but class and urban-rural differences in the use of private vs. public centers were found (Flood et al., 2022; Morrissey et al., 2022). Enrollment disparities may be due to a number of factors, including the availability of ECE slots, cost, parent work schedules, transportation, availability of providers who meet parents’ criteria, awareness of ECE options, and parents’ priorities for ECE placement (Archambault et al., 2020).

1.2.2. Adequate capacity

Although we lack accurate data on how many families need and/or want ECE, the consensus is that most communities have insufficient capacity relative to demand. In their seminal work on child care deserts, Malik and colleagues found that 51 % of U.S. families lived in areas with three or more children per seat (Malik et al., 2018). Rural, urban, and low-income communities, as well as those with higher shares of Hispanics and American Indian/Alaska Natives were more likely to be deserts; conversely, high-income areas and those in the suburbs or with a higher share of Black residents were less likely to be deserts. Another national analysis using the 2012 wave of the National Survey of Early Care and Education (Paschall et al., 2021) found striking disparities based on child age: 1.6 children per ECE slot for 3- and 4-year-olds, compared to 4.3 children per seat for infants and toddlers. Hispanic families also had less access to infant-toddler slots than White or Black families, but better access to preschool-age care than did Whites.

1.2.3. Cost

ECE is a major expense in most family budgets, rivaling or even exceeding the cost of housing or in-state college tuition (Child Care Aware of America [CCAoA], 2023), and by parental report, cost was the greatest obstacle to finding child care (NCES, 2022). Affordability based on family resources is perhaps a more important issue than cost per se. The federal government defines affordable care as comprising no more than 7 % of family income for all children combined, yet more than one-quarter of U.S. families were found to have out-of-pocket costs in excess of 10 % of their income (Hardy & Park, 2022). Cost burdens were highest for families just above the poverty line (Hardy & Park, 2022), rural families (Madill et al., 2018), and single parents (CCAoA, 2023; Child Care and Development Fund (CCDF) Program, 2016) .

Public pre-K, Head Start, and state or federal child care subsidy programs reduce or even eliminate the cost burden for many families. However, only a minority of eligible children are served. Results from national samples have indicated that 6 % of all 3-year-olds and 32 % of all 4-year-olds participated in state-funded public pre-K (Friedman-Krauss et al., 2023). Furthermore, 9 % and 41 % of eligible children were enrolled in Early Head Start and Head Start, respectively (Friedman-Krauss et al., 2022); and only 16–23 % of eligible children received tuition subsidies (based on federal vs. state eligibility rules, respectively) (Chien, 2022). For low-income parents, access to free infant-toddler care was much more limited than free preschool-aged care (Paschall et al., 2021).

1.2.4. Quality

The potential of ECE to promote healthy development and reduce early learning disparities hinges on program quality. Studies have found that higher-SES families are more likely to use formal settings, especially child care centers (Dowsett et al., 2008; Flood et al., 2022), which usually offer higher-quality environments than informal care settings (Bassok et al, 2016; Dowsett et al., 2008; Flood et al., 2022). Higher-SES children and those living in advantaged neighborhoods received higher-quality care (Burchinal et al., 2008; Dowsett et al., 2008; Flood et al., 2022), while Black children were especially likely to be served in low-quality centers (Hillemeier et al., 2013). However, Head Start and public pre-K are higher-quality settings that preferentially served low-income children (Bassok et al., 2016; Burchinal et al., 2008; Hillemeier et al., 2013). Selective placement of these target-population programs in higher-need communities may explain patterns seen in studies not using national datasets. For example, in Minnesota, metro areas had a better supply of high-quality private providers while nonurban areas had a better supply of high-quality public ECE (Davis et al., 2019). However, even within programs intended to increase equity, disparities may still be found (Bassok & Galdo, 2016; Friedman-Krauss et al., 2022; Hillemeier et al., 2013).

1.2.5. Neighborhoods

Neighborhoods have a substantial influence on children’s healthy development (Acevedo-Garcia et al., 2020), including via their ECE resources. Because families rarely use ECE services more than 3–6 miles outside their neighborhoods, the strength or paucity of resources within the “ECE access zone” is an important and potentially malleable community characteristic (Hardy et al., 2021, p. 11). Hardy and colleagues stressed the need to collect neighborhood-level data in order to prioritize and direct resources to communities with large numbers of children who simultaneously experience individual or family vulnerability, high community risk, and poor ECE access.

1.3. Spatial approaches to understanding ECE access

Spatial approaches involve the use of location-based variables and/or map-based visualizations. It has been suggested that spatial analysis is an especially useful tool for understanding ECE access, because of the highly localized nature of ECE services (Lin & Madill, 2019). However, few examples of spatial analysis can be found in the ECE literature. The most common application is the use of maps to visualize the distribution of variables by geographic area. For example, Fantuzzo and colleagues (Fantuzzo et al., 2021) measured the concentration of children with multiple risk factors and the availability of high-quality ECE in each of 158 neighborhoods in Philadelphia, then mapped the location of 25 high-quality ECE deserts, i.e., neighborhoods high on child risk and low on quality slots.

A second approach uses spatial autocorrelation to determine whether community characteristics are geographically clustered at levels above chance. Acevedo-Garcia et al. (2011) found a strong, positive autocorrelation for level of neighborhood opportunity, i.e., clusters of adjacent census tracts of concentrated high or low opportunity. Low-SES, ethnic minority, and immigrant children tended to live in low-opportunity clusters, which also had less access to high-quality ECE; as a result, these families could not easily commute to another neighborhood to access better-quality care. As one might expect, high-quality Head Start centers were differentially located in low opportunity clusters; however, they were too few in number to equalize the overall quality of care.

A sophisticated application of spatial analysis is found in the work of Davis and colleagues (Davis et al., 2019). Disregarding geographic boundaries, they used two-step floating catchment area techniques to create measures based on the demand-adjusted supply of ECE slots located within a 20-min drive of a prototypical child's home. Their innovative "family-centered" (p. 1) measures reflected the likelihood of accessing a nearby ECE slot and allowed the group to analyze the demand-adjusted availability, cost, and quality of slots as a function of estimated income level, ethnicity, and urban vs. non-urban locale.

