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ORIGINAL ARTICLE

Deprivation at local level: Practical problems and policy implications for the province of Milan

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Abstract
Composite indicators are often used to assess the structure of urban deprivation to promote sustainable development. However, the refined spatial scale of analysis poses problems related to data availability. In this paper, we define a spatial deprivation index in the province of Milan, using both census data and areal interpolation. Disaggregation methods are applied to obtain variables at lower spatial level, and a geographically weighted principal component analysis is applied to measure socio-economic deprivation at local level. Components of deprivation are investigated in their spatial structure and some policy implications deriving from the application of a spatial approach are discussed.

KEYWORDS
areal interpolation, composite indicators, GWPCA, spatial heterogeneity

JEL CLASSIFICATION
C01; C21; C43; C54

1 | INTRODUCTION

In recent years, many have supported the idea that well-being is not only related to the material sphere (ISTAT, 2015; Sen & Fitoussi, 2009). Besides well-being, socio-economic deprivation has been often addressed as a multivariate concept to evaluate social and material conditions (Somarriba & Pena, 2009). Measuring socio-economic

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deprivation is strictly connected to the idea of measuring inequalities. In fact, deprivation may be defined as "a state of observable and demonstrable disadvantage relative to the local community or the wider society or nation to which an individual, family or group belongs" (Townsend, 1979, 1987).

In many empirical experiences (Bell, Schuurman, Oliver, & Hayes, 2007; Padilla et al., 2014; Pampalon, Hamel, Gamache, & Raymond, 2009), measures of deprivation are meant as a key tool for policy-makers. Deprivation indices are flexible instruments useful to assess the level of inequalities, material needs, social exclusion, and to support regional and local policies. However, in many cases composite indicators are generically derived without including spatial features that can be extremely helpful for policy-makers (Cartone & Postiglione, 2020). In fact, in setting policies to reduce disparities it is not desirable ignoring spatial scale. Additionally, not considering spatial dimension (for example, local diversities) can lea d to very biased and inefficient policies that cannot tackle actual drivers of deprivation (Andreano, Benedetti, & Postiglione, 2017).

This paper proposes a strategy for the measurement of deprivation that we apply for the province of Milan. We investigate deprivation by developing a composite indicator at a refined spatial scale for the whole metropolitan area in a fast-growing city as Milan. Considering those features appears as improving the dashboard for local authorities and helpful to develop policies targeted to metropolitan areas and city regions (Camagni, 2001; Rodríguez-Pose, 2008). For those reasons, we particularly refer to composite indicators for regional, municipality, and very local governments, called to reduce disparities. The year considered is 2011, the census year.

Further, our strategy aims at facing two major challenges in the derivation of composite indicators at low spatial scale. The first problem concerns data availability. The second relevant issue relates to the aggregation of different dimensions involved in the definition of the final indicator.

Inputs for the composite indicators are considered with reference to a low spatial scale, that is, locality level, which corresponds to a level between census tract and municipality. Nevertheless, data on personal average income are not available at this selected spatial scale. In order to avail average income at locality level we adopt the Bayesian interpolation method (BIM), introduced by Benedetti and Palma (1994).

Unlike other areal interpolation methods, BIM considers spatial dependence in the disaggregation process, a desirable feature when dealing with georeferenced data. According to BIM, the data generating process is modelled through a conditional autoregressive (CAR) specification, which introduces spatial dependence in the covariance structure of the process as a function of a proximity matrix and of a spatial autocorrelation parameter. Following a Bayesian approach, the prior information on the distribution of the data generating process is combined with the data available at the aggregated spatial level to derive the posterior probability distribution with the BIM estimates as parameters. Hence, any inference on the variable of interest at the desired spatial scale can be based upon this posterior distribution (Benedetti & Palma, 1994; Panzera & Viñuela, 2018).

Aggregation of indicators can be carried out in several ways (e.g. Cabrera-Barona, Murphy, Kienberger, & Blaschke, 2015; Decancq & Lugo, 2013; Mazziotta & Pareto, 2016). A common way to operationalize this multidimensional perspective is principal component analysis (PCA), as shown particularly for deprivation index in Pampalon and Raymond (2000). Multiple criticisms may be raised in spite of the use of PCA. Some authors raise the problem of compensation between the considered variables (Mazziotta & Pareto, 2016), while others criticize that PCA synthetize variables based on a statistical technique (Decanq & Lugo 2013). Nevertheless, PCA can be applied in a variety of analysis, and its properties (Jolliffe, 2002) make it a standard approach (OECD, 1993).

Surprisingly, the use of geographically distributed data for PCA is an often-underrated issue. This would suggest paying more attention on the presence of spatial effects (Sarra & Nissi, 2019). In fact, ignoring spatial heterogeneity, defined as the instability of a given relation in space (Anselin, 1988), is likely to bring misspecification, that could lead to a difficult understanding of the phenomenon under consideration (Andreano et al., 2017). In the paper, to address these spatial instabilities, we adopt geographically weighted principal component analysis (GWPCA, Fotheringham, Brunsdon, & Charlton, 2002; Lloyd, 2010; Harris, Brunsdon, & Charlton, 2011), which allows for differences in the variance–covariance matrix (see the methodological framework for a detailed description), so that the results embed local peculiarities (Harris, Clarke, Juggins, Brunsdon, & Charlton, 2015).

Results indicate that drivers of deprivation tend to change across the whole metropolitan area. The analysis reveals how critical zones can be targeted with more effectiveness by policy-makers at both regional and municipality levels, which justifies a deeper use of both data disaggregation techniques and spatial techniques.

The remainder of the paper is as follows: Section 2 offers additional information about deprivation in the area of Milan. Section 3 describes the methodology adopted for data disaggregation and derivation of the composite indicator. In Section 4 the empirical results are presented. Section 5 discusses the geographical distribution of deprivation index and its links with economic and social policies, while Section 6 concludes.

2 | SOCIO-ECONOMIC DEPRIVATION IN THE MILAN AREA

The Milan area represents an interesting context to investigate local disparities. In fact, Milan and its province are among the richest areas in Italy and they reflect a model of development where the issues of economic growth intersect problems of social cohesion.

Until the 1990s, the greater job opportunities in the city of Milan determined the development and consolidation of a welfare provision tailored to local needs, and greater investments in social and educational policies (Costa, Cucca, & Torri, 2016). After this period, the city adopted a new approach to welfare, with the progressive reduction of the public expenditure in social services and the greater involvement of private and non-profit organizations in their provision (Costa et al., 2016). The residuality assumed by public social policies contributed to the worsening of the social conditions and the spatial inequalities in the Milan area, mainly because of the neglect of housing policies (Cucca, 2010; D'Ovidio, 2009). Further, in the last decades, a new attention towards social policies has been compromised by the economic crisis and the austerity measures, that greatly restricted the welfare investments (Costa et al., 2016).

The global economic crisis severely hit the Lombardy region and the area of Milan, also because of the strong concentration of firms and economic activities. Between 2007 and 2009 production decreased meaningfully in all sectors, with an additional heavier impact on manufacturing (Costa & Sabatinelli, 2012).

