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REVIEW PAPER

Service coverage level considering user mobility: spatial modelling of Italian day-cares

Lucia Zanotto[1] · Emanuele Aliverti[2] · Federico Caldura[3] · Stefano Campostrini[3]

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Abstract

Early childhood services are characterized by substantial variability in Italy, and notable differences can be observed between and within regions. Traditionally, the level of service coverage is measured by the ratio of available places to potential resident users. However, this metric can be biased, as it does not account for citizen mobility or cross-territorial agreements, such as shared management partnerships among municipalities. For instance, in zones without day-cares, parents may be required to enroll their children in facilities outside their residential area, and some municipalities may fund services provided in neighboring areas. As a consequence, the conventional raw coverage rate is often underestimated. This paper proposes a methodology that adjusts for user flows between different territories, refining the assessment of the number of individuals who can access the service. Adjusted data are incorporated into a spatial Poisson regression model to estimate service coverage levels across representative Italian regions, providing a more accurate fit of service supply and demand.

Keywords Service coverage level · Spatial modeling · Poisson regression · Bayesian modeling · Day-cares

1 Introduction

Childcare services play a critical role in fostering a healthy society, and quantitative studies on supply and demand of such facilities are fundamental tools for informing policy-makers. For example, early access to childcare promotes fertility and female employment by contributing to greater equality between roles in both the labor market and the household (Stier et al. 2001); also, several studies have shown a positive correlation between the presence of day-cares and working mothers in different

Extended author information available on the last page of the article

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countries (Baker et al. 2008; Buddelmeyer et al. 2005; Del Boca et al. 2009; De Henau et al. 2010; Jaumotte 2004), both at the micro and macro level (Olivetti and Petrongolo 2017), although with varying effects. Focusing on children development, it has been shown that high-quality childcare and competent staff can encourage the behavioral development (Clarke-Stewart et al. 2002; Early et al. 2007), cognitive skills (Hansen and Hawkes 2009) and non cognitive skills–such as tenacity, motivation, perseverance– (Heckman 2006), leading to increased reading and problem solving abilities in scholar age (Del Boca et al. 2018) and better social and labor prospects in adult life (Barnett and Masse 2007; Del Boca et al. 2018). In particular, children from socially and economically disadvantaged families seem to benefit the most from childcare services (Del Boca et al. 2018; Esping-Andersen et al. 2002), as they promote equality and social justice and contribute to economic and social productivity (Hansen and Hawkes 2009; Heckman 2006). Unfortunately, most day-care users seem to come mostly from families with higher educational level (Van Lancker 2013; Van Lancker and Ghysels 2016) and where both parents are employed (Sirén et al. 2020). This trend exacerbates the gap between advantaged and disadvantaged children, creating a "rich-get-richer" effect in the access to early childhood services (Bonoli and Liechti 2018). According to recent studies that consider European countries, these disparities are primarily driven by the limited availability or affordability of childcare, rather than by the lack of parental demand (Pavolini and Van Lancker 2018). Since the presence of day-cares significantly influences the socioeconomic structure of an area, the European Union established a target coverage ratio of 33% for early childhood services for all member states by 2010 at the Barcelona European Council in 2002 (Ludlow 2002). Accordingly, monitoring the coverage level of early childhood services remains essential.

In this work, we focus on measuring the level of childcare services coverage in some representative Italian regions. In Italy, many family, education, and health care policies are "decentralized": the central government allocates funds and defines overarching goals, regions establish general criteria, and municipalities are responsible for primary decision-making (Brilli et al. 2016). This layered governance structure often leads to significant disparities among territories, and regional childcare services offer a clear example (DIPOFAM et al. 2020). Also, such disparities exist both across regions, but also within regions: provincial capitals and more populous areas generally offer more opportunities and serve as attractive hubs for residents from peripheral or semi-peripheral municipalities. In this context, citizens may deliberately travel to access services, while municipalities increasingly share costs to ensure more sustainable budget management. These peculiarities pose additional challenges in monitoring the level of demand and supply of childcare services. Indeed, the primary metric used in service planning to evaluate childcare provision is the coverage ratio, defined as the ratio of available childcare places to the number of children aged 0 to 2 years. However, policy recommendations based on the raw coverage ratio might be misleading, as such a quantity generally underestimates true service coverage. For example, in areas lacking local childcare facilities, parents may enroll their children in nearby municipalities, and municipalities themselves may choose to fund services in neighboring areas rather than establish new facilities. Furthermore, municipalities often form aggregations to share childcare services, yet, administratively, the number of available places is recorded only within one municipality. Another potential issue of the raw ratio arises in municipalities where childcare services are available but the target population is zero. Under such conditions, the index cannot be calculated, leading to an underestimation of coverage.

This work aims to provide an improved estimate of the coverage level for early childhood education services, taking into account potential inter-area flows and spatial dependence. The analysis will focus on four Italian regions, serving as representative models at the national level.