1.4. Application of the two-step floating catchment area technique

Most often, administrative reports, policy analysis, and research on ECE access use area-bounded metrics, such as the ratio of slots per child within a census tract, county, or state. This assumes that ECE resources are allocated only to the area in which they are located and accessed only by families living in that same area. However, families often travel outside the boundaries of their neighborhood, census tract, or county to use care located elsewhere. The two-step floating catchment area technique (2SFCA) offers a solution to the problem of static area boundaries and is commonly used in other fields to measure access to resources such as health care or social service providers (e.g., Luo and Wang, 2003; McGrail 2012; Radke & Mu, 2000). The 2SFCA approach considers both supply and demand and quantifies spatial accessibility. In step 1, a catchment area, or geographic boundary, is defined for each resource and a corresponding capacity-to-population ratio is calculated. The geographic unit of analysis moves, or floats, from one resource location to the next, hence the "floating" in the method's name. In the second step, provider ratios are summed for each consumer, or demand point. For example, we delineated an irregularly-shaped polygon centered on each ECE provider that included all areas within a five-mile driving distance via public roads. Each provider's ratio was their licensed capacity divided by the number of young children living within the catchment area. Note that catchment areas may overlap, and any given child's house may fall within the catchment area(s) of zero, one, or several ECE providers. The second step in the 2SFCA method focuses on consumers and creates an access score by summing the ratios of all accessible providers. Continuing our example, the access score for a child's house would be the sum of the ratios for all providers whose catchment areas included that particular house.

1.5. The current study

1.5.1. The Hawaiʻi context

Hawaiʻi offers a unique lens through which to examine the issue of equity. The state is small in land mass (6,422 square miles) and population size (1.44 million) (U.S. Census Bureau, 2022), which makes a statewide analysis feasible. Hawaiʻi is also ethnically diverse. Whites, Native Hawaiian/part-Hawaiians, Filipinos, and Japanese comprise the four largest ethnic groups (25 %, 22 %, 15 % and 13 %, respectively). Other Asian groups combined represent 10 % of the population, multiracial persons (excluding part-Hawaiians) 9 %, and other Pacific Islanders about 4 % (Azuma et al., 2019).

Due to historic trauma and contemporary conditions, patterns of social privilege and vulnerability in Hawaiʻi differ from those for the U.S. overall. Within 100 years of first Western contact in 1778, infectious diseases introduced by Western contact reduced the size of the Native Hawaiian population by 90 % (Kanaʻiaupuni & Malone, 2006). Later, colonialist legal manipulations (including the establishment of private land ownership and taking of native lands) and the U.S. military-backed overthrow of the Hawaiian monarchy in 1893 further eroded the rights and well-being of the indigenous people (Andrade & Bell, 2011; Kanaʻiaupuni & Malone, 2006; McDermott & Andrade, 2011). From the early nineteenth through the mid- twentieth centuries, plantation owners recruited successive waves of immigrants from Europe, Asia, and the Pacific, using job duties, wage differentials, and housing segregation to create an ethnicity-based social hierarchy (McDermott & Andrade, 2011; Takaki, 1983) . The earlier waves of East Asian immigrants gradually moved into positions of power in business and politics, taking their place alongside the White elite (Okamura, 2008). Starting in the 1980s, the Compacts of Free Association (COFA) resulted in immigration from Micronesia. Established in part to address the devastation caused by nuclear testing, COFA allows the U.S. to maintain its military presence in the region. In return, citizens of the Freely Associated States do not need a visa or green card to live, work, or study in the U.S.; they may also access certain health and social services (Palafox et al., 2011). Based on this history, current patterns of disparities in health, education, criminal justice system encounters, and economic well-being in Hawaiʻi create a spectrum that generally favors Whites and East Asians; Filipinos are in an intermediate position, with Native Hawaiians and Pacific Islanders, especially, facing the greatest challenges (Kaholokula et al., 2020; Look et al., 2020; Mokuau et al., 2016; State of Hawaiʻi Department of Business, Economic Development & Tourism, 2020; State of Hawaiʻi Department of Education 2023; United for ALICE, 2023).

Hawaiʻi's formal ECE system, i.e., licensed child care centers, regulated family child care homes, and public pre-kindergarten, has the capacity to serve about 28 % of children under age five (DeBaryshe et al., 2023). The majority of slots (71 %) are in private centers with no eligibility restrictions, 9 % are in Head Start or Early Head Start, 7 % in family child care homes, and 3 % each in public pre-kindergarten (pre-K) and military child care. Unique to Hawaiʻi is the influence of Kamehameha Schools, a philanthropic trust that offers accredited, low- or no-cost pre-K to children of Hawaiian ancestry; this program sponsors 7 % of the state's ECE slots (DeBaryshe, 2022). Public pre-K may only be delivered by Department of Education or Public Charter School staff; while small in size, Hawaiʻi's public pre-K receives high quality ratings from the National Institute for Early Education Research (Friedman-Krauss et al., 2023). Hawaiʻi does not have a quality improvement rating system, and consistent with the state's high cost of living, Hawaiʻi has among the least affordable center-based care in the nation (CCAoA, 2023).

1.5.2. Research question

The current study used spatially-based, family-centered techniques to define three measures—adjusted slots, cost burden, and quality—representing the reasonable effort, affordability and quality dimensions of the Friese et al. (2017) ECE access framework, respectively. Each of these measures reflected what was available within a reasonable proximity of a family's home, and adjusted for the number of nearby children in potential competition for these slots. Census tract was the unit of analysis, based on the assumption that this was both an appropriate level of granularity to inform policy actions for our state's ECE system and roughly equivalent to a community or neighborhood.

Our research question was whether community characteristics were associated with ECE access and whether any such patterns suggested access disparities or equity. The selection of community demographic characteristics came from the literature indicating that disparities are often associated with low income, rural vs. urban location, and race/ethnicity. County was included to account for the unique island geography of the state. We tested whether county, population density (a proxy for urbanicity), median income, or the ethnic composition of a community were systematically related to adjusted slots, affordability or quality, taking into account between-community effects using spatial dependency. We did not have specific hypotheses about these associations. In general, we expected that access would be better in wealthier, urban communities and those with high shares of East Asians and Whites. However, we also thought the presence of Head Start and public pre-K in low-income communities, and the presence of Kamehameha Schools preschools in areas with a high share of Native Hawaiians might counteract patterns of neighborhood privilege. We focused on five target ethnic groups that comprise the large majority of the state population and reflect the range of social conditions of Hawai'i: East Asian, Filipino, Native Hawaiian/part-Hawaiian, Pacific Islander, and White.

