Social Indicators Research (2021) 153:651–674
https://doi.org/10.1007/s11205-020-02510-9

ORIGINAL RESEARCH

Estimating Household Consumption Expenditure at Local Level In Italy: The Potential of the Cokriging Spatial Predictor

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Accepted: 3 October 2020 / Published online: 14 October 2020

Abstract

Measuring well-being and living conditions at local level is essential for policy makers who wish to study inequalities and formulate targeted and effective economic and social intervention policies. In Italy, the available official statistics in this field are usually provided at regional level and several studies have been carried out in order to obtain the estimates of those measures at disaggregated level, which is done in order to obtain estimations at provincial level. However, due the heterogeneity of these phenomena within each province, it is important to possess data at micro-territorial level, that is at the municipality level, in order to study and monitor territorial development and inequalities in depth. This paper proposes an estimation of household consumption expenditure, one of the most important indicator of the economic material well-being of an area, for the 7893 Italian municipalities.To this end, the cokriging spatial interpolation technique was employed in order to explore its potentialities. This method is normally used in natural sciences to predict variables of interest at micro territorial level, using available sample data or population aggregates, analysing their spatial dependence and introducing information on auxiliary correlated variables available at micro level. In this study, the available information on household consumption expenditure at provincial level was combined with the data on taxable income at municipality level as auxiliary variable.The evaluation of model performance enabled us to confirm the validity of this approach to obtain a more detailed picture of the local systems for which intervention policies are important.

Keywords Economic-material well-being · Cokriging method · Consumption expenditure · Micro-territorial level

1 Introduction

Over the last few years, increasing attention has been paid towards analysing and monitoring individuals' material living conditions or economic well-being—which determines people's consumption possibilities and their command over resources (OECD 2013)—not

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only at national level but also at regional and micro-territorial levels. This is because the more detailed policy makers' level of knowledge of the area they are governing, the more solid the foundation for managing and planning socio-economic interventions (Biggeri et al. 2014). Moreover, using reliable well-being measures at micro territorial level would offer better opportunities for improving life today and opportunities tomorrow (OECD 2014). Alaimo and Maggino (2020) expressed similar considerations with reference to the measures adopted within the framework of Sustainable Development Goals (SDGs).

With specific reference to economic well-being, the availability of measures and indicators—referring to income, consumption and wealth as part of a conceptual framework (OECD 2013)—at micro territorial level can provide policy makers with a better understanding of citizens' needs and inequalities in order to draw up more effective and targeted policies (Steuer and Marks 2008; Brown et al. 2017; Cao et al. 2020a).

Among the possible measures to be used for these purposes, Consumption Expenditure (CE) has become more and more important as a suitable measure to be used by policy makers for assessing both household living standards and conditions (Attanasio and Pistaferri 2016; Cutillo and Scanu 2020), inequalities (Aguiar and Bils 2015) and, therefore, material well-being (Gillish et al. 2001). In fact, determining the consumption patterns of individuals and households is essential for monitoring and explaining socio-economic disparities as well as for describing changes in citizens' material needs, general welfare and poverty gaps (Meier and Sullivan 2003; Krueger and Perri 2006). For these reasons, there has recently been increasing interest in whether CE provides more appropriate measures of standards of living than income (Serafino and Tonkin 2017; Cao et al. 2020a) both for assessing individuals' economic well-being and for studying inequalities, since the relationships between consumption and subjective well-being are stronger than those observed between income and subjective well-being (Serafino and Tonkin 2017). From this perspective, in their essay Attanasio and Pistaferri (2016) stated that "a basic utility function of individuals typically refers to consumption and leisure" and that the "distinction between income and consumption could make a meaningful difference in thinking inequality". In fact, consumption can differ from income "if consumers borrow or save, or if they receive transfers from other family members or the government in response to income shocks" (Attanasio and Pistaferri 2016). On the other hand, other authors claim that distributional measures of well-being as joint functions of income and consumption are required (Cutillo and Scanu 2020).