1. Lombardia (mixed public-private services): characterized by a mixed public-private system (53% public, 47% private), with spending per user close to the Italian average (844 euros) and a raw coverage rate of 14.5%.
2. Veneto (prevalence of private services): exhibits a predominantly private supply (over 60%), with a 11% raw coverage rate for early childhood services. Parish-run day-cares are common, typically accepting children at least one year old (*nido integrato*). Spending per user (551 euros) is below, but close to, the national average.
3. Emilia-Romagna (prevalence of public services): demonstrates high territorial homogeneity, unlike Veneto and Lombardia. It features substantial average expenditure per child (1724 euros) and a higher raw coverage rate (almost 25%), mainly of a public nature (62%).
4. Puglia (lack of services): characterized by a very low raw coverage level (6.7%) and predominantly public facilities (71%). The region's per capita spending (284 euros) is unsurprising low given the scarcity of facilities. *Sezioni primavera* services are prevalent, allowing children to enroll in kindergarten at age 2 instead of 3. (DIPOFAM et al. 2020).

Data on childcare services from these regions will be included in the analysis and integrated with expenditure information to model outflows across municipalities, allowing a more reliable assessment of the number of resident children. The proposed approach builds on established methodologies in the spatial analysis of service coverage, which often leverage Geographic Information Systems (GIS) to better understand service accessibility and its spatial diffusion. For example, Murray (2005) introduced a model to estimate coverage levels in cases where the geographic location of services is known, but area-level coverage remains uncertain. Similarly, Kurniawati et al. (2022) employed nearest neighbor analysis to evaluate health facility coverage in residential areas. Instead, we propose to model directly the coverage level using the number of childcare services and resident children, and incorporating these information into a Poisson spatial regression model to estimate the spatial intensity of coverage, accounting for municipal differences in labor systems composition and population characteristics.

2 Data description

The dataset under investigation has been provided thank to a joint work among the National Institute of Statistics (ISTAT), the Department of Family Polices of the Presidency of the Council of Ministers (*Presidenza del Consiglio dei Ministri – Dipartimento per le Politiche della Famiglia* – DIPOFAM) and the Ca' Foscari University of Venice, which includes information on all public and private day-cares and kindergartens. Such an agreement provides unique access to detailed data on municipal expenditures for day-cares, thereby providing a more comprehensive view on the funding of those services and allowing to account for potential flows across municipalities. We will focus on data from the 2018 survey, that can be accessed through the website of the Italian National Institute of Statistics (ISTAT 2024) in the section "Assistenza previdenza, servizi sociali, Servizi socio-educativi per la prima infanzia".

For each municipality $i = 1, \ldots, n$, the data comprise the pair (y_i, c_i), where y_i represents the number of available childcare places and c_i denotes the number of resident children aged 0–2. The raw coverage ratio can be calculated as y_i/c_i; summary statistics for these indexes are reported in Table 1, providing an overview of childcare service characteristics. All values are calculated by excluding the six municipalities with zero children, ensuring that the coverage ratios accurately reflect areas where demand exists.

Lombardia reports the highest average raw coverage, followed by Emilia-Romagna and Veneto. Municipalities in Lombardia exhibit greater variability compared to those in Veneto and Emilia-Romagna. In this region, some areas show extremely high coverage, with a ratio above 1, indicating more available places than potential users, while others lack services entirely, with a ratio equal to zero. In Veneto, the presence of municipalities without day-cares is also common. Emilia-Romagna, on the other hand, is characterized by larger uniformity, though some municipalities still lack services. The values calculated for Puglia reflect the unfortunately typical situation in southern Italy, where coverage is consistently low across the region.

In order to account for regional differences in terms of economic structure, we supplemented the data with ISTAT's Local Labour Systems (SLL) for each region, which have been included as covariates in the modeling phase of Sect. 3.2. This classification framework, developed by ISTAT, accounts for the spatial distribution of the economic activities within a given territory. The SLLs are defined as self-contained areas where the majority of the resident population both lives and works, thus capturing the functional economic relationships within a region; the detailed boundaries of these systems can be found on the ISTAT website (ISTAT 2015). For the purpose of this analysis, the 9 subclasses of SLLs suggested in ISTAT (2015) were used, with an

Table 1 Summary statistics for municipal coverage levels (raw, unadjusted data)

	Mean	SD	Min	Q1	Q2	Q3	Max
Lombardia	0.378	0.773	0.000	0.000	0.224	0.455	9.250
Veneto	0.257	0.230	0.000	0.000	0.248	0.367	1.429
Emilia-Romagna	0.312	0.211	0.000	0.189	0.326	0.435	1.143
Puglia	0.192	0.197	0.000	0.000	0.156	0.287	0.984

Average, standard deviation, minimum, quartiles and maximum additional one labeled as "Others" that include other minor systems as well as unclassified ones (see also ISTAT-GIS, 2023). These subclasses offer a view of the economic and labor market characteristics across different areas, highlighting the regional variability of labor systems. Table 2 shows the absolute and relative frequencies of the various districts in the four key regions, and outlines significative territorial differences across them. For example, districts specializing in the mechanical industry and textiles are predominant in Lombardia. The same specializations are observed in Veneto, with an additional focus on the household goods market. Emilia-Romagna is primarily characterized by mechanical industry districts, whereas in Puglia there is no strong district specialization.