While a smaller impact of the crisis affected most creative and innovative sectors that are particularly important in Milan, difficulties in accessing credit have put firms and population under pressure by the fall of sales and by credit crunch. Those issues lead to an increase of youth unemployment rate. In some cases, population in Lombardy was, as other areas of the Country, exposed to difficulties and inadequate articulation between the education sector and the labour market (Fellini, Negrelli, & Rossi, 2011).

Despite figures had kept quite low compared to Southern areas, in the following years Lombardy suffered consequences from the global crisis in terms of opportunities for SMEs and households. In this direction, the number of the people who cannot make ends meet rose around 3% from 2007 to 2009 (from 10.6% to 13.3%) against an increase of 1.5% in the close region of Veneto (ISTAT, 2015). Also, the rate of poor households had faced a low and stable trend in the region before the start of the crisis. After 2007, the number of poor households started to rise, nearing 3.5% (ISTAT, 2015). In this context, studying the structure of deprivation in Lombardy helps us to offer a clearer picture of increasing disparities due to immediate consequences of the crisis within the richest areas in Italy.

If a promising recovery had been achieved in the years preceding EXPO 2015, the effect of urban policies to improve socio-economic conditions was highly concentrated in more attractive localities, where both private and local actors have intervened to improve conditions, especially in downtown Milan (Morandi, 2018). Some other areas have been considered as less attractive, and, despite improvements, investments have not made an equal improvement of living conditions. In fact, investments have different impacts across the province and this analysis aims at offering a deeper insight to assess the geographical dimension of deprivation to avoid persistence of critical situations.

To capture deprivation in this peculiar context, we follow a multidimensional approach with roots in previous experiences (Pampalon et al., 2009; Pampalon & Raymond, 2000) but integrate this approach with a deeper attention to the effects of space, particularly spatial heterogeneity. Moreover, considering their relevance in a policy perspective (in this regard, see, among others, Balducci, 2003; Bricocoli & Cucca, 2016), two additional variables are included in this study, the percentage of people living in a rented house and the share of foreigners.

In this paper deprivation is studied with reference to a refined spatial scale, using localities in the province of Milan. In this case, a composite indicator is calculated to stress socio-economic differentials in a context of spatial disparities between highly developed part of the province and the rural and former industrial area in the region. Focusing on socio-economic variables at a refined spatial scale improves the understanding of dynamics that could be masked when considering data at a more aggregated geographical level. Furthermore, understanding the spatial structure of deprivation at a very low scale helps policy-makers in the development of a wide set of policies (Havard et al., 2008).

A comparison of the economic performance of Milan with respect to other provinces in the region is offered in the Appendix.

3 | METHODOLOGICAL FRAMEWORK

3.1 | Bayesian interpolation method for data disaggregation

Accurate data at local level are fundamental for a broad range of socio-economic analyses. However, socio-economic information is often collected at a relatively aggregated spatial level. The process by which information at a coarse spatial scale is translated to finer scales, maintaining the consistency with the original dataset, is known as spatial disaggregation. Different areal interpolation techniques can be used in this context to transform data from a set of source zones to a set of target zones (Goodchild, Anselin, & Deichmann, 1993; Goodchild & Lam, 1980).

A few areal interpolation techniques consider the special features of spatial data. Specifically, spatial dependence, which refers to value similarity in space (Anselin, 1988) could provide useful information in the spatial disaggregation procedure. Benedetti and Palma (1994) introduced a Bayesian solution to the areal interpolation problem which exploits this general property of spatial data. The method, which is known as BIM, is described below. For recently proposed areal interpolation methods that consider spatial nature of data see Gotway and Young (2007) and Murakami and Tsutsumi (2011).

In BIM, the spatial stochastic process generating the data related to the target zones (i.e., the areal units corresponding to the finer spatial scale) is referred to as the original process. The spatial stochastic process generating the data for the source zones (i.e., the areal units corresponding to the aggregated spatial level) is referred to as the aggregated process. Assuming that data are available only at the aggregated spatial level, the objective becomes to restore the realizations of the original process given the realization of the aggregated one.

The assumption upon which the BIM is based concerns the joint probability distribution of the original process, which is assumed to be a Gaussian distribution. According to this assumption, a CAR specification (Besag, 1974) can be assumed for the original process. This specification introduces the spatial dependence effect in the covariance structure of the process as a function of a scalar parameter of spatial autocorrelation and of a spatial weight matrix, which summarizes the proximity between any pairs of spatial units. Following a Bayesian approach, the prior information on the distribution of the original process is combined with the data available at the aggregated spatial level in order to derive the posterior probability distribution of the original process. Benedetti and Palma (1994) derived the parameters of this posterior distribution, that correspond to the BIM estimates. Thus, any inference on the original process can be based upon this posterior distribution.

In order to formalize the described methodology, consider n areal units which form a partition $\boldsymbol{\Omega}$ over a geographical domain. Denote by $\mathbf{z} = (z_1, z_2, \ldots, z_n)^t$ the data related to a variable of interest Z observed on the n areal units. The vector $\mathbf{z}$ can be interpreted as a realization of the original process expressed by the random vector $\mathbf{Z} = (Z_1,$

$Z_2, \ldots, Z_n)^t$. By grouping the n units into larger areas we obtain a set of $m < n$ areal units which define a new partition Ω^* over the same geographical domain. The data observed for this new partition can be denoted by $\mathbf{z}^* = \left(z_1^*, z_2^*, \ldots, z_m^*\right)^t$, and the underlying spatial stochastic process, that is expressed by the random vector $\mathbf{Z}^* = \left(Z_1^*, Z_2^*, \ldots, Z_m^*\right)^t$, represents the aggregated process.

Assume that data are only available for the partition Ω^*, while we are interested in the spatial scale corresponding to Ω. The issue becomes to restore the realizations of the original process given the realization $\mathbf{z}^*$ of the aggregated one. The solution proposed by Benedetti and Palma (1994) consists in identifying the posterior probability distribution of $\mathbf{Z} \mid \mathbf{Z}^*$. According to the Bayes' rule this posterior probability distribution can be derived as follows:

$$P(\mathbf{Z}|\mathbf{Z}^*) \propto P(\mathbf{Z})P(\mathbf{Z}^*|\mathbf{Z}), \tag{1}$$

where $P(\mathbf{Z})$ is the prior probability distribution of the random vector $\mathbf{Z}$, and $P(\mathbf{Z}^* \mid \mathbf{Z})$ is its likelihood function.

Assuming a CAR specification, the random vector $\mathbf{Z}$ has a multivariate normal distribution, with the following parameters:

$$\mathbf{Z} \sim MVN\left(\boldsymbol{\mu}, (\mathbf{I}-\rho\mathbf{C})^{-1}\sigma^2\right), \tag{2}$$

where $\boldsymbol{\mu} = (\mu_1, \mu_2, \ldots, \mu_n)^t$ is the mean vector, and the specification of the variance–covariance matrix is based upon the scalar parameter σ^2, and the matrix $(\mathbf{I} - \rho\mathbf{C})$, that is a $n \times n$ non-singular matrix. The matrix $\mathbf{I}$ is specified as an n – dimensional identity matrix, ρ is a scalar parameter of spatial autocorrelation, and $\mathbf{C}$ is a $n \times n$ proximity matrix with elements $c_{ij} = 1$ if the units i and j can be considered as neighbours according to any proximity criteria, $c_{ij} = 0$ otherwise, and $c_{ii} = 0$.