Traditional sources of data for determining household and individual CEs are National *Household Budget Surveys* (HBS)[1] launched in most EU member States in the beginning of the 1960′s which are widely implemented today at global level. The main purpose of this type of survey is to estimate CE defined as *the activity in which persons, acting either individually or collectively, use goods and services to satisfy their needs and wants* (European Commission 2015). According to this definition, CE can be used to measure household and individual economic well-being in terms of access to goods and services at both micro and macro levels, in order to determine how and why individuals and society consume goods and services and how this affects society and human relationships (European Commission 2015).

Despite the shared aims of the HBS surveys, the common EU framework and their potentiality for supporting evidence-based policy activities, the standard sampling

[1] This general term also includes the Living Standards and Food Survey in the United Kingdom (former Family Expenditure Survey up to 2001) as well as the Consumer Expenditure Survey (CES) in the United States. Similarly in Italy, this specific survey, carried out by ISTAT, from 2014 is called Consumer Expenditure Survey.

schemes adopted for collecting data in these surveys are generally planned to produce reliable estimates of indicators and measures concerning household living conditions for large geographic domains, generally NUTS-1 and NUTS-2 levels corresponding to national and regional levels, according to the EU territorial nomenclature.

Focusing on the Italian context, ISTAT (the Italian National Statistical Institute) has carried out the HBS since 1968, which is based on a two-stage stratified sample of approximately 28,000 households representing the overall Italian households (ISTAT 2019). However, the regional domain (NUTS-2) is also the territorial level at which ISTAT provides estimates.

Therefore, it is impossible to obtain reliable data and accurate direct estimates from sample surveys for smaller areas. This lack of knowledge and the need of local-based estimates of well-being (economic) measures have become well acknowledged issues for researchers in recent years, who obtain reliable data at sub-national level, generally represented by NUTS-3 or LAU-1 levels, using specific methods and estimators. As regards the estimation of Household CE (HCE), Marchetti and Secondi (2017) applied SAE methods in order to obtain robust estimates at provincial level (LAU-1 level) in Italy for the year 2012.

This paper aims at estimating HCE for the Italian Municipalities (LAU-2 level). To this aim, we explore the potentialities of spatial predictors, and more specifically of the *co-kriging* (CK) interpolation technique (Cressie 1993; Maroufpoor et al. 2020). This method is generally used in natural sciences for estimating variables of interest at micro territorial level, using available sample data or on an aggregate of the population, analysing their spatial dependence and introducing auxiliary correlated variables available at micro level.

In this study, we used the information on HCE provided annually at provincial level by the G. Tagliacarne research institute included within the Italian National Statistical System (SISTAN)—in order to estimate HCE at municipal level. As auxiliary variable we referred to the taxable per capita income for each municipality (LAU-2 level) extracted from the open archive of the Italian Ministry of Finance (MEF). By explicitly taking into consideration the spatial dependence across administrative units, we therefore extended the approach of spatial interpolation methods used above all in natural environments for the spatial distribution of economic quantities and measures.

To the best of our knowledge, this is the first study that applies cokriging spatial predictors for predicting economic-related indicators for all the municipalities within a country and specifically to estimate material well-being measures at micro-territorial level. Our aim is to expand the science policy debate by introducing a procedure which could prove useful for obtaining HCE at municipal level within the realm of possibility.

The remainder of the paper is structured as follows. Section 2 provides a short review on the applied research and methods used for estimating material well-being indicators at local level in Italy. Section 3 presents the methodological approach adopted by describing the main principles of the CK estimator, the assumptions and the performance measures and tools used for evaluating our CK approach. Section 4 focuses on the available data used and the preliminary autocorrelation analyses. Section 5 describes the model specification used and the spatial obtained estimates are reported, analysed and discussed. Finally, Sect. 6 highlights the potential of the proposed approach and some concluding remarks and future research suggestions are made.