3 Methods

3.1 Data transformation

As outlined in Sect. 1, several Italian municipalities do not offer childcare services, necessitating parents enroll their children in neighboring areas. Unfortunately, these cross-municipal enrollment patterns are not officially recorded and cannot be reconstructed from raw and public-available data, such as those provided by ISTAT (2024). As a potential proxy, information on commuting flows could be useful for capturing parental movement, but unfortunately the available matrices are outdated and no longer reflect current market dynamics. However, when expenditure data are available,

Table 2 Absolute (and relative) frequencies of the local labor systems in the analyzed regions

	Lombardia	Veneto	Emilia Romagna	Puglia
Household goods	27 (2%)	72 (13%)	15 (5%)	Not present
Mechanical industry	363 (24%)	199 (36%)	65 (20%)	Not present
Metallurgical industry	57 (4%)	Not present	6 (2%)	Not present
Food industry	69 (5%)	7 (1%)	18 (5%)	4 (2%)
Paper and printing industries	Not present	Not present	Not present	Not present
Jewellery, musical instruments, etc.	3 (0%)	23 (4%)	Not present	Not present
Leather and footwear	26 (2%)	24 (4%)	Not present	7 (3%)
Textiles and clothing	214 (14%)	77 (14%)	3 (1%)	13 (5%)
Chemical, petrochemical, rubber				
and plastics industries	65 (4%)	Not present	Not present	Not present
Others (or unclassified)	681 (45%)	156 (28%)	221 (67%)	232 (91%)

this limitation can be partially addressed by identifying municipalities with positive childcare costs but no local service provision. Indeed, such outlay indicates financial contributions toward external childcare services to cover resident children's costs, suggesting that these children are enrolled as external users, likely in neighboring municipalities; therefore, they should be considered appropriately in the computation of the effective coverage level.

We propose a simple heuristic to approximate these flows, identifying *out-taker* and *in-takers* municipalities and matching them as follows. We define a municipality as an *out-taker* if (a) it reports a positive number of children and an annual spending for childcare service that exceeds euro 50 per child and (b) no childcare places are available within its boundaries. It is acknowledged that this heuristic may underestimate the extent of cross-municipal enrollment, as some placements may occur without financial contributions from the local government, and parents may still choose for childcare outside their municipality even when local services are available. Nevertheless, such criteria effectively filter out a substantial number of non-relevant municipalities, providing a manageable initial classification.

The following step involves identifying likely destinations for these outflows. A municipality is defined as a potential *in-takers* if its ratio of childcare places to children is above the 0.8 quantile for the province. These municipalities are labeled as potential *in-takers*, as they will be included in the analysis only if they can be matched with at least one *out-taker*. A conservative selection of municipalities at this stage is thus reasonable, as many potential *in-takers* are expected to be excluded in the subsequent matching process.

In the final stage, each *out-takers* is paired with the closest potential *in-takers* based on travel time. This time, measured in minutes between municipalities, is derived from distance matrices provided by ISTAT (2024). The result of the matching is, for the selected municipalities, an adjusted child count $\tilde{c}_i$: the number of users, increases by including, in the *in-taker* municipality, all children aged 0–2 who reside in the associated *out-taker* municipality, while the available places, y_i, remain fixed. Figure 1 illustrates estimated flows in Lombardia, with marked movement in the northeast where certain hubs meet the demand from surrounding areas. In the southeast, flows are also notable, though of lower intensity. Estimated flows for other regions are provided in Appendix A.

Table 3 presents summary statistics for adjusted coverage levels, excluding municipalities that, after the redistribution of children, report zero users. Comparing this with Table 1, it becomes evident that in municipalities where the number of available places was relatively high (within the regional context), the coverage rate decreases due to the redistribution of users. Conversely, the variance is consistently lower, indicating greater uniformity across municipalities. More municipalities now exhibit similar coverage rates, reducing disparity in the provision of early childhood services; this effect is particularly pronounced in Lombardia, where movements appear to be more common.

Clearly, the proposed approach has some limitations. First, it is not possible to verify whether the estimated redistribution of childcare users across municipalities accurately reflects actual patterns, as there is no data on the actual flows. Although information on resource-allocating municipalities is available, the specific destina-

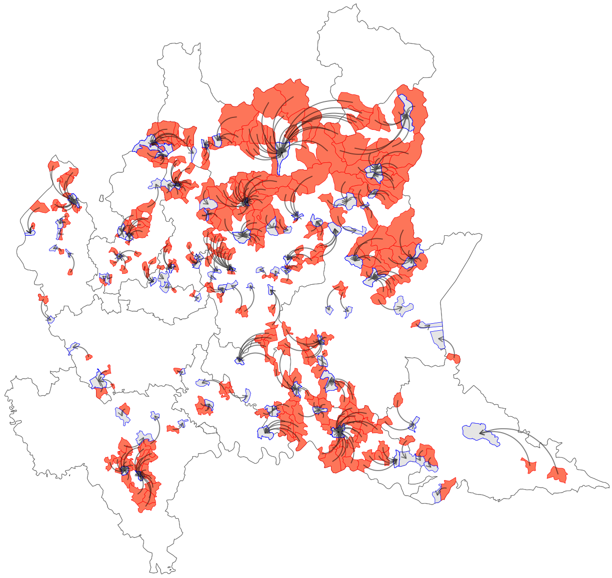

Fig. 1 Estimated children flows in Lombardia. Out-takers municipalities are reported in red, *in-takers*s in blue. Arrows denote the estimated flows