2. Material and methods

2.1. Data preparation and index calculation

2.1.1. ECE provider location and characteristics

The ECE programs included in the study were registered family child care homes; state-licensed group child care homes, infant-toddler and preschool centers; and public preK classrooms. Administrative datasets were obtained in the fall of 2019 from the state Child Care Resource and Referral Agency and the public schools. Data included provider location, license type, maximum capacity, ages served, tuition, and accreditation status. Provider addresses were geocoded to the street level using the Google Geocoding API (Google, 2023). Annual full-time tuition for each provider was calculated using the enrollment-weighted average of tuition cost for each age group served.

2.1.2. Estimated count, family income, and residential location of young children

In the absence of data on the characteristics and home addresses of all young children in the state, we had to estimate these data points. Population counts were taken from the American Community Survey (ACS) 2014–2018 five-year estimates of children under age six (U.S. Census Bureau 2019a). We included census tracts located on the six main inhabited Hawaiian islands, omitting tracts located on military bases and those with no residential housing lots; this resulted in a count of 292 tracts and an estimated child population of 91,150. We geocoded the location of each residential housing lot in the state ($n = 281{,}124$ lots and 458,000 discrete housing units) using street addresses from a real property database (Digital Lightbox, 2017). Within each census tract, we distributed the headcount of children across all residential lots in proportion to the number of housing units on each lot (e.g., a ten-unit apartment building would have 10 times the number of children than a single-family home). ACS five-year estimates of the median income of families with children under 18 were used as a proxy measure of income (U.S. Census Bureau, 2019b). Each residential lot was assigned the median income of the census tract in which it was located.

2.1.3. Catchment areas and index calculation

Using state geospatial road and public transit data (Hawai'i State Office of Planning, n.d.), we employed the Network Analyst in ArcGIS Pro to compute optimal driving and public transportation routes from each ECE provider to nearby residential lots. These network maps were used to establish three different catchment areas for each residential lot: a 5-mile drive, a 10-mile drive and a 30-min public transit commute. These choices were selected in consultation with an advisory committee of local ECE stakeholders and are intended to represent reasonable commutes for families in urban areas, rural areas, and without a car. The road distances are also consistent with the national average commute of four to five miles from home for center-based care (National Survey of Early Care and Education Project Team, 2016) . We then used the 2SFCA method to calculate three ECE access indexes—adjusted slots, cost burden, and quality—for each catchment area definition for each of the 281,124 residential lots in the state, yielding nine access scores per lot. Although ECE access indexes were calculated at the micro level of each residential lot, the unit of analysis for this study was the census tract. Accordingly, we aggregated each index to the tract-level by taking the average lot score within each census tract, weighted by the estimated number of children per lot.

2.2. Measures analyzed

Details of the method used to calculate adjusted slots, cost burden, and quality are provided in the supplementary materials or in Azuma et al. (2022).

2.2.1. Adjusted slots

Adjusted slots was the demand-adjusted supply of ECE slots within the catchment area of a child's home, i.e., the sum of the ratio of slots offered by each nearby ECE provider to the number of children in each provider's catchment area. This variable represents the number of nearby slots a child could access if all nearby children were also competing for these slots. Adjusted slots was expressed as slots per child and high scores indicated a more favorable ECE supply.

2.2.2. Cost burden

Cost burden was the availability-weighted average cost of a seat within the catchment area of a child's home, i.e., the fees for each accessible provider weighted by that provider's proportional contribution to total nearby slots. This average cost was then divided by the median family income for the census tract in which the residential lot was located. The cost burden index was expressed as a percentage of the median family income for that census tract, and represents the percentage of annual income a typical family would expect to pay for a seat in their catchment area. High scores indicated greater cost relative to incomes in that area. Programs that do not charge tuition were included in this calculation and lowered the cost burden. Note that cost burden was based on market rates and did not account for subsidies or scholarships that might reduce a particular family's out-of-pocket cost.

2.2.3. Quality

Quality was the availability-weighted likelihood that a seat inside the catchment area was in a high-quality program, i.e., the quality of each provider (scored as 0 vs. 1) weighted by that provider's proportional contribution to total slots. Private providers holding one of the following accreditations were considered high-quality sites: National Association for the Education of Young Children, National Early Childhood Program Accreditation, National Association for Family Child Care. Public-preK classrooms were also coded as high quality, based on the state's annual ratings by the National Institute for Early Education Research (Friedman-Krauss et al., 2023). High scores represented a larger proportion of high-quality slots.

2.2.4. Population density

The population density of each tract was computed by dividing the total population count, obtained from the American Community Survey (ACS) 2014–2018 five-year estimates, by the tract area in square miles (U.S. Census Bureau, 2019c).

2.2.5. Median family income

We used 2014–2018 ACS five-year estimates to obtain the median family income of each census tract (U.S. Census Bureau, 2019b).

2.2.6. Ethnic composition

Again, we used ACS five-year population estimates, combining information across tables to compute the percentage of the total population that was White, East Asian, Filipino, Native Hawaiian/part-Hawaiian, Pacific Islander, and Other (U.S. Census Bureau, 2019d,e,f,g). The East Asian group was the sum of Chinese, Japanese, Korean, Okinawan, and Taiwanese population counts. Native Hawaiian include those who were Native Hawaiian alone as well as those who were part Hawaiian, i.e. Native Hawaiian in combination with any other race or ethnic group. This definition of Native Hawaiian is the one used for state administrative purposes and to determine eligibility for many targeted services. Pacific Islander included any single or multiple Pacific Island sub-group (e.g. Samoan, Marshallese) excluding Native Hawaiian. The Other group included the remainder of the population, predominantly persons of Southeast Asian or multiethnic heritage.

2.2.7. Population centroids

We used ArcGIS to obtain the latitude and longitude coordinates of the geographic population center of each tract. Because we were interested only in populated areas, we excluded areas with non-residential zoning, using data obtained from the state geospatial open database (Hawaiʻi State Office of Planning, n.d.). Each coordinate was weighted by the tract population count and used to determine the spatial autocorrelation across census tracts.

2.3. Analysis

Taking census tract as the unit of analysis, we used multivariate spatial mixed effects regression to determine whether community characteristics were associated with ECE access indexes that were aggregated at the census tract level, while taking spatial dependency into account. Since it was expected that adjacent census tracts share more commonality than distant tracts, we first checked the spatial correlations of each access score, using Moran's I test (Moran, 1950) to assess autocorrelation due to proximity. For each catchment area definition, the spatial correlations for the ECE indexes were statistically significant ($p < .001$), ranging in magnitude from $I = .11$ to .24. These positive correlations indicated that nearby neighborhoods had similar levels of ECE access and suggest that spatial factors influence the indexes.