2 The Estimation of Local-Level Material Well-Being Indicators in Italy: A Short-Review

There has long been interest in the measurement and analysis of spendable and available economic resources for assessing individual material well-being. Historically, there have been two different approaches for measuring economic well-being: i) a macro-level approach based on national accounts and in particular on the accounting-based standards established by the System of National Accounts (SNA) and ii) a micro-level approach based on micro-economics and particularly on the study of wealth, inequality and its effects on different socio-economic groups within society (OECD 2013). Both economists and statisticians are aware of the limitations of using aggregate income measures as proxies of well-being since they only provide aggregate measures for the household sector as a whole. However, micro-data sets can be used to analyse not only entire aggregates, but also the distribution of income, consumption and wealth across the population, for various sub-groups at both territorial (spatial) and temporal levels.

Over the last few decades, there has been a growing interest in this topic and these measures were obtained at a more disaggregated territorial levels than at national and regional levels, which are generally represented at European level by LAU-1 (provincial level) LAU-2 (municipal level).

The estimations of Gross Domestic Product (GDP) and well-being indicators at the levels mentioned above are generally carried out using two types of regression models.

The first refers to the territorial disaggregation of data available at regional level, estimated within the National Accounts. The correlation between the GDP (or other indicator), the dependent variable and other independent variables, whose data are available at lower territorial level, is studied at regional level. The estimated relationship is then applied to compute the dependent variable at provincial and municipal levels.

The second type of model refers to the so-called Small Area Estimation (SAE) which is a collection of statistical methods for producing statistically-sound estimates from surveys and administrative data when the sample size in the target area is too small. The estimates are based on the specification of a model, which borrows strength across the related areas and links the study variable to the existing auxiliary information (Rao 2003) which can be obtained from administrative archives and by analysing the geography of the territory under study.

Focusing on the Italian context, we present some of the studies applying these two types of models with specific attention to the estimates obtained at municipal level.

One of the first and most significant contributions is the study by Marbach (1985), who proposed the reconstruction of municipal incomes for the entire national territory. In determining household disposable income, the proposed methodology started by considering the income constituent elements (gross salaries of employees; income from dependent jobs; income from capital divided between income from agricultural land, income from buildings, interest, profits and dividends; family transfers; indirect taxes) and compares this aggregate with the data on loans and cross-checks them with the final consumption household data (from ISTAT source) and savings data provided by the Bank of Italy in order to determine their reliability. The same aggregates at regional level were then downscaled at municipal level by identifying the following factors: resident population; electricity consumption for domestic use; registered cars; telephone expenses of private users and taxable income as explicative and control variables. Bollino and Polinori (2005) remarked on the centrality of Marbach's research which has acted as a foundation for several other studies aimed at constructing local economic indicators.[2]

Moreover, research activities for single regions or sub-groups of regions have been carried out in order to fill the information gap mentioned above. In this light, Bollino and Polinori (2005) provided estimates of value-added for the Umbrian municipalities (Italy) for the years 2001–2003.

Following Marbach's approach, the G. Tagliacarne research institute, as a research body belonging to SISTAN, has produced several economic indicators at sub-national level. More specifically in reference to the economic well-being, the G. Tagliacarne institute has made per capita consumption expenditure available for all of the Italian provinces (LAU-1 level), combined with other information such as disposable income and household patrimonial assets. Indeed, due to its long-term experience, the Tagliacarne research institute has produced a very large set of indicators focused on different macro-areas such as population and demography, business and entrepreneurial fabric, job market, economic results and well-being within the "Atlas of province and region competitiveness" (Atlante della competitività delle province e delle Regioni, in Italian)[3] for the period 1998–2013 and, more recently, it has produced detailed indicators using the GeoWebStarter statistical territorial system.

SAE methods were applied to carry out estimations at local level especially in the fields of poverty (Pratesi 2016) and agricultural (Pratesi 2015) measures.