The distribution in (2) is assumed for the original process and a correspondence between the original process and the aggregated one can be established by introducing a linear transformation operator $\mathbf{G}$ such that $\mathbf{Z}^* = \mathbf{GZ}$. The operator $\mathbf{G}$ is constructed as a $m \times n$ matrix whose elements can be specified according to any averaging or sum operations. The distribution of the random vector $\mathbf{Z}^*$ can be thus derived by the distribution of $\mathbf{Z}$ as follows (Anderson, 1958):

$$\mathbf{Z}^* \mid \mathbf{Z} \sim MVN\left(\mathbf{G}\mu, \mathbf{G}\boldsymbol{\Sigma}_{\mathbf{Z}}\mathbf{G}^t\right). \tag{3}$$

Since a normal prior distribution for $\mathbf{Z}$ is known by assumption 2, and, for the result in 3 $\mathbf{Z}^* \mid \mathbf{Z}$ is distributed according to a multivariate normal distribution, the posterior distribution of $\mathbf{Z} \mid \mathbf{Z}^*$ derived as in (1) is again multivariate normal. Under the additional hypothesis of known covariance matrix of the original process, we obtain:

$$\mathbf{Z} \mid \mathbf{Z}^* \sim MVN\left(\hat{\mathbf{Z}}, \mathbf{V}_{\hat{\mathbf{Z}}}\right), \tag{4}$$

where $\hat{\mathbf{Z}}$ and $\mathbf{V}_{\hat{\mathbf{Z}}}$ are the BIM estimates defined as follows:

$$\mathbf{V}_{\hat{\mathbf{Z}}} = \left[\mathbf{G}^t\left(\mathbf{G}\frac{(\mathbf{I}-\rho\mathbf{C})}{\sigma^2}\mathbf{G}^t\right)^{-1}\mathbf{G} + \frac{(\mathbf{I}-\rho\mathbf{C})}{\sigma^2}\right]^{-1}, \tag{5}$$

$$\hat{\mathbf{Z}} = \mathbf{V}_{\hat{\mathbf{Z}}}\left[\frac{(\mathbf{I}-\rho\mathbf{C})}{\sigma^2}\boldsymbol{\mu} + \mathbf{G}^t\left(\mathbf{G}\frac{(\mathbf{I}-\rho\mathbf{C})}{\sigma^2}\mathbf{G}^t\right)^{-1}\mathbf{Z}^*\right]. \tag{6}$$

The solutions in (5) and (6) can be conditioned to the linear constrain $\mathbf{G}\hat{\mathbf{Z}} = \mathbf{Z}^*$ obtaining the constrained BIM estimates, specified as follows:

$$\hat{\hat{\mathbf{Z}}} = \hat{\mathbf{Z}} + \mathbf{V}_{\hat{\mathbf{Z}}}\mathbf{G}^t\left[\mathbf{G}\mathbf{V}_{\hat{\mathbf{Z}}}\mathbf{G}^t\right]^{-1}(\mathbf{Z}^* - \mathbf{G}\mathbf{Z}), \tag{7}$$

$$\mathbf{V}_{\hat{\hat{\mathbf{Z}}}} = \mathbf{V}_{\hat{\mathbf{Z}}} - \mathbf{V}_{\hat{\mathbf{Z}}}\mathbf{G}^t\left[\mathbf{G}\mathbf{V}_{\hat{\mathbf{Z}}}\mathbf{G}^t\right]^{-1}\mathbf{G}\mathbf{V}_{\hat{\mathbf{Z}}}. \tag{8}$$

The imposed constraint allows to preserve the pycnophylactic property which consists in finding an estimate of $\mathbf{Z}$ such that, by applying the transformation operator $\mathbf{G}$, the observed data are again obtained.

Any inference on the original process can be based on the posterior distributions with parameters defined as in Equations (7) and (8). Point estimates of $\mathbf{Z}$ can be obtained by using $\hat{\hat{\mathbf{Z}}}$. Confidence intervals and hypothesis tests can be performed in the standard way using multivariate normal distributions.

3.2 | Geographically weighted principal component analysis

Deriving a composite indicator means synthetizing different variables. This result may be pursued by adopting a wide range of techniques. Intuitively, a common way to synthetize reality is simply summing values of standardized variables for each unit to define scores. However, researchers may prefer different dimensions not to compensate and to adopt non-compensatory techniques. The geometric mean and the Mazziotta-Pareto approach (Mazziotta & Pareto, 2019) are two examples on how to obtain not compensated indicators. Furthermore, composite indicators are often conceived as weighted means so that weights determine different relevance to the variables included. Derivation of weights may be pursued following either normative approaches (i.e., expert consensus), assuming hybrid weights based on survey, and considering weights based on the use of statistical tools (see Decancq & Lugo, 2013 for an extensive overview).

Exploiting matrix eigenstructure properties, principal components are orthogonal, so that PCA is a rotation to transform the original data into a restricted set of independent components, which is very useful to manage high dimensional datasets.

Given a $n \times q$ matrix of scaled data $\mathbf{X}$, its covariance matrix can be expressed as:

$$\boldsymbol{\Sigma} = \frac{1}{n}\mathbf{X}^t\mathbf{X}. \tag{9}$$

The observed variables are than manipulated in order to get new system of coordinates $\mathbf{Y}$ (the scores) as:

$$\mathbf{Y} = \mathbf{X}\mathbf{A}, \tag{10}$$

where $\mathbf{A}$ is the projection matrix given by the decomposition of the following variance–covariance matrix:

$$\boldsymbol{\Sigma} = \mathbf{A}\boldsymbol{\Lambda}\mathbf{A}^t. \tag{11}$$

Here, $\mathbf{A}$ is the matrix of eigenvectors of $\boldsymbol{\Sigma}$ and $\boldsymbol{\Lambda}$ its corresponding diagonal matrix of eigenvalues.

PCA relies on the assumption that variance–covariance matrix has the same structure in all the localities included into the sample. This means ignoring possible presence of spatial heterogeneity, that assumes the form of instability across space of behaviours and relations.

Capturing the consequences of spatial heterogeneity is crucial to relax the hypothesis of an invariant structure of the variance and allows us to model the difference of variables over space. Thus, a more appropriate way to derive a composite indicator may be represented by GWPCA (Harris et al., 2011). In this technique the variance–covariance matrix is estimated at each locality in order to pursue data decomposition accounting for spatial heterogeneity.