Table 3 Summary statistics for coverage levels (adjusted data)

	Mean	SD	Min	Q1	Q2	Q3	Max
Lombardia	0.317	0.323	0.000	0.132	0.276	0.417	3.667
Veneto	0.257	0.222	0.000	0.097	0.252	0.362	1.429
Emilia-Romagna	0.318	0.192	0.000	0.210	0.326	0.431	1.143
Puglia	0.189	0.152	0.000	0.090	0.175	0.252	0.984

Average, standard deviation, minimum, quartiles and maximum

tions of these resources remain unknown. Additionally, the method does not consider scenarios where parents might choose childcare facilities closer to workplaces or relatives, such as grandparents, rather than to their residence, which may affect estimated flows. Nevertheless, this approach offers a more realistic representation compared to raw data, which disregard these patterns and artificially concentrate services in single hubs with unrealistic levels of provision; for a numeric comparison with results using raw data, see Sect. 4.

3.2 Spatial modeling

In this section, we estimate the spatially-varying intensity for the coverage level, relying on a regression model. Instead of focusing on the raw ratio $y_i/\tilde{c}_i$, coverage is modeled based on the number of childcare places, y_i, and the number of children, $\tilde{c}_i$, as an inhomogeneous log-Gaussian Cox point process (e.g., Diggle 2013, Chapter4). This approach assumes that the distribution of available places follows a stochastic process with an intensity function, $\Lambda(s) = \exp\{Z(s)\}$, where $Z = \{Z(s), s \in \mathbb{R}^2\}$

is a Gaussian process accounting for spatial dependence across municipalities. Given the intensity function $\Lambda(s)$, the number of childcare places follows a Poisson process, implying that the number of places within a municipality of area A is Poisson-distributed with mean $\int_A \Lambda(s)\,\mathrm{d}s$; refer, for example, to Moraga (2021) for more details. Under such an approach, the coverage level can be implicitly modeled including an offset term $\log(\tilde{c}_i)$ (e.g., Agresti 2015, sec7.1.6), that accounts for varying level of the adjusted number of children. To achieve this, we denote as a_i the area of each municipality, and let for each $i = 1, \ldots, n$

$$\begin{aligned}(y_i \mid \lambda_i) &\sim \ \mathrm{Poisson}(a_i \lambda_i),\\ \log(\lambda_i) &= \log(\tilde{c}_i) + \alpha + \sum_{j=1}^{p} x_{ij}\beta_j + u_i.\end{aligned} \tag{1}$$

In Eq. (1), $\log(\lambda_i)$ denotes the linear predictor and α the intercept term. Each regression coefficient β_j corresponds to labor district *j*, and the dummy indicator x_{ij} is 1 if municipality *i* belongs to labor district *j* (see Table 2). In Lombardia, nine coefficients are estimated (one for each SLL, including the reference category), while Veneto, Emilia-Romagna, and Puglia have seven, six, and four coefficients, corresponding to the number of SLLs observed in that region. The coefficients for SLLs that are not present in a given region are not estimated.

The terms u_i denote municipality-specific random effects, specified with a spatial dependence structure. This is accounted following a standard approach in modeling areal data, via an intrinsic conditional autoregressive structure (ICAR) on the vector of random effects $(u_i, \ldots, u_n)$. Such a prior induces a distribution on the joint vector $(u_i, \ldots, u_n)$ imposing dependence across each u_i and its neighbors $\{u_{i'}, i' \in \mathcal{N}_i\}$, where $\mathcal{N}_i$ denotes the set of spatial location with whom *i* shares a border (i.e. its neighbors). Denoting as m_i the cardinality of $\mathcal{N}_i$ and with τ_u a precision parameter, it holds that

$$(u_i \mid \{u_{i'}, i' \in \mathcal{I}_i\}) \sim \mathrm{N}\left(\frac{1}{m_i}\sum_{i' \in \mathcal{I}_i} u_{i'}, \frac{1}{\tau_u m_i}\right). \tag{2}$$

The model is completed specifying diffuse Gaussian and log-normal priors on $(\alpha, \beta_1, \ldots, \beta_p)$ and τ_u, respectively. Posterior inference is performed via the Integrated Nested Laplace Approximation (INLA; Lindgren and Rue 2015; Rue et al. 2009).

According to the proposed specification, each municipality's coverage rate is modeled by combining the observed number of available childcare places, the adjusted number of children, and the municipality's area. This spatial model not only accounts for geographic dependence between neighboring areas, including socio-economic similarities driven by labor district composition, but also removes the deterministic constraint that coverage must be zero in municipalities without resident children. Indeed, the model leverages spatial information to infer the coverage level by modeling the expected value for the number of children. As a result, such a model allows the estimation of a smooth coverage intensity influenced by proximity, reflecting similarities between neighboring areas while controlling for potential confounding due to regional structural differences.