Separate models were run for the 5-mile, 10-mile, and 30-min catchment area definitions. Adjusted slots, cost burden, and quality scores served as the multiple dependent variables. The independent variables were county, population density, median family income, income squared (to model quadratic effects), and the percentage of the total population from each of five target ethnic groups. Income was median centered (median=$94,264). Population density and percentage of other Pacific Islander presented heavy positive skewness. This was manifested as heteroskedastic patterns in the relationships between the ECE access indices and those covariates. To stabilize skewed distributions and heteroskedastic relationship patterns (Errington et al., 2021; Im & DeBaryshe, 2020), a natural logarithm transformation was chosen (Kaufman, 2013). We also multiplied each dependent measure by 100 to rescale them. One tract was excluded for being an extreme outlier (7–11 *SD*s above the mean on seat density, depending on the catchment area definition), resulting in a sample size of 291 tracts. For the 30-min model, an additional census tract that had no ECE slots within a 30-min transit commute was omitted due to missing data; this is because cost burden and quality are undefined when seat density equals zero.

A spatial multivariate mixed-effects model was presented as $\boldsymbol{Y}=\boldsymbol{X}\beta+\boldsymbol{Z}u+\boldsymbol{e}$, where $\boldsymbol{Y}$ is a matrix of the ECE access indices; $\boldsymbol{X}\beta$ is the fixed component; the random part $\boldsymbol{Z}u$ models the spatial dependency or autocorrelation; and $\boldsymbol{e}$ is a residual error vector. Specifically, $\boldsymbol{X}$ is the design matrix for the fixed effects, β is a vector of the fixed effects of the predictors, $\boldsymbol{Z}$ is the design matrix for random effects, and u is the vector of the spatial random effects. The variance of random spatial effect was denoted as λ. The spatial dependency among the census tracts was modeled using the Matérn function with a smoothness parameter (ν) and a scale parameter (ρ), representing the strength and the speed of decay in the spatial effect (Rousset & Ferdy, 2014). Moran's I was calculated using the R package spdep (Bivand, 2022). The spatial mixed-effects modeling was conducted using spaMM (Rousset & Ferdy, 2014), incorporating the Matérn function with population-weighted longitude and latitude. Specifically, the straight-line distances among census tracts were calculated based on the population-weighted geographic centroids.

3. Results

3.1. Descriptive statistics and bivariate associations

Descriptive statistics are shown in Table 1. The ECE access indexes are also visualized on an interactive website. The mean tract scores were quite similar across catchment area definitions. Mean adjusted slots of .32, .31, and .29 for 5 miles, 10 miles, and 30 mins, respectively, show that ECE capacity was roughly .3 slots per child (or 3 slots per 100 children when rescaled). Corresponding cost burden means of .11, .11, and .10 indicate that families could expect to pay 10–11 % of their median area income for tuition for one child. Mean quality scores of .42, .43, and .37 indicate that depending on the catchment area definition, about 37–42 % of slots were in a high-quality program. Note that each measure had a wide range of scores.

Within each catchment area definition, adjusted slots and cost burden showed modest associations ($r = .26$–.44, all $p < .001$), and slots and quality showed small but still significant associations ($r = .12$–.16, p

Table 1
Descriptive statistics for study variables.

Variable	M	SD	Range
Population density (people/sq. mile)	13,254	18,316	17–117,480
Median Income ($1,000)	94.69	29.59	22.48–192.68
White (%)	24.96	17.95	0.94–83.04
East Asian (%)	20.89	15.88	0.94–65.48
Filipino (%)	13.61	14.76	0.10–71.54
Native Hawaiian (%)	20.74	13.39	0.73–85.07
Pacific Islander (%)	4.10	7.23	0.10–72.59
Other Race (%)	15.70	5.85	2.09–36.49
Adjusted slots 5 miles	0.32	0.14	0.05–0.71
Cost burden 5 miles	0.11	0.05	0.02–0.50
Quality 5 miles	0.42	0.15	0.00–0.99
Adjusted slots 10 miles	0.31	0.12	0.06–0.56
Cost burden 10 miles	0.11	0.05	0.01–0.50
Quality 10 miles	0.43	0.12	0.02–0.96
Adjusted slots 30 min	0.29	0.21	0.00–1.43
Cost burden 30 min	0.10	0.05	0.00–0.39
Quality 30 min	0.37	0.22	0.00–0.99
	n	%	
Honolulu County	212	72.85	–
Kauaʻi County	13	4.47	–
Maui County	33	11.34	–
Hawaiʻi County	33	11.34	–

Note. N=291 census tracts.

= .005–.036). Cost burden and quality were not significantly correlated, perhaps because public pre-K did not charge tuition. Autocorrelations of the corresponding measure at five and ten miles were high, $r = .79$, .97, .81, all $p < .001$ for adjusted slots, cost burden, and quality, respectively. Cost burden at 30 min was also highly autocorrelated with cost burden at five and ten miles, both $r = .62$, $p < .001$. Slots showed modest autocorrelation at greater distances, $r = .26$, $p < .001$ and $r = .13$, $p < .03$ for 30 min with five and ten miles, respectively. A full correlation matrix of study variables and detailed tabular displays are provided in the supplemental materials.

3.2. Spatial regression

Results from the multivariate spatial regression are shown in Table 2

Table 2
Fixed and random effects of spatial multivariate regression.