Consider a vector $\mathbf{\mu}$ of q means and let be $\mathbf{\Sigma}$ the variance–covariance matrix for the variables $\mathbf{X}$. Hence, let (u_i, v_i) be the coordinates for each spatial unit $i = 1,2,\ldots,n$, one may relax the hypothesis of homogeneity of the covariance matrix using GWPCA approach. This assumes that both the mean vector and covariance matrix are expressed in function of each pair of coordinates as $\mathbf{\mu}(u_i, v_i)$ and $\mathbf{\Sigma}(u_i, v_i)$, respectively. Consequently, Harris et al. (2015) define for each unit i a geographically weighted variance–covariance matrix as:

$$\mathbf{\Sigma}(u_i, v_i) = \mathbf{X}^t\mathbf{W}(u_i, v_i)\mathbf{X}, \tag{12}$$

where $\mathbf{W}(u_i, v_i)$ is a diagonal matrix including geographical weights generated by the use of a kernel function. In our application, we adopt a bi-square kernel function:

$$w_{ij} = \exp\left(-\frac{1}{2}\left(\frac{d_{ij}}{\gamma}\right)^2\right), \tag{13}$$

where w_{ij} are the entries of $\mathbf{W}(u_i, v_i)$, d_{ij} is the geographical distance between the centroids of the localities i and j, γ is the level of the bandwidth.

As it can be noted, GWPCA weights depend on the choice of the kernel function and on the bandwidth. If the type of kernel may be less influencing the results (Fotheringham et al., 2002), the bandwidth represents a crucial feature and for this reason must be addressed carefully. In this study a cross-validation method for the bandwidth selection (Harris et al., 2015) is adopted.

Based on (12) we have:

$$\mathbf{\Sigma} = \mathbf{A}(u_i, v_i)\mathbf{\Lambda}(u_i, v_i)\mathbf{A}(u_i, v_i)^t, \tag{14}$$

where $\mathbf{A}(u_i, v_i)$ is the matrix of local eigenvectors, and $\Lambda(u_i, v_i)$ is the diagonal matrix including the local eigenvalues. Moreover, in GWPCA we may also select a robust version to reduce the effects from spatial outliers which estimate local variance–covariance matrices based on robust minimum covariance determinant (Harris et al., 2015).

Finally, we can define the composite indicator y_{is} for the principal component s, with $s = 1,\ldots,p$ at each (u_i, v_i) as (Kallio, Guillaume, Kummu, & Virrantaus, 2018):

$$y_{is}(u_i, v_i) = x_i^t A_{is}(u_i, v_i), \tag{15}$$

where y_{is} is the value of the composite indicator for the selected locality.

A special advantage of GWPCA is the possibility of considering the variation in the structure of the variance covariance matrix in order to obtain a better fit and a better specification of the model. In this way, indicators can be better defined to its purposes and the policy-maker could get further information about the structure of the phenomenon in each locality. This could help in the aim of building more refined indicators of deprivation and track more precisely inequalities across different locations.

4 | RESULTS

To assess the relative level of deprivation for the 621 localities of the Milan province we take into account a set of variables widely adopted in the deprivation literature (see, among others, Havard et al., 2008). Following the rationale of Pampalon and Raymond (2000), we consider a set of socio-economic variables, which includes the share of people living alone (Mono), share of people divorced, separated, or widowed (SDV), and the percentage of single parents over the population (Single Parent). Variables attaining marital status are included in the original form of this indicator due to their relation to a large number of health and welfare issues (Pampalon et al., 2009).

Besides, the level of unemployment (Unemp) returns us information about the labour market that is linked to deprivation (Muffels & Fouarge, 2004). In fact, even if labour local markets represent the natural scale for unemployment, this is identified in the paper at the localities level to consider lower spatial scale.

The share of people without high school diploma (School) and the average income per worker (Income) are both added to the composite indicator following in the original definition by (Pampalon et al., 2009). Those variables tend to be generally related, as educational attainment tends to boost income. However, considering both indicators may help policy decisions in situations where educational attainment may be only partially suggestive of the actual income distribution, especially due to unemployment in young educated segments. Finally, two additional variables are considered, namely the percentage of families living in a rented house (House) and the percentage of foreigners living in the localities (Foreign). Those two variables complete the set of single indicators to take into account relevant policy issues as social mix and social housing (Bricocoli & Cucca, 2016).

Data comes from the ISTAT Census Database 2011[1] with the exception of the average income per worker. Data on average personal income are available for the 134 municipalities in the province of Milan, from the dataset of the Italian *Agenzia delle Entrate* and the Ministry of Economics and Finance.[2] This variable is then disaggregated at locality level, and is then considered, together with the above-mentioned economic and social variables, in the definition of a composite indicator of deprivation at locality level. As the level of average personal income is considered reducing the level of deprivation, the locality income is changed in sign before the composite indicator is calculated. In this fashion, all variables are expected to be positively correlated to multivariate deprivation.

Data on income per worker at locality level are derived from data available at the municipality level by using the BIM. The correspondence between income per worker at the aggregated and the disaggregated levels is defined by specifying the aggregation matrix $\mathbf{G}$. The matrix $\mathbf{G}$ is specified so that when it is applied to data on income per worker estimated at the municipality level, data on income per worker at municipality level are again obtained. Thus, $\mathbf{G}$ is defined as a $m \times n$ matrix, with m the number of municipalities (i.e., $m = 134$), and n the number of localities (i.e., $n = 621$),with elements $g_{ij} = b_{ij}\frac{emp_i}{emp_j}$, where the element b_{ij} is such that $b_{ij} = 1$ if the locality j belongs to the municipality i, and $b_{ij} = 0$ otherwise, and emp_i and emp_j denote the working population in municipality i and in locality j, respectively.

The calculation of the BIM estimates requires specifying the prior mean vector $\boldsymbol{\mu}$ and the variance covariance matrix $(\mathbf{I} - \rho\mathbf{C})\sigma^2$. In presence of covariates at municipality level, the prior mean vector can be expresses as $\boldsymbol{\mu} = \mathbf{X}\hat{\boldsymbol{\beta}}$, where $\mathbf{X}$ is a $m \times l$ matrix that includes $l - 1$ explanatory variables, and a column of ones, and $\hat{\boldsymbol{\beta}}$ is a $l \times 1$ vector of estimated regression parameters including an intercept term. As explanatory variable used to estimate the prior mean vector $\boldsymbol{\mu}$, we consider the working population at municipality level. The regression residual's variance is used to estimate the scalar parameter σ^2. The definition of the variance–covariance structure of the original process also requires specifying the scalar parameter ρ, as well as the proximity matrix $\mathbf{C}$. The choice of the spatial autocorrelation parameter is based following previous successful application (Panzera & Postiglione, 2014). Therefore, a level of $\rho = 0.30$ is considered. However, different values of ρ have been tested. Spatial patterns of the average income tend not to change dramatically by modifying the values of spatial autocorrelation between the range of 0.1 and 0.5. The proximity matrix is specified according to the k near neighbours' criterion, with $k = 10$.

After defining the above-mentioned parameters, the BIM estimates are calculated in their constrained version (see Equations (7) and (8)). The values in the vector $\hat{\mathbf{Z}}$, obtained as in Equation (7), are used as point estimates of the

[1]https://www4.istat.it/en/population-and-housing-census/population-and-housing-2011
[2]https://www1.finanze.gov.it/finanze3/analisi_stat/index.php?tree=2012

average income per worker at locality level. Results are shown in Figure 1. Darker colours refer to higher values of the average income per worker, light colours indicate lower level of income per worker.