In particular, from a methodological perspective, SAE methods have proved to be efficient in providing local-level estimates regarding both HCE and other economic measures such as income and poverty indicators (Pratesi et al. 2012; Pratesi 2014). Within this methodological framework, Giusti et al. (2017) used a SAE model to compute the mean household equivalized income and the Head Count Ratio for the 57 labour local systems of the Tuscany region in Italy for the year 2011 while Marchetti and Secondi (2017) used SAE method for obtaining monthly HCE estimates in real terms for all of the 110 Italian provinces. For estimations at municipality level it is worth mentioning the study by Casini-Benvenuti et al. (2007) which provided estimates of internal consumption at municipal level for the Italian regions of Lombardy, Tuscany and Sicily, for which they used SAE methods and the amount of the regional tax on productive activities (IRAP) known at municipal level as auxiliary variable.

Finally, within the Italian Equitable and Sustainable Well-being project (the BES project, Benessere Equo e Sostenibile in Italian) and the international SDG perspective, much attention has been paid to the issue of sub-national estimates in order to underline the importance of territorial well-being evaluation policies using various methodologies (Alaimo et al. 2020a, b; D'Urso et al. 2020; D'Urso and Vitale 2020; Monte and Schoier 2020; Onori and Jona Lasinio 2020; Sarra and Nissi 2020) and the need for disaggregated indicators and economic measures covering all of the territorial areas within a country. Indeed, as emphasized by Alaimo and Maggino (2020), sub-national level indicators are even more essential for Italy, which is historically characterized by strong regional specificities and differences that have given rise to the so-called North–South gap.

In accordance with this research stream, ISTAT in association with local-level institutions has launched the Provincial BES project, consistent and integrated with the national BES, in order to assess well-being in-depth and explore the unexpressed potential of

[2] In the research by Bollino and Polinori (2005), Table 2.1 shows applied research focusing on the estimation of economic local-level measures, whose foundations can be found in the Marbach's research.

[3] https://www.unioncamere.gov.it/Atlante/selreg_frame.htm.

territorial administrative archives.[4] As regards the economic well-being dimension, the Provincial BES focuses on indicators related to income, wealth economic difficulty and inequality whose detailed micro-data at provincial level were taken from the National Social Security Institution (INPS), the Italian Ministry of Interior, the Bank of Italy and the "Guglielmo Tagliacarne" Chamber of Commerce study centre. In 2018, ISTAT issued a system of BES indicators related to metropolitan cities (in Italian BES dei territori) for the first time, which consider indicators related to the economic material well-being among the 11 domains.

3 The Co-Kriging Spatial Predictor

3.1 The Methodological Approach, Main Principles Of The CK Estimator And The Assumptions

Geostatistical methods represent a type of interpolation method that accounts for spatial autocorrelation (Matheron 1963; Wackernagel 2013; Golden et al. 2020) which are aimed at re-constructing the entire spatial distribution of a phenomenon, starting from some points sampled within a defined spatial frame. These estimators include kriging methods initially introduced by the mining engineer Daniel Krige who applied the estimation methodology for the first time in order to obtain the distribution of precious metals in the soil (Krige 1951). These estimators are now frequently used in natural sciences for predicting a study (response) variable in unknown spatial locations—generally identified as a part of a pixel population (Corona et al. 2014)—by weighting the surrounding measured points for which the study (response) variable is observed.

Let us assume a study area divided into a population of N spatial locations. For a sub set of n spatial locations selected from N, a variable of interest y (response variable) is available, thus indicating y_i as the value of the response variable observed for the spatial location i, with $i = 1,\ldots n$. Without loss of generality, the Ordinary Kriging (OK) estimator uses the available data and the spatial autocorrelation among spatial points by weighting the surrounding measure points to calculate a prediction for each unknown location (Hengl 2009), therefore predicting the value $\hat{y}_j$ for the j unknown location pertaining to the subset (N–n) as:

$$\hat{y}_j = \sum_{i=1}^{n} w_{ji} y_i \tag{1}$$

where w_{ji} represent the kriging weights attached to the n sampled observations summing to one in order to ensure model-based unbiasedness of the predictor (Di Biase et al. 2018) while y_i refer to the observed (measured) values at sampled locations.