	Adjusted slots		Cost burden		Quality	
	b	Cond. *SE*	*b*	Cond. *SE*	*b*	Cond. *SE*
5-mile catchment area						
Fixed effects						
Intercept	10.135	6.405	5.866*	2.642	71.817***	8.104
Kaua'i	−0.353	5.130	−0.172	3.639	−8.137	5.982
Maui	−3.739	4.116	−2.185	3.220	−12.857**	4.659
Hawaii	−1.684	4.141	−6.028*	2.948	−14.699**	4.825
Pop. Density	2.397***	0.590	0.449**	0.138	−3.539***	0.765
Income	−0.140***	0.029	−0.152***	0.006	−0.123**	0.037
Income^2	0.001	0.001	0.001***	0.000	0.003***	0.001
Other Race	−0.322*	0.133	0.016	0.026	−0.162	0.174
East Asian	0.280***	0.060	−0.013	0.013	0.096	0.078
Filipino	−0.113*	0.053	−0.023	0.012	−0.024	0.069
Native Hawaiian	0.054	0.060	−0.033*	0.014	0.029	0.078
Pacific Islander	−0.603	0.543	0.029	0.097	−1.047	0.708
Random effects						
Spatial variance	λ=16.36					
Matérn estimate	ν=1.02	ρ=7.59				
Residual variance	119.66		2.81		204.28	
10-mile catchment area						
Intercept	9.018	5.277	7.444*	2.973	70.098***	6.641
Kaua'i	0.808	5.039	−0.301	4.253	−12.468*	5.624
Maui	−3.484	4.197	−2.747	3.734	−12.180**	4.556
Hawaii	−0.302	4.093	−7.293*	3.468	−13.106**	4.560
Pop. Density	1.819***	0.445	0.242*	0.121	−3.413***	0.596
Income	−0.102***	0.022	−0.154***	0.005	−0.140***	0.029
Income^2	0.001***	4×10^{-4}	0.001***	1×10^{-4}	0.002**	0.001
Other Race	−0.261**	0.100	0.003	0.023	−0.093	0.135
East Asian	0.285***	0.045	−0.018	0.012	0.135*	0.061
Filipino	0.100*	0.040	−0.027*	0.011	−0.029	0.056
Native Hawaiian	0.032	0.045	−0.027*	0.012	0.028	0.060
Pacific Islander	−0.190	0.409	0.042	0.090	−1.518**	0.551
Random effects						
Spatial variance	λ=17.52					
Matérn estimate	ν=1.49	ρ=6.83				
Residual variance	67.93		2.66		123.74	
30-min catchment area						
Intercept	−20.105*	9.676	5.951***	1.654	17.962	11.271
Kaua'i	24.436***	6.127	2.002	1.724	5.359	7.088
Maui	20.043***	4.434	−0.249	1.479	−7.106	5.107
Hawaii	25.566***	4.929	−0.655	1.371	−11.117	5.704
Pop. Density	3.942***	0.948	0.618***	0.167	−0.877	1.104
Income	−0.089	0.046	−0.122***	0.006	−0.112*	0.054
Income^2	−0.001	0.001	0.001***	1×10^{-4}	0.001	0.001
Other Race	0.191	0.214	−0.062*	0.025	1.065***	0.250
East Asian	0.089	0.097	0.002	0.013	0.134	0.113
Filipino	−0.040	0.085	−0.040**	0.013	0.261**	0.099
Native Hawaiian	0.332***	0.096	−0.007	0.017*	0.233*	0.112
Pacific Islander	−1.015	0.873	0.176	0.095	−0.991	1.019
Random effects						
Spatial variance	λ=18.42					
Matérn estimate	ν=16.67	ρ=191.84				
Residual variance	310.61		1.93		424.01	

Note. N=291 census tracts for 5- and 10-mile models, $N = 290$ for the 30-min model.
Honolulu County is the reference category for the county dummy variables and White is the omitted ethnic group.
Log-likelihood values are −2938.72, −2756.49, and −3213.14 for 5-mile, 10-mile, and 30-min catchment area models, respectively.
$^*p < .05$. $^{**}p < 0.01$. $^{***}p < 0.001$.

and Fig. 1. Spatial autocorrelations are available in the supplemental materials.

3.2.1. 5-Mile catchment area

The 5-mile catchment area model yielded five significant coefficients predicting adjusted slots; these should be interpreted as expected change in the dependent variable holding the other independent variables constant and accounting for spatial autocorrelation. Scaling for the dependent variables should be interpreted as 1 adjusted slot per 100 children, percentage of median income required to pay for one slot, and percentage of high-quality slots, respectively.

Net of the other variables in the model, slot availability within five miles was higher in tracts that were densely populated, $b = 2.40$, $p. < .001$. Since population density was logged and the dependent variable was not, each 1 % increase in population density was associated with a 0.024 % increase in adjusted slots, i.e., about 1 additional slot per 4,000 children. High-income tracts had fewer adjusted slots, $b = -0.14$, $p < .001$; for each $1,000 above the state median income, adjusted slot scores decreased by .14 units, or 1.4 fewer slots per 1,000 children. Again, controlling for all other ethnic proportion and background variables in the model, tracts with higher proportions of East Asians compared to Whites had a better supply of adjusted slots, $b = 0.28$, $p < .001$. On the other hand, tracts with higher proportions of Filipinos, $b = -0.11$, $p < .05$, and Other ethnicities compared to Whites, $b = -0.25$, $p < .05$, had fewer adjusted slots. For each 1 % increase in the share of East Asians and corresponding decrease in the share of Whites, slots rose by 0.28 units, or 2.8 slots per 1000 children. The reverse pattern was seen for Filipino and Other ethnicities, where adjusted slots decreased by 0.11 units and .32 units for each 1 % rise relative to Whites, respectively.

Cost burden within five miles was lower in Hawai‘i County compared to Honolulu County, $b = -6.03$, $p < .05$. When all covariates are held constant, Hawai‘i County families spent about 6 % less of their income on ECE tuition. Cost burden was also higher in more densely populated tracts, $b = 0.45$, $p < .01$. The curvilinear effect of income (i.e., significant coefficients for both income and income squared) is shown in panel A of Fig. 1. The equation that determines the instantaneous change in cost burden was $-0.152 + 0.002 * \text{income}$. The negative coefficient of -0.152 indicates that increasing income reduces cost burden, while the positive coefficient of 0.002 suggests that the effect of higher income on easing the cost burden gradually becomes weaker in wealthier areas. As seen in Fig. 1, cost burden was highest in low-income areas, declining gradually until the curve flattened at the highest income levels. Finally, for each percentage point increase in the share of the Native Hawaiian population relative to Whites, cost burden decreased by.03 %, $b = -.03$, $p < .05$.