4 Results

In order to select the most appropriate specification for each region and justify the approach of Sect. 3.1, we compare the proposed model with some alternatives. Focusing on the linear predictor $\log(\lambda_i)$ of Eq. (1), four other models are considered, as detailed in the first column of Table 4. The first row of Table 4 corresponds to the model specified in Eq. (1), which includes SLLs as dummy covariates and spatial random effects u_i; Tables 5 and 6 illustrate the variance components for the random effects and the posterior estimates for the fixed-effect parameters, respectively. The second row shows a model with only the spatial random effects u_i, excluding the SLL covariates; the third row corresponds to a standard Poisson GLM with an offset and the dummy variables for the SLL covariates. The fourth row combines the SLL covariates with an exchangeable specification, letting $v_i \sim \mathrm{N}(0, \tau_v^{-2})$ and thereby inducing a Poisson GLMM specification. The fifth row presents a model with SLL covariates and both spatial and independent random effects, as recommended by Blangiardo and Cameletti (2015). The last row of of Table 4 indicates the model from Eq. (1) that uses as offset the raw child count c_i, instead of the adjusted count $\tilde{c}_i$; since such a model focuses on the same response y_i as the other approaches, it can be used as a benchmark for assessing the utility of the adjustment method proposed in Sect. 3.1. All approaches are estimated with INLA, assuming the same diffuse priors outlined in Sect. 3.2. For each model, the Deviance Information Criterion (DIC) (Spiegelhalter et al. 2002) is calculated and used for the evaluation.

Current empirical findings underscore the importance of spatial random effects, as models excluding this component (third and fourth row of Table 4) consistently perform worse. Also, spatial random effects result in better model performance compared to exchangeable random effects (first and fourth row of Table 4). Furthermore, the model with only spatial random effects improves the approach that includes both spatial and exchangeable effects (fifth row), suggesting that, once spatial dependence across municipalities is accounted for, no additional correlation structure is

Table 4 Deviance information criterion (DIC) for different model specification

Linear predictor	Lombardia	Veneto	Emilia Romagna	Puglia
$\log(\tilde{c}_i) + \alpha + \sum_{j=1}^{p} x_{ij}\beta_j + u_i$	9051.55	**3461.91**	**2274.61**	1609.73
$\log(\tilde{c}_i) + \alpha + u_i$	**8934.24**	3464.07	2275.74	**1609.67**
$\log(\tilde{c}_i) + \alpha + \sum_{j=1}^{p} x_{ij}\beta_j$	66139.36	19257.88	14024.58	14909.05
$\log(\tilde{c}_i) + \alpha + \sum_{j=1}^{p} x_{ij}\beta_j + v_i$	9203.02	3549.30	2316.80	1649.05
$\log(\tilde{c}_i) + \alpha + \sum_{j=1}^{p} x_{ij}\beta_j + u_i + v_i$	9067.72	3506.31	2289.63	1617.23
$\log(c_i) + \alpha + \sum_{j=1}^{p} x_{ij}\beta_j + u_i$	9846.810	3475.149	2326.660	1706.743

Lowest value denoted in boldface

necessary. The exclusion of SSL covariates (first and second row of Table 4) shows improved performance in Lombardia and Puglia; therefore, for these regions, we will consider models that include only spatial information in the following discussion of empirical findings. This choice is in agreement with the results from Table 6, that indicate that most coefficients are not statistically significant. Finally, Table 4 highlights that the adjustment proposed in Sect. 3.1 yields significant improvements in modeling the number of children. Specifically, all models with random effects perform better when using the adjusted offset $\tilde{c}_i$ compared to the original one, based on the raw c_i (last row of Table 4); for further comparison, results from this model are included in Appendix C.

Figures 2 and 3 display the coverage rates and the spatial random effects estimated by the selected regional models. Such quantities are obtained as $(\hat{\lambda}_i/\tilde{c}_i)$, where $\hat{\lambda}_i$ denotes the posterior mean of the linear predictor of Eq. (1) and $\tilde{c}_i$ is the adjusted number of children. Municipalities with coverage levels below the reference threshold of 33% are shaded in blue and shown in the left panels, while those with higher levels are shaded in red and presented in the middle panels. Municipalities lacking available data are left uncolored and appear white in both plots. Lastly, the posterior mean of the spatial random effects $\hat{u}_i$ is reported in the right panels of Figs. 2 and 3.