The methodology returns some interesting insights in the spatial distribution of average income at low spatial scale in the metropolitan area of Milan. The highest values are situated in the core area of Milan at the centre of the map, where the main tertiary district is situated. However, some neighbourhood situated in the periphery of Milan tend to be poorer, especially in the Southern areas where large part of the neighbourhoods is less inhabited. Conversely in the North, even localities not contiguous to downtown Milan, some areas tend to show higher average income, being integrated in terms of daily work activities in the tertiary district of Milan (Secchi, Vantini, & Vitelli, 2015).

The use of BIM allows the visualization of spatial differences in terms of income at a very local level and the analysis of the spatial inequalities itself represents an interesting tool for the policy-makers (see, for example, Panzera & Postiglione, 2020). However, this study is not limited to the analysis of spatial inequalities in terms of income, as the income per worker is included in a broader definition of socio-economic deprivation to obtain both a spatial distribution and a rank of more deprived areas in the province.

In Figure 2, deprivation levels are obtained as scores from the standard PCA of standardized variables, so that higher levels of the indicator express higher deprivation. Accordingly, in Figure 2, darker areas point localities that are characterized by higher deprivation. As can be observed from the map, the area of downtown Milan is individuated as a low deprived locality, while areas at the West, and the Southern localities are more deprived. By focusing on the localities surrounding the core area of Milan, we observe that those located at the South are affected by higher deprivation, while at the Eastern border of the municipality of Milan deprivation is lower.

In Figure 2, the indicator (i.e., the scores) is obtained considering the first components loadings as global weights. In Table 1 the loadings of the first two components are presented.

Considering the first components, Table 1 shows how all the variables have a positive correlation with the level of deprivation, including the level of income as it has been previously changed in sign. School attainment is the most important variable for the composite indicator, as lack of high school diploma relates to higher deprivation. The loadings of the first component point also the high relevance of some social variables as the Single Parent variable and

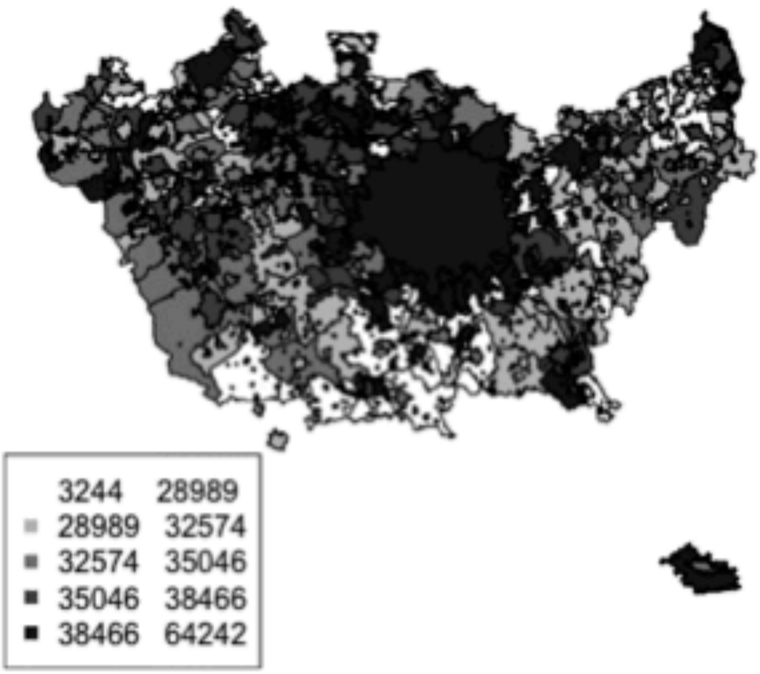


FIGURE 1 Level of income per worker for 621 localities situated in the province of Milan obtained by BIM

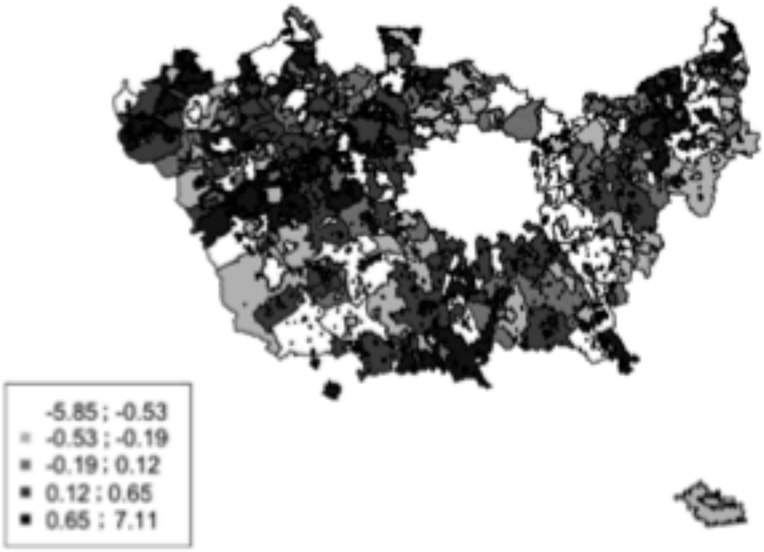


FIGURE 2 Level of deprivation for 621 localities situated in the province of Milan. Composite indicator obtained by PCA

TABLE 1 Loadings of first two components obtained by standard PCA

	PC 1	PC 2
Income	0.092	0.063
School	0.492	−0.145
Unemp	0.346	−0.288
Mono	0.417	0.492
Single Parent	0.393	−0.412
SDV	0.287	0.665
Foreign	0.281	−0.187
House	0.375	−0.433
Proportion of Variance	0.250	0.180

Mono (i.e., people living alone). Importantly, also the share of people living in a rented house emerges as influencing the composite indicator. The second component is characterized by positive correlation to social variables, particularly people living alone or being divorced, even if in aproperty owned house. Hence, it attains more loneliness.

The level of representativeness for the first component indicator (i.e., the percentage of the accounted variance in Table 1) is quite low. A scarce level of fit can be considered as one of the consequences that standard PCA is a global statistic, and it does not consider problems related to the heterogeneity affecting the metropolitan area of Milan. Hence, in the current study, the use of a spatial technique in order to purse aggregation would help to increase representativeness of the composite measures.

Further, to visualize the extent of spatial heterogeneity we also consider local indicators of spatial association (LISA, Anselin, 2010) to indicate likely presence of local instabilities in the PCA composite indicator. Figure 3 indicates LISA clusters obtained from calculation of local Moran's I on PCA first component composite indicator. Results are obtained using a k-nearest neighbours contiguity matrix, setting $k = 10$. The map suggests the presence of significant clusters (especially in high-high values) as well as local instabilities in the Southern localities.