For quality within five miles, net of the other variables and controlling for spatial dependence, Maui and Hawai‘i Counties had lower quality access than Honolulu County, $b = -12.86$, $p < .05$, and $b = -14.70$, $p < .01$. Since the dependent variable represents the share of high-quality slots, this translates into about 13 and 15 fewer quality slots per 100 slots, respectively. Quality was also lower in densely populated tracts, $b = -3.54$, $p < .001$; for each 1 % increase in density, the share of high-quality slots dropped by 0.035 %. To illustrate this effect, a 400 % increase in population density would yield an expected 14 % drop in high quality slots; this is approximately what happens when comparing a community at the 25th percentile for population density (1,454 people per square mile) with one at the median population density (7,239 people per square mile, a density increase of 398 %). The curvilinear effect of income on quality was striking (Fig. 1, panel A). Net of the other variables, instant change in high-quality slots was a linear function of income, $-0.123 + .006 \% * \text{income}$. Quality was most favorable in both the lowest- and highest-income tracts (albeit slightly better in the poorest areas). Quality access was lowest for families earning $20,000 above the state median (i.e., $114,264).

3.2.2. 10-mile catchment area

Results for the five-mile and ten-mile catchment area models were quite similar. For seat density within 10 miles, there were significant effects for population density, b=1.82, $p < .001$; and shares of East Asians, b=0.29, $p < .001$; Others, $b = -0.26$, $p < .05$; and now Filipinos, $b = .10$, $p < .05$ compared to Whites. Income now had a curvilinear effect (see panel B of Fig. 1). Net of the other variables, the supply of adjusted slots was better in tracts that were densely populated, had either very high or very low incomes, had larger shares of East Asians and Filipinos, and smaller shares of Others compared to Whites.

Results for cost burden within 10 miles were also very similar to the 5-mile model, the only difference being the addition of a significant coefficient for Filipinos vs. Whites. There were effects for Hawai‘i vs. Honolulu County, b=−7.29, population density, b=0.24, Filipinos, $b = -0.03$, and Native Hawaiians, b=−0.03 (all $p < .05$). A curvilinear effect of income on cost burden (panel B of Fi. 1) showed a similar pattern to that of the 5-mile model.

At ten miles, net of the other predictors, predominantly urban Honolulu County had the best quality access; the other counties had 12.17 to 13.11 fewer high-quality slots per 100 (b = 12.18– 13.11). Less densely populated tracts had better quality access, $b = -3.41$, $p < .001$. Quality was higher in tracts with more East Asians relative to Whites, $b = .14$, $p < .05$, and lower in tracts with more Pacific Islanders compared to Whites b=−1.52, $p < .01$. Again, there was a quadratic effect of income on quality (Fig. 1, panel B) that was similar to that of the 5-mile model.

3.2.3. 30-min transit catchment area

Results for the 30-min model were in some ways distinct from results for the other two catchment area definitions. Surprisingly, adjusted slots in the 30-min catchment area were higher for all neighbor island counties than in Honolulu County (b = 20.04–25.57, all $p < .001$). Although Honolulu has a more extensive public transit network, residential areas there are also more uniformly spread out across the island. In the rural counties, housing, ECE providers, and bus service cluster along the main roads, which likely explains the different pattern of access via public transit. Similar to the other catchment area definitions, net of the other variables, densely-populated tracts had more adjusted slots, b=3.94, $p < .001$ and now, also tracts with a higher share of Native Hawaiians compared to Whites, b=.33, $p < .001$.

Consistent with the 5- and 10-mile models, cost burden within the 30-min catchment area was higher in densely populated census tracts, b=0.62, $p < .01$ and there was a curvilinear effect of income on cost burden (Fig. 1, panel C) which was similar to those of the 5-mile and 10-mile models. Cost burden was lower in areas with a higher share of Filipinos compared to Whites, b = -0.04, $p < .01$. Within the 30-min catchment area, there were no longer any effects of county or population density on quality access. Income had a simple linear effect, $b = -0.11$, $p < .05$, and quality was more favorable in areas with higher shares of Others, $b = 1.07$ $p < .001$, Filipinos, $b = 0.26$ $p < .01$, and Native Hawaiians $b = 0.23$, $p < .05$, all relative to Whites.

4. Discussion

Neighborhood context has lasting implications for children’s development and well-being, and the detriments associated with living in areas of concentrated disadvantage are well documented (e.g., Acevedo-Garcia et al., 2020; Hardy et al., 2021). Equitable access to ECE is of heightened concern in this post-pandemic recovery period, given the decreased enrollment (Fabina et al., 2023), incomplete and inequitable recovery (Barnett & Jung, 2023; Malik et al., 2020; NCES, 2023a), and increased vulnerability of the nation’s ECE system (CCAoA, 2023). It is even more important now to have accurate and informative ways to identify disparities and track changes in access over time vis-à-vis evolving ECE market conditions and ameliorative policies.