Current empirical findings reveal substantial inhomogeneity among municipalities in Lombardia (top row of Fig. 2). High coverage levels are concentrated in

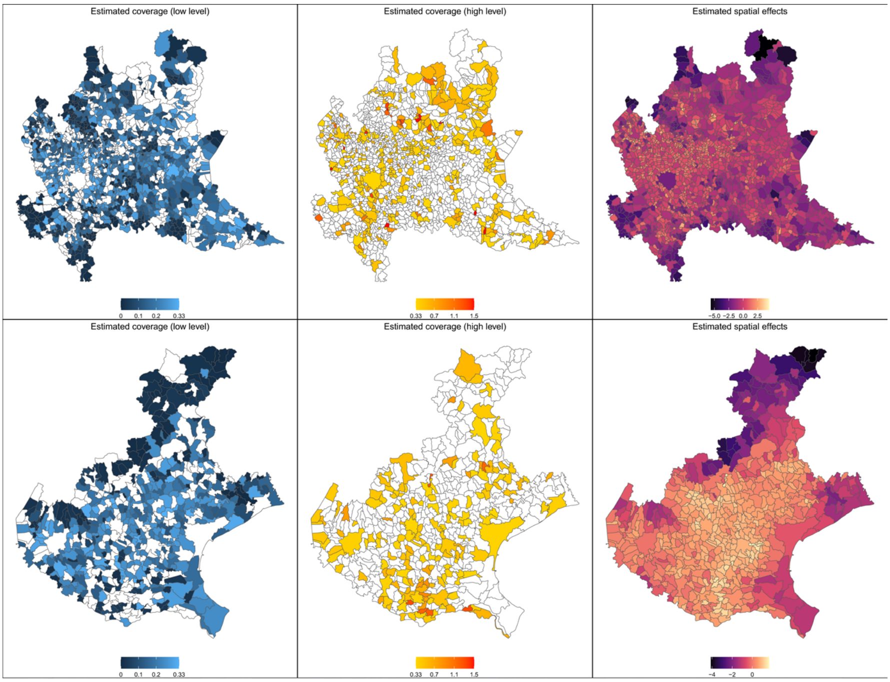

Fig. 2 Estimated coverage level for Lombardia (top panels) and Veneto (bottom panels). Left and middle panels show model estimates for low (< 0.33) and high (> 0.33) levels of coverage, respectively. Right column reports the estimate spatial effects u_i

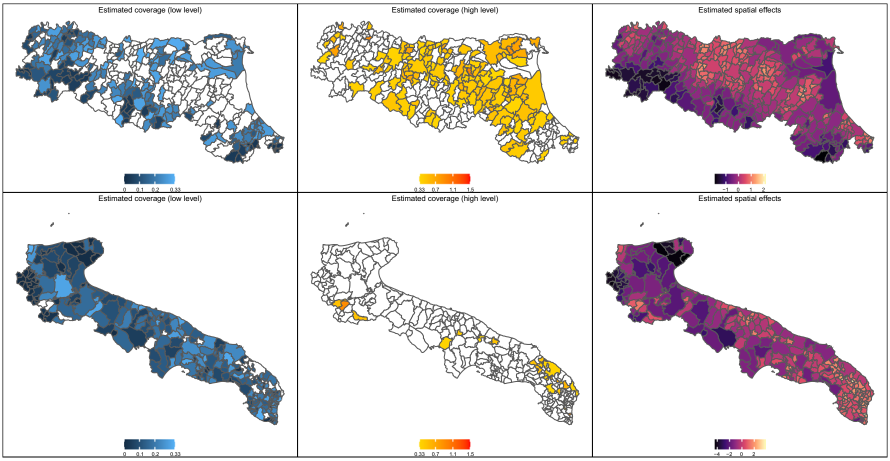

Fig. 3 Estimated coverage level for Emilia-Romagna (top panels) and Puglia (bottom panels). Left and middle panels show model estimates for low (< 0.33) and high (> 0.33) levels of coverage, respectively. Right column reports the estimate spatial effects u_i

Milano city and its surrounding areas, while most municipalities exhibits rates below the 33% threshold. Notably, elevated rates of childhood service coverage are also observed in northern mountain areas, such as Chiesa Valmalenco and Torre Maria. In Veneto (bottom row of Fig. 2), high variability in coverage levels is evident. The lowest rates are concentrated in mountainous regions, including the Cadore area and the Dolomiti Bellunesi mountains, while provincial capitals display higher coverage. Nevertheless, most municipalities in Veneto provide coverage for less than one-third of potential users. In Emilia-Romagna (top row of Fig. 3), a higher degree of homogeneity is observed, with the majority of services concentrated in the Po Valley area, where coverage rates frequently exceed 33%. Certain areas within this region are particularly noteworthy for their exceptional coverage levels. However, municipalities in the southwestern portion of Piacenza province (Val Trebbia) remain comparatively disadvantaged. Puglia (bottom row of Fig. 3) exhibits a stark scarcity of early childhood services, particularly in Gargano area and Daunia mountains. Even in provincial capitals, the availability of services does not show substantial improvement; few municipalities in Puglia are entirely devoid of early childhood services.

5 Discussion and conclusions

In Italy, certain policies are decentralized, with municipalities responsible for providing and managing services within their territories. However, significant mobility between towns often leads citizens to utilize services outside their area of residence. Focusing on modeling the coverage of childcare services in four Italian regions using official data, this study demonstrates how accounting for such movements can offer a more realistic representation of the actual level of service provision. Coverage levels are estimated using a Poisson model that includes an iCAR component for spatial smoothing and fixed effects to control for regional labor force composition and potential confounders–such as local economic structure–that may influence natality levels. Model evaluation underscores the importance of including spatial components and adjusting for the number of children to achieve accurate coverage estimates.