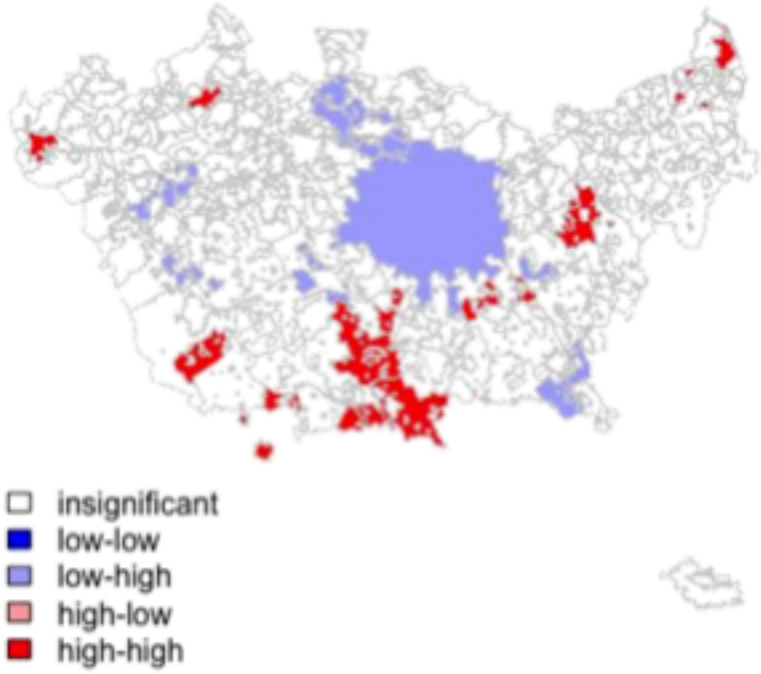


FIGURE 3 LISA cluster map for first component PCA composite indicator in the province of Milan. Results obtained using a k = 10 nearest neighbour contiguity matrix

To consider spatial heterogeneity in the definition of composite measures of deprivation, we use a GWPCA approach, and, to reduce the effect of potential spatial outliers at a low scale, we prefer the robust version of GWPCA. The use of GWPCA imposes some previous choices to the researcher, especially in terms of the adopted kernel and bandwidth. In the present study, an adaptive kernel is preferred to a fixed one because of the irregular shape and size of the spatial units (Sarra & Nissi, 2019). In the application a bi-square kernel function is selected.

However, in all GW approaches results are particularly sensitive to the choice of the bandwidth. For this reason, the level of the bandwidth has been carefully selected by a cross-validation procedure carried out using the GWmodel package available in the R environment (Gollini, Lu, Charlton, Brunsdon, & Harris, 2015). For a bi-square adaptive kernel the optimal bandwidth selected according to the cross-validation procedure is 84.

A first attempt to summarize the presence of spatial heterogeneity in the composite indicator can be achieved by mapping the *winning variables* that represent the variables corresponding to the loading which has higher magnitude in absolute value (Harris et al., 2011). Figure 4 identifies, for each locality, the *winning variables* for the first local components.

The map stresses differences in the structure of local variance–covariance matrix. Figure 4 points to the presence of substantial spatial heterogeneity in terms of composition of deprivation at local level. Hence, in our spatial composite indicator defined in function of the first local component, loadings should not be considered constant across the area under study.

By looking at the map of the *winning variables*, we observe how lack of school attainment is a key issue in the large part of the metropolitan area. This evidence is in line with the contemporary economic structure of the city of Milan, mainly based on advance services and financial sectors where innovation is fundamental (Simmie, Sennett, Wood, & Hart, 2002).

Income also plays a relevant role in terms of deprivation. However, its role is limited to a few localities compared to school attainment. Those areas are situated especially at the Southern border of the metropolitan area. The value for other social variables is higher for few spatial units located in periphery of the metropolitan area, at the South and the West. Among the social variables considered, only Mono and Single Parent are identified as *winning variables* for a small number of localities.

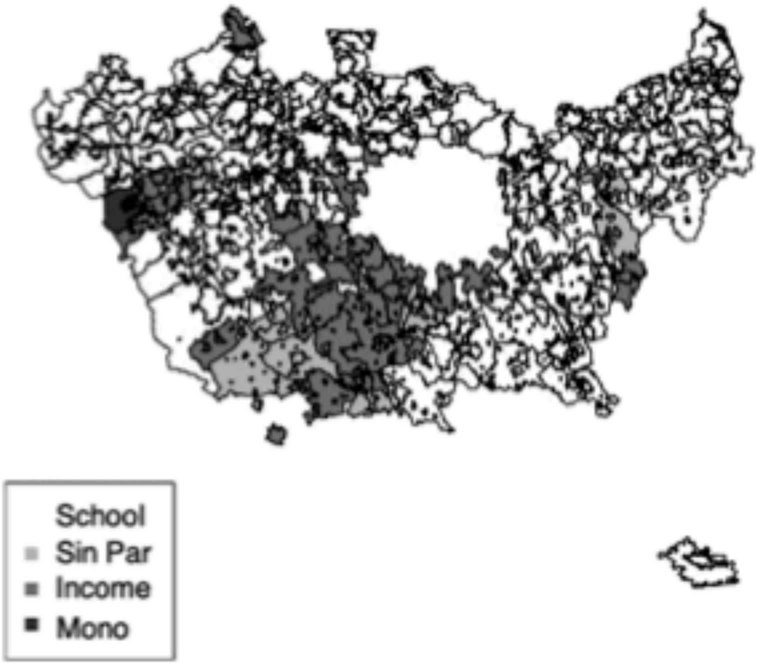


FIGURE 4 Map of the winning variables for the first local component obtained by GWPCA

As previously mentioned, in this study two other variables, such as the percentage of people living in a rent house and the share of foreigners, are considered in their effect on multivariate deprivation compared to Pampalon and Raymond (2000). The choice is also supported by the magnitude of their respective loadings in the global indicator (see, for example, the first column of Table 1). For this reason, those variables are further analysed by GWPCA, in order to explore their effect on local deprivation. The relation between foreign inhabitants and deprivation is reported in Figure 5.

Figure 5 indicates how the share of foreigners relates to deprivation. Therefore, darker areas show localities where the presence of foreigners implies a higher level of deprivation. For the year 2011, the effect appears as stronger at the Southern and Western periphery.

As for the foreigners, the relation between multivariate deprivation and the share of rented houses is summarized in Figure 6.

The evidence in Figure 6 poses the problem of housing as particularly relevant in a large part of the province. Even if this issue is influences more deprivation in the peripheral areas and also in the core area of Milan, the effect of housing is relevant to determine local deprivation. In fact, downtown Milan is situated in the third quintile of Figure 6.

After investigating local peculiarities by exploring the structure of local variance–covariance, GWPCA local loadings can be adopted as weights to derive a spatial composite indicator of deprivation according to Equation 15. In fact, differences in the structure of the local loadings lead to differences in the weights used to synthetize local deprivation and summarized in Table 2.

In Figure 7, the spatial indicator of deprivation, defined using the loadings of the first local principal component, is reported for localities in the province of Milan. Differences can be observed by this map when compared to Figure 2.