This study contributes to the literature of equitable ECE access by

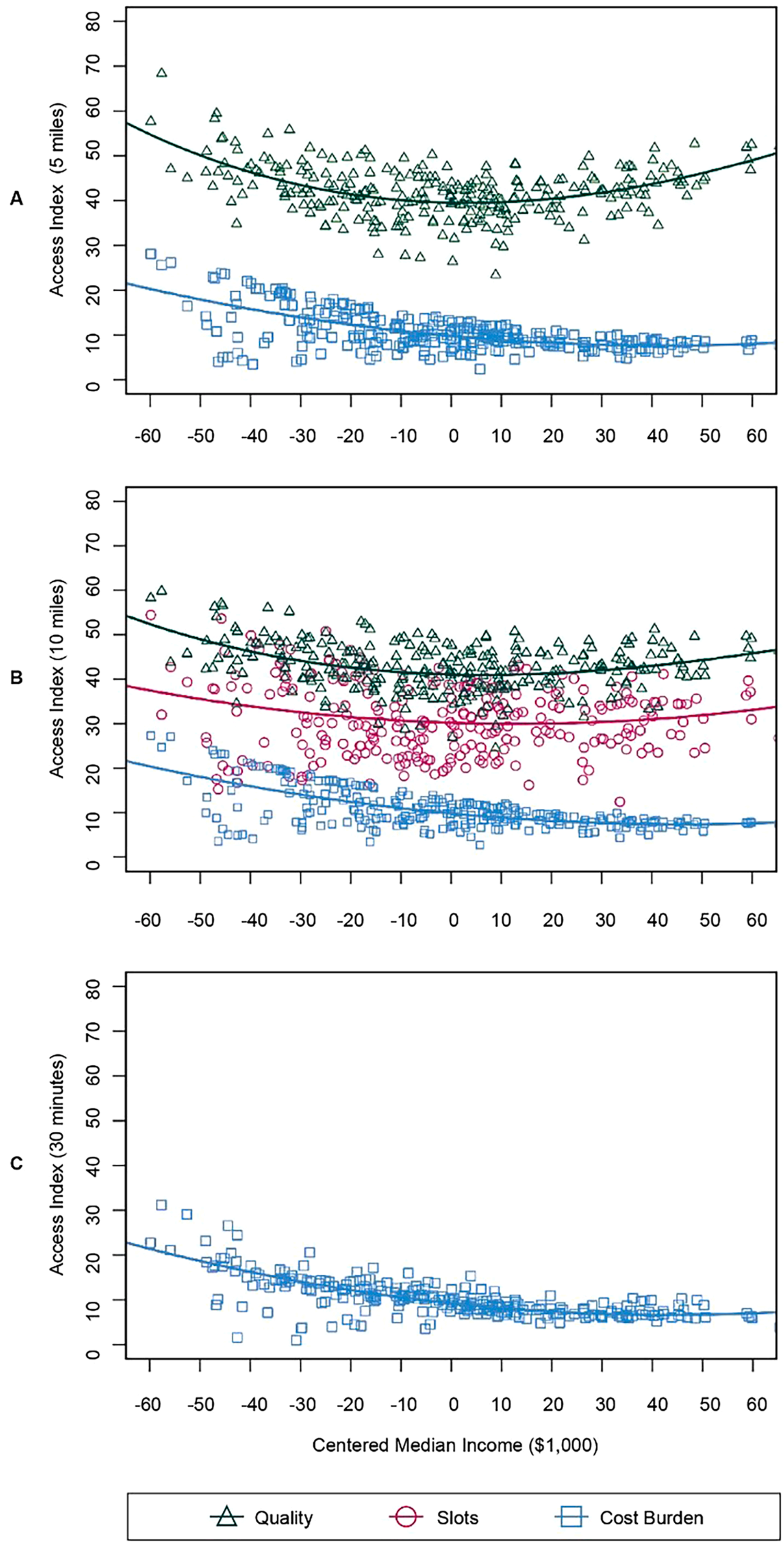

Fig. 1. Non-Linear Effects of Income on ECE Access.

Note. Combined linear and quadratic effects of income. Only models with a significant quadratic effect are shown. Plots are the model-estimated ECE access at different levels of median income. Panels A through C show results for the 5-mile, 10-mile, and 30-min catchment areas, respectively.

investigating potential disparities in a population that includes many Asian-American and Pacific Islanders. While it was clear that ECE access was not equally distributed across geographic areas in Hawai'i, results concerning equitable distribution were more complex. Some aspects of access were consistent with patterns of social privilege. Densely populated communities had the best supply of adjusted ECE slots, regardless of catchment area definition; this finding is consistent with national data on the distribution of formal ECE services across the rural-urban continuum (NCES, 2023b). For the 5- and 10-mile catchment definitions, wealthier communities had a lower cost burden, tracts with a high share of East Asian residents had more slots, and Honolulu County (with the lion's share of the state population and high-paying jobs) had the best ECE quality. Although densely populated areas had the best supply of slots, these areas had higher cost burden and lower quality Despite the better supply of slots in urbanized (i.e., densely-populated) areas, ECE in these communities was more costly, but generally lower quality. This suggests that high quality, private providers preferentially located in wealthier suburban neighborhoods and in business districts with many commuters, but small residential populations.

Some aspects of ECE access were actually better in less privileged communities, so in this regard, Hawai'i provides an example of public policy working as intended. Our most striking findings concerned neighborhood income. ECE quality in Hawai'i's poorest communities rivaled or even exceeded quality in the wealthiest communities; low-income areas also had the best supply of adjusted slots at five and ten miles. It appears that the strategic placement of targeted programs–-public pre-K, Head Start, Early Head Start and Kamehameha Schools–brought more slots, and more high-quality slots, into economically struggling neighborhoods. Although more work is needed to raise access to the point of fully meeting all families' needs, the trend is promising. While it is more the exception than the rule, other researchers have sometimes found evidence of better capacity (Davis et al., 2019) or quality access for very low-income families (Davis et al., 2019; Hillemeier et al., 2013).

Publicly-funded programs play a pivotal role in bringing ECE access to under-served areas (Morrissey et al., 2022), and most roadmaps for improving access focus on public policy solutions (e.g., CCAoA, 2022; Davis & Sojourner, 2021; Schulman, 2023). However, Morrissey and colleagues (2022) noted the dearth of philanthropic investment in rural communities and looked towards this sector as a possible equalizing influence. In our state, this is exactly what Kamehameha Schools has done by prioritizing rural, low-income communities with a high share of Native Hawaiian children. Our results also highlight the needs of middle-income communities, which had the fewest adjusted slots at five miles and the lowest quality access at five and ten miles. Middle-income families may be an underserved gap group—ineligible for means-tested ECE programs but with less freedom than wealthy families to access high-quality slots at a distance from their homes (CCAoA, 2022; Child Care and Development Fund (CCDF) Program, 2016).

We did not find consistent patterns of ethnic privilege in ECE access. This may be the result of Hawai'i's unique diversity, where no group is in the majority. It may also be a positive outcome of targeted ECE programs, which disproportionately serve Native Hawaiian, Pacific Islander, and Filipino children, and help to level the access playing field. Controlling for income, urbanicity, and county location in the analyses also likely reduced the variance left to be explained by community ethnic composition.

Overall, the nation may be realizing a shift toward greater equity in ECE access. Public pre-K serves an increasing number of preschoolers (Friedman-Krauss et al, 2023), and in some cases, has brought more experienced teachers or better teacher-child ratios to low-income and/or minority neighborhoods (Bassok & Galdo, 2016). Furthermore, the National Study of Early Care and Education (NSECE) shows reduced inequity in the distribution of formal ECE providers in 2019 compared to 2012 (National Survey of Early Care & Education Project Team, 2023; Borton et al., 2023). The overrepresentation of centers and regulated family child care in low-poverty, low-Hispanic, and low urban density areas is starting to equalize, with provider distribution more closely matching that of the child population. Results of the newest waves of the NSECE and National Household Education Survey will be highly informative in this regard.

This study also contributes to the very small literature that uses spatial techniques to understand ECE access. The 2SFCA approach has several advantages: it reflects the fact that families cross geographic boundaries when accessing ECE, accounts for both supply and demand, and scores are easy for policy-makers to understand. Our contributions to the literature include the use of multiple catchment area definitions, addressing multiple dimensions of ECE access, and using spatial apply spatial modeling techniques to predict the spatial distribution of ECE access. Because ECE access is so localized, policy-oriented researchers highlight the need for neighborhood-level data (Hardy et al., 2021) and spatial analyses (Lin & Madill, 2019) in order to reveal patterns of neighborhood privilege vs. disadvantage, prioritize resources, and evaluate outcomes of policy solutions.