In this way, kriging represents a geostatistical method of interpolation for random spatial processes as a method for predicting or estimating optimal quantities in a geographical space. Unlike deterministic methods, which only take into account the systematic or deterministic variation for estimating variables, kriging makes better use of existing knowledge (Fisher and Getis 2009) and takes into account both the way in which a variable changes in

[4] The description of the project, the related indicators and the methodological approach are available at: https://www.istat.it/it/benessere-e-sostenibilit%C3%A0/la-misurazione-del-benessere-(bes)/il-bes-dei-territori.

space, through the variogram, and the error component. Over the years, kriging has become a standard procedure for the interpolating spatially distributed data in several nature-based disciplines such as geology, climatology, meteorology, etc. (Corona et al. 2014).

In order to take advantage of the covariance between the interest (response) variable and one or more auxiliary variables, the CK was introduced as an appropriate estimator to use when the response variable is sparsely sampled while some related auxiliary information is abundant (Corona et al. 2014) in the same spatial area (spatial frame). As stressed by Waller et al. (2004) CK is an extension of kriging to the case of two or more spatial covariates. It was originally developed as a technique for improving the prediction of a variable for which only a few samples could be taken, by using its spatial correlation with other more easily measured variables. It is worth noting that CK differs from “kriging with external drift” since the explanatory variable(s) are no longer assumed to be fixed variables thus indicating the nature of a trend in the primary variable, but are in fact spatial random variables with expected values and variograms (Waller et al. 2004). The CK estimator has been widely applied in environmental (Vessia et al. 2020), forestry (Corona et al. 2014; Günlü et al. 2020; Qin et al. 2020), engineering (Misaka et al. 2020) and natural sciences—while it has not been used up to now for predicting material well-being indicators at micro territorial level, such as HCE.

The CK spatial estimator for value $\hat{y}_j$ at the unsampled location j is obtained as the linear combination of all of the available values of the studied variable y_i and of the auxiliary variable(s) observed for all the spatial N locations:

$$\hat{y}_j = \sum_{i=1}^{n} \lambda_{ji} y_i + \sum_{l=1}^{q} \sum_{h=1}^{N} \delta_{jlh} x_{lh} \tag{2}$$

where λ_{ji} are the kriging weights attached to the n sampled observations (summing to one) and $\delta_{jlh}s$ are the CK weights attached to the N values of the q auxiliary variables, summing to zero for each l = 1,…,q (Corona et al. 2014), thus representing the bias-free constraints which characterize CK:

$$\sum_{i=1}^{n} \lambda_{ji} = 1 \tag{3}$$

$$\sum_{h=1}^{N} \delta_{jlh} = 0 \tag{4}$$

Spatial observations and their autocorrelation structure are essential when using spatial predictors and more specifically Kriging and CK estimators. The variogram which is defined as a function based on the differences—in terms of expected squared increment (Calderón 2009)—between values and shifted values enables researcher to capture these issue and it can be distinguished into experimental variogram—which can be estimated from point pairs—and fitted variogram, defined according to theoretical models equipped with different well-defined analytical forms, such as the Spherical, Exponential, Gaussian, Power and Matern models (Ardilly et al. 2018). All of these functional forms of variograms are characterized by the following three components: i) range representing the value of distance for which the variogram has a plateau thus indicating that covariance is cancelled. This is the “range” of spatial dependence, since it is assumed that there is no longer any relationship (correlation) between the values observed from a distance beyond this point; ii) nugget representing the limit of the variogram at zero and therefore related to the amount of short-range variability in the data and, lastly, iii) sill representing the value that the variogram model achieves the range, i.e. the value on the y-axis, while the partial sill is the sill minus the nugget.