The urban geography of local deprivation differs from the one obtained through the global indicator. For example, areas of higher deprivation are especially in the Southern and Eastern areas for the global indicator, while the spatial indicator points to pockets of deprivation throughout the whole periphery. This feature is helpful in a policy-making perspective, as it allows decision-makers and stakeholders to better exploit the low scale of the data.

FIGURE 5 Level of the loadings obtained from GWPCA for the variable foreign inhabitants

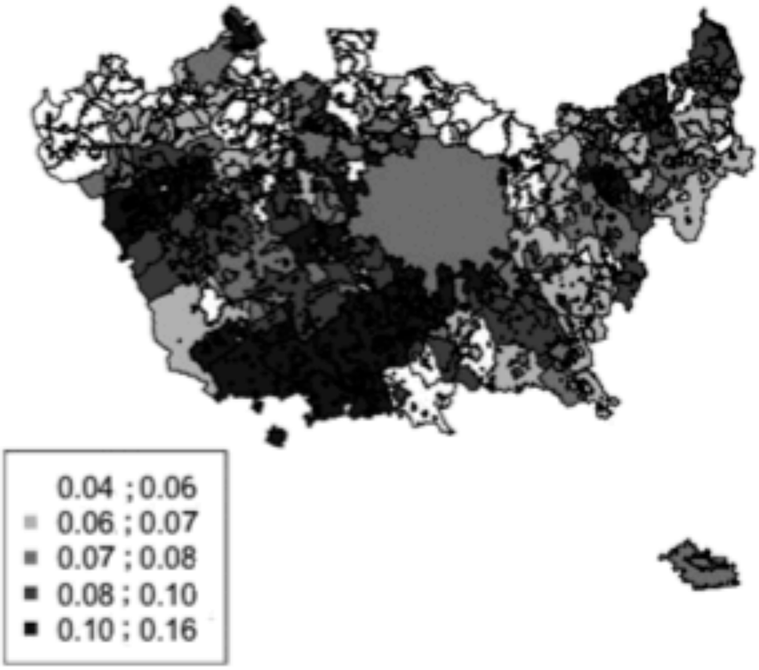
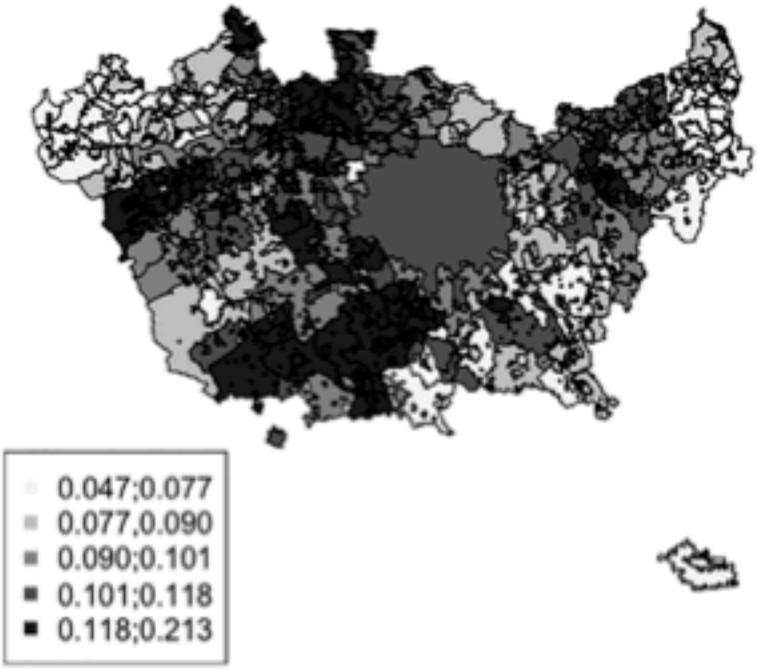


FIGURE 6 Level of the loadings obtained from GWPCA for the variable house property



The GWPCA approach permits the structure of deprivation to change across the area under study and to model the presence of spatial heterogeneity. In fact, socio-economic deprivation and disparities may be determined by multiple factors which relevance is expected to change depending on the specific context (Barbieri, Benassi, Mantuano, & Prisco, 2019). In essence, this feature brings higher precision in the individuation of more deprived areas and policy

TABLE 2 Minimum, maximum, 1st and 3rd quartiles, median and mean of eigenvectors calculated for different variables by GWPCA

	Min	1st quart	Median	Mean	3rd quart	Max
Income	0.099	0.422	0.464	0.454	0.526	0.783
School	0.177	0.598	0.640	0.574	0.659	0.799
Unemp	0.072	0.108	0.119	0.126	0.138	0.234
Mono	0.214	0.257	0.271	0.297	0.330	0.511
Single Parent	0.219	0.482	0.512	0.502	0.539	0.748
SDV	0.131	0.157	0.169	0.181	0.193	0.304
Foreign	0.044	0.064	0.074	0.803	0.091	0.168
House	0.047	0.080	0.093	0.097	0.109	0.198

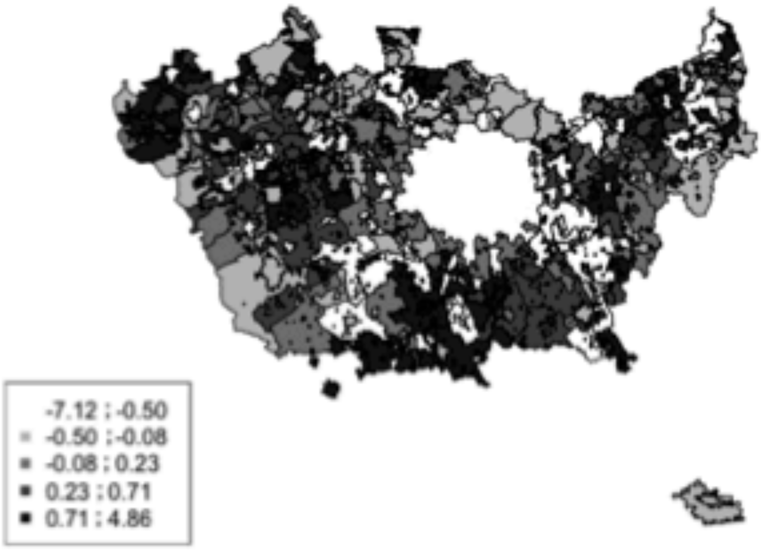


FIGURE 7 Level of deprivation for 621 localities situated in the province of Milan. Composite indicator obtained by GWPCA

decisions. This is also evidenced by representativeness for the first principal component indicator around 0.82, measured as an average of the proportion of accounted variance for the local PCAs.

5 | DISCUSSION

The attention given to the spatial dimension of inequalities has spread in the European debate (Capello & Perucca, 2019; Panzera & Postiglione, 2020). In the context of the metropolitan area of Milan, this issue is considered among the priorities as highlighted by a series of programmes and interventions in the province to tackle poverty and deprivation. Among these, the recent food policy of the metropolitan area of Milan has been introduced to address lack of basic needs. Additionally, as the urban form of Milan is increasingly sprawling (Camagni, Gibelli, & Rigamonti, 2002), those policies are more developed in the direction of integrating the whole metropolitan area. Indeed, those aspects call for a deeper consideration of space in policy direction.