Our findings indicate that shared services can be a key strategy for achieving broader coverage and allow to identify the most vulnerable municipalities (particularly small, resource–limited towns in mountainous, foothill, or hilly areas). Although this pattern is not entirely new, it underscores the need for strategic planning and policy action in regional childcare provision. Both central and local governments should prioritize the expansion of childcare services, the enforcement and maintenance of quality standards, and the regulation of parental fees. Achieving the European Union's target of 33% coverage, as well as the new goal of enrolling 45% of children in day-cares by 2030, remains a primary objective.

Beyond addressing the specific issue of measuring childcare services, the proposed methodology highlights the broader need for more accurate tools to measure service coverage at the local level. For example, updated measures for commuting flows or effective data on childcare enrollment are not available, but incorporating them in future work could further refine our understanding of regional childcare coverage disparities. While the inclusion of specific data would improve precision, the use of models such as the one proposed in this article provides reasonable and robust estimates relying on available data and it can be employed to analyze other types of services with similar features.

Estimated flows between municipalities

See Appendix Fig. 4.

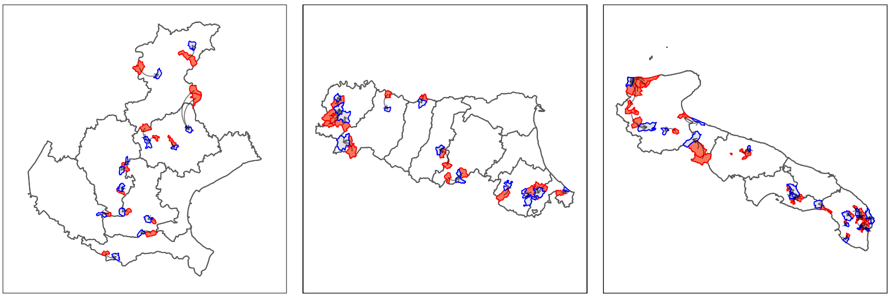

Fig. 4 Estimated flows for Veneto (left), Emilia-Romagna (middle) and Puglia (right)

Parameters estimates

See Appendix Tables 5 and 6.

Table 5 Spatial random effects, precision parameters τ_v

Region	Mean	SD	CI
Lombardia	0.410	0.295	(0.080,1.180)
Veneto	0.350	0.013	(0.325,0.375)
Emilia-Romagna	0.545	0.023	(0.501,0.592)
Puglia	0.239	0.011	(0.217,0.261)

Posterior means, standard deviations and 95% credible intervals

Table 6 Regression coefficients

Region		Mean	SD	CI
Lombardia	Intercept	− 4.135	0.093	(− 4.317, − 3.954)
	Household goods	0.746	0.595	(− 0.420, 1.912)
	Mechanical industry	0.409	0.199	(0.019, 0.798)
	Metallurgical industry	0.058	0.336	(− 0.600, 0.717)
	Food industries	0.527	0.54	(− 0.531, 1.586)
	Jewelry, musical instruments, etc.	− 6.905	11.333	(− 29.128, 15.317)
	Leather, hides, and footwear	0.166	0.569	(− 0.950, 1.283)
	Textile and apparel	− 0.164	0.214	(− 0.584, 0.255)
	Chemical, petrochemical, rubber and plastics industries	− 0.073	0.345	(− 0.749, 0.604)
Veneto	Intercept	− 5.170	0.163	(− 5.492, − 4.851)
	Household goods	− 0.081	0.327	(− 0.723, 0.559)
	Mechanical industry	0.057	0.242	(− 0.419, 0.531)
	Food industries	0.236	0.806	(− 1.346, 1.819)
	Jewelry, musical instruments, etc.	0.166	0.504	(− 0.822, 1.154)
	Leather, hides, and footwear	− 0.460	0.414	(− 1.274, 0.351)
	Textile and apparel	0.092	0.309	(− 0.515, 0.699)
Emilia-Romagna	Intercept	− 5.378	0.059	(− 5.495, − 5.263)
	Household goods	− 0.288	0.356	(− 0.987, 0.409)
	Mechanical industry	0.046	0.196	(− 0.338, 0.431)
	Metallurgical industry	− 1.136	0.641	(− 2.397, 0.120)
	Food industries	0.039	0.353	(− 0.652, 0.732)
	Textile and apparel	− 1.040	0.533	(− 2.087, 0.007)
Puglia	Intercept	− 5.967	0.061	(− 6.089, − 5.85)
	Food industries	0.519	0.586	(− 0.632, 1.670)
	Leather, hides, and footwear	− 0.617	0.558	(− 1.712, 0.479)
	Textile and apparel	0.154	0.452	(− 0.733, 1.041)

Posterior means, standard deviations and 95% credible intervals

Coverage levels estimates on raw data

See Appendix Figs. 5 and 6.