This study is most directly comparable to the work of Davis and colleagues (Davis et al., 2019). The two studies used similar, but not identical measures and methods (e.g., a distance decay function vs. three catchment area definitions, factoring travel time as an ECE cost, expressing cost relative to family income), but taken together, the illustrate the usefulness of the 2SFCA approach. Researchers using the 2SFCA method must make several choices, usually with little theoretical or empirical guidance. For example, many 2SFCA studies use population centroids to estimate residential locations; this assumes that all persons live at the center of respective geographic, i.e., all children in a census tract live in the same exact location (e.g., Fransen et al., 2015; McGrail, 2012). Davis et al. (2019) estimated child counts for each census block; our estimated location using residential lots was even more granular, however it is not clear whether increased granularity makes a practical difference. Another choice to be made is the definition of catchment area boundaries. ECE access studies have used a 10- to 20-min walk (Kawabata, 2015), a 10-min drive (Fransen et al., 2015), and 20-min drive (Davis et al., 2019). We used driving distance and public transit options. Ideally, catchment area definitions would be based on stakeholder input, because what is reasonable or desirable may differ based on location or other family characteristics. For example, rural families may accept longer travel distances or fewer choices of provider type, wealthier families may accept higher fees, and families living in an urban core may define accessible providers as those located within a several-block walk or a short subway ride.

Fantuzzo and colleagues (2021) spoke to the obligation of social scientists to provide "actionable intelligence" (p. 5). This study was conducted, in part to, inform the strategic expansion of Hawai'i's early childhood system. Our results show where needs are greatest, suggest where new classrooms could be located, and provide a baseline for evaluating progress. Actionable data must suit the policy question at hand (Hardy et al., 2021; Morrissey et al., 2022). The flexibility of the 2SFCA lends itself to many policy applications. We calculated access indexes at the micro level of the residential housing lot. Such micro-level data may be especially useful in showing variation within neighborhoods within a census tract, or pinpointing the best location for a new ECE site. Access scores can also be aggregated to higher levels as needed, e.g., municipal precinct, school attendance zone, county, or state legislative district. Overall the approach used in this study holds much promise, not only for the field of early childhood education and care, but for understanding disparities in access to a variety of services and neighborhood features that contribute to children's quality of life, e.g. pediatric care, child-friendly play spaces, or parenting support groups.

4.1. Limitations and implications for future research

Our study has several limitations, most of which are due to a lack of available data. As with most applications of the 2SCFA, we had to estimate the residential locations and family incomes of hypothetical children. In doing this, we used five-year ACS estimates that may not fully reflect recent population shifts. In the absence of a QRIS system or other administrative data relating to observed quality, we dichotomized quality using public pre-K or accreditation status, both of which are only crude proxies for actual quality. We included a single measure for each access dimension: when multiple measures would have been preferable. We also measured only three dimensions of ECE access, not addressing the dimension of meeting parents' needs. Information about family needs and preferences is rarely included in administrative datasets, although others have estimated family constraints, for example by using off-hour employment rates to gauge the need for evening and weekend child care (Sandstrom et al., 2018). In centering catchment areas on the home, we assumed that families seek care based on where they live, not on where they work. With this in mind, Franzen at al. (2015) defined accessible providers as those that added 10 min or less to a parent's direct home-to-work commute.

An important methodological shortcoming of our study is that we did not add a distance decay function when using the 2SFCA, to preferentially weight providers within the catchment area that are closer to family's home (Davis et al., 2019; Fransen et al., 2015; McGrail, 2012). Use of a decay function models the likelihood that families prefer to use the nearest resource, and is especially important when catchment areas are large (McGrail, 2012). However, there are many possible decay functions, e.g., inverse power, Gaussian, continuous, stepped, and researchers rarely have an empirical basis for selecting a particular function (Fransen et al., 2015; McGrail, 2012). A second key limitation of our study was not having child- or family-level data. We did not know where actual children lived, their demographic characteristics, the ECE provider they used, or whether their families received tuition subsidies. Rich administrative data on child-level characteristics are rare (see Fantuzzo et al., 2021, for an exception), but when obtained, the ability to answer important questions rises exponentially. For example, one could calculate access scores for particular populations of interest, such as subsidy recipients, dual language learners, or children with special needs.

A next step for our work is to create access indexes for sub-populations. Rather than treating ECE slots as available to all children in the catchment area, we will distinguish slots in programs with restricted eligibility, such infant-toddler centers or Head Start. We plan to calculate separate infant-toddler and preschool-age indexes and consider other groups, such as low-income children. In doing so, the reliability of available population estimates may be a limiting factor, since the margin of error for small area estimates of sub-populations may be unacceptably high. Taking a more community-based participatory approach would also be an enhancement. The use of tracts as a proxy for community most likely violates subjective definitions of neighborhood boundaries. Based on residents' input, one can aggregate lot-level access scores to align with any boundary, allowing for a more authentic neighborhood analysis. Community informants could also define thresholds for reasonable effort, affordability, and desired quality that make sense for their locale. Greater stakeholder input should yield results that better inform and improve policy decisions.

In sum, this study offers significant contributions to the growing literature on spatial analysis in the measurement and evaluation of equitable access to ECE. This approach can serve as a model for other researchers aiming to inform policy direction at various geographic levels. These methods are highly flexible and can be adjusted to suit the conditions, issues, and data available in different locales. We were pleased to find some evidence of equitable access in the state of Hawai'i and hope that future research will find this to be a growing trend nationwide.

CRediT authorship contribution statement

Barbara D. DeBaryshe: Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization, Supervision, Writing – original draft, Writing – review & editing. **Seongah Im:** Formal analysis, Methodology, Writing – original draft, Writing – review & editing. **Javzandulam Azuma:** Writing – review & editing, Writing – original draft, Visualization, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Ivette Stern:** Writing – review & editing, Writing – original draft, Supervision, Funding acquisition. **Minh Nguyen:** Writing – review & editing, Validation, Data curation. **Qi Chen:** Methodology, Writing – review & editing.

Declarations of competing interest

None.

Data availability

Data will be made available on request.

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.ecresq.2024.04.003.

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