Interestingly, spatial techniques help us to explore different dimensions of deprivations. The use of areal interpolation is relevantly increasing the possibilities to explore different dimensions, including data as income that are generally not available in Italy at this spatial scale. In this sense, the BIM can return dimensions that would be lost in the definition of a composite indicator at local level, and it allows us to better define deprivation for the metropolitan area of Milan.

The use of GWPCA completes the consideration of the spatial issues by modelling spatial heterogeneity (Harris et al., 2011). The map returned by GWPCA indicates the presence of major deprivation especially in the peripheral areas of Milan and in some of the former industrial areas of the province. Thus, this stresses the point of considering the socio-economic challenges that involve former industrial areas. In fact, those areas have been called to develop opportunities in a dynamic context, by managing deindustrialization over the last years by urban policies in order to generate economic growth (see, for the case of Milan, Savini, 2014).

The ability to model instabilities present in standard PCA indicators allows GWPCA to highlight relevant pockets and critical situations of deprivation. In this sense, the standard PCA major drawback is to consider drivers of deprivation equivalently all over the province which leads to the impossibility of individuating critical differences. Conversely, the great advantage that we have in GWPCA is the chance to indicate and develop localized policies to cope with various dimensions of deprivation. In our application, for example, this results in a series of policy implications for policy-makers at locality level as the need for improving accessibility to education in the surroundings of Milan, as also stressed by Cordini, Parma, and Ranci (2019).

The insights offered by GWPCA in the study of areal deprivation also shed more light on useful features in the developing of urban and regional policies. Social mix policies have been debated in Europe for long. In some contexts, local authorities have set precise policies to determine the quota of foreign residents (see, for Germany, Münch, 2009). However, there is no clear evidence that shows that neighbourhoods or communities benefit from determined social mix policies (Van Kempen & Bolt, 2009). In this sense, a deeper knowledge of the geography of deprivation could enhance the regional policies to set *ad hoc* interventions that exploit the existing relations between deprivation and social mix at a very local level.

Similar conclusions can be drawn for the case of house property. In fact, Milan has been affected by a scarcity of affordable housing during the last years (Mugnano & Palvarini, 2013). GWPCA helps in visualizing areas where this problem is more relevant. In this direction, the tools discussed in this paper can be widely adopted as a first step in the analysis of social housing policies. Furthermore, the problems related to house scarcity assume more importance from the perspective of local governments as this may affect the attractiveness in the case of a large metropolitan area (Rodriguez-Pose & Storper, 2020).

6 | CONCLUSIONS

In this paper, we measure multivariate deprivation by using both the BIM disaggregation technique and GWPCA. The combination of disaggregation techniques and local principal component analysis enable us to exploit properties of spatially distributed data, and to derive a very localized measure for deprivation below the municipality level.

The results show how spatial tools are able to better summarize multivariate reality. In fact, in our application GWPCA returns a detailed picture that should be considered both for really localized policies and integrated interventions in a city region like Milan. Furthermore, the individuation of criticisms in former industrialized areas poses attention on deprivation also in a developed city. Spatial characteristics appear as extremely important for the case of deprivation.

Generally, the use of PCA could be replaced in order to also extend the analysis to non-compensatory methodologies (Mazziotta & Pareto, 2019). However, more research would be required in this sense to extend non-compensatory approaches to take into account the presence of local spatial effects for considering the presence of spatial instabilities.

Promising results for the current application also stress the need for future research in local deprivation. In fact, this study focused on the province of Milan, but the need for local multivariate composite indicators could be extended to the whole Country. More and more policy-makers require for statistics that take into account local peculiarities, so that a future research line could be the analysis of deprivation for the country by also adopting a refined scale, at the municipality level.

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APPENDIX A.

In this Appendix the province of Milan is localized in the regional context (Figure A1). Figure A2 displays the level of GDP *per capita* for the Province of Milan and the other Provinces in the Lombardy region.

FIGURE A1 Map shows Lombardy region. The Province of Milan is highlighted in dark grey

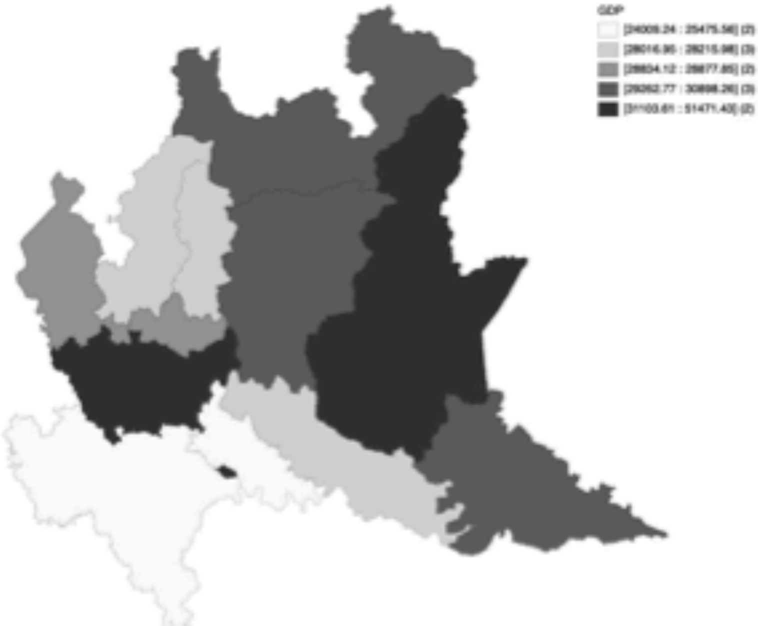

FIGURE A2 GDP *per capita* at Province level in the Lombardy Region 2011

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Resumen. Los indicadores compuestos se suelen utilizar para evaluar la estructura de las carencias urbanas dirigidas a promover el desarrollo sostenible. Sin embargo, la refinada escala espacial del análisis plantea problemas relacionados con la disponibilidad de datos. En este artículo se define un índice espacial de carencia en la provincia de Milán, mediante el uso de datos del censo y la interpolación de áreas. Se aplicaron métodos de desagregación para obtener variables a un nivel espacial más bajo, y se aplicó un análisis de componentes principales ponderado geográficamente para medir la carencia socioeconómica a nivel local. Se investigó la estructura espacial de los componentes de la carencia y se discuten algunas consecuencias políticas derivadas de la aplicación de un enfoque espacial.

抄録: 複合的指標は、持続可能な開発を促進するために都市部の剥奪の構造を評価するために用いられることが多い。しかしながら、精密化された分析の空間スケールは、データ利用可能性に関連する問題を引き起こす。本稿では、国勢調査データと地域内挿の両方を用いて、ミラノ州における空間的剥奪指数を定義した。より低い空間レベルでの変数を得るために分解手法を採用し、地域レベルでの社会経済的剥奪を測定するために地理的に重み付けした主成分分析法を採用した。剥奪の構成要素をその空間構造の中で検討し、空間的アプローチの適用から導出された政策的含意を考察する。