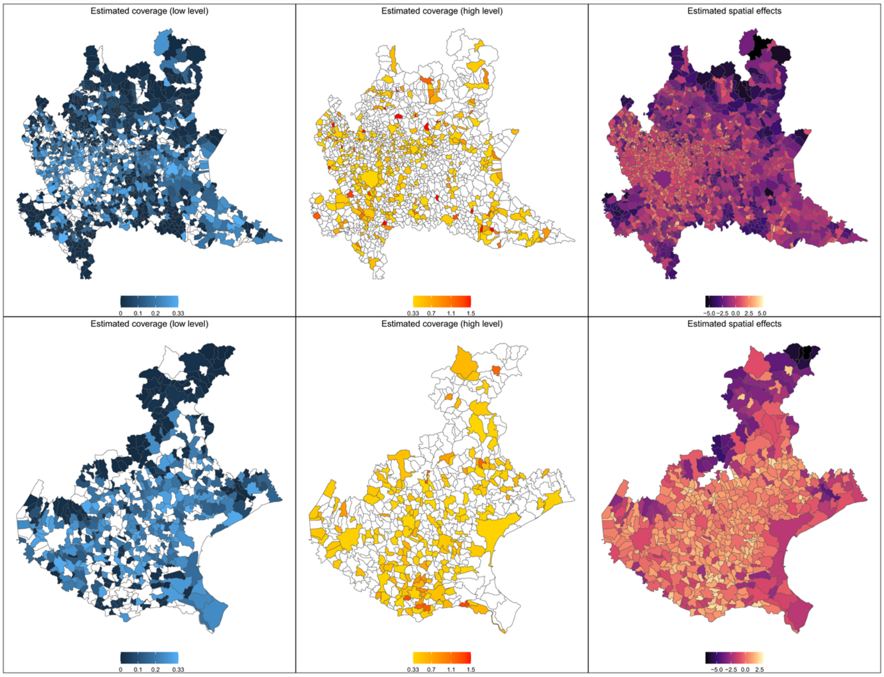

Fig. 5 Estimated coverage level for Lombardia (top panels) and Veneto (bottom panels) using raw unadjusted data. Left and middle panels show model estimates for low (< 0.33) and high (> 0.33) levels of coverage, respectively. Right column reports the estimate spatial effects u_i

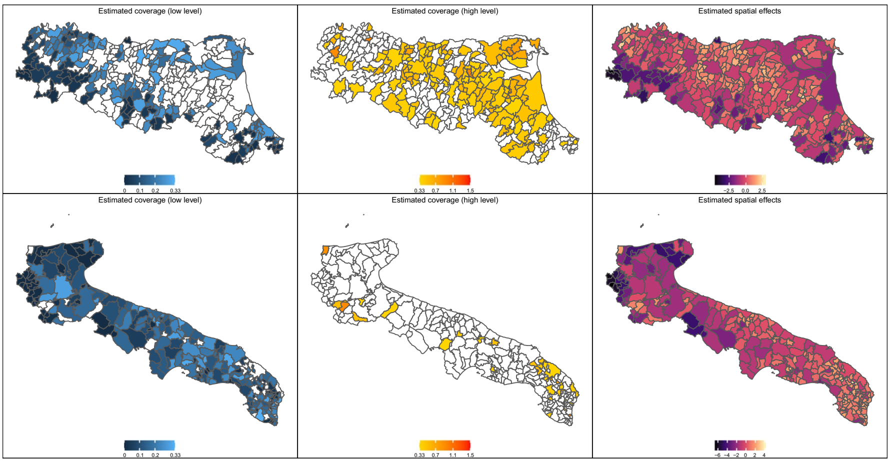

Fig. 6 Estimated coverage level for Emilia-Romagna (top panels) and Puglia (bottom panels) using raw unadjusted data. Left and middle panels show model estimates for low (< 0.33) and high (> 0.33) levels of coverage, respectively. Right column reports the estimate spatial effects u_i

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Declarations

Conflict of interest The Authors declare that there is no conflict of interest.

Author Consent All authors hereby give their consent for the publication of the manuscript. We confirm that the work is original, has not been published previously, and is not under consideration for publication elsewhere. All authors have read and approved the final version of the manuscript and agree to its submission to Statistical Methods and Applications.

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Authors and Affiliations

Lucia Zanotto[1] · **Emanuele Aliverti**[2] · **Federico Caldura**[3] · **Stefano Campostrini**[3]

✉ Lucia Zanotto
lucia.zanotto@unibo.it

Emanuele Aliverti
emanuele.aliverti@unipd.it

Federico Caldura
federico.caldura@unive.it

Stefano Campostrini
stefano.campostrini@unive.it

[1] Department of Statistical Sciences, Alma Mater Studiorum-University of Bologna, via delle Belle Arti 41, 40126 Bologna, Italy

[2] Department of Statistical Sciences, University of Padua, via Cesare Battisti 241, 35121 Padova, Italy

[3] Department of Economy, Ca' Foscari-University of Venice, Cannaregio 873, 30100 Venezia, Italy