3.2 Tools Used for Evaluating Our CK Approach

The estimated CK models are generally evaluated using the Leave-one-out Cross Validation (LCV) method (Cao et al. 2020b), which enabled us to effectively analyse the model performance by comparing the observed and the estimated values (i.e. the subset of the observations for which we have both real and predicted values) for each spatial location *i*. Indeed, according to this technique, each sampled point y_i is excluded separately from the set of available data and a value $\hat{y}_i$ in the same spatial location is therefore estimated using the $n-1$ remaining sampled points and by using the (same) selected variograms. The LCV results and the comparisons between the two values (observed and fitted values) can be used to compute various indicators, including the Mean Squared Error (MSE), the Absolute Relative Bias (ARB) and the Relative Root Mean Squared Error (RRMSE):

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left(e_i\right)^2 \tag{5}$$

where $e_i = y_i - \hat{y}_i$ is the difference between the observed response value removed at the h-iteration and the predicted value obtained by fitting the model to the remaining $n-1$ points.

The empirical relative root mean squared error (RRMSE) adapted from Corona et al (2014) can be also computed as follows:

$$RRMSE_i = \frac{MSE^{1/2}}{y_i} \tag{6}$$

Lastly, the empirical ARB is obtained as:

$$ARB_i = \frac{\left|\hat{y}_i - y_i\right|}{y_i} \tag{7}$$

The quartiles from the *n* values of the ARB and RRMS are used as indicators of bias and accuracy performance of the predictors, respectively.

4 The Available Data and Preliminary Explorative Spatial Analyses

4.1 Data

Two types of data were available which were used for obtaining the per capita HCE estimates for all Italian municipalities (LAU-1 level).

Firstly, by focusing on the study (response) variable data regardingthe internal final HCE for all the 110 Italian provinces for the year 2017 were available which was provided

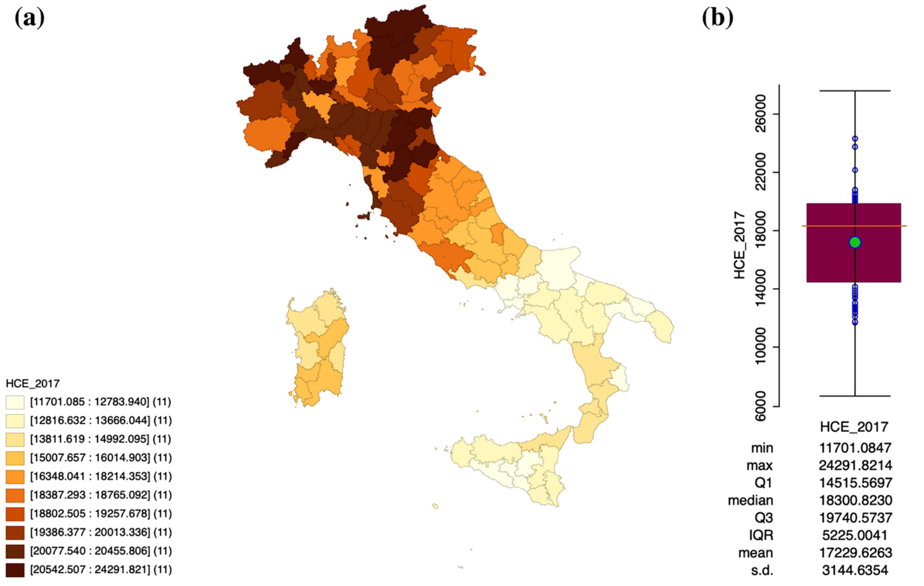


Fig. 1 **a** HCE spatial distribution at provincial level (year 2017) and **b** box-plot

by the Tagliacarne research institute.[5] According to the methodological definition of the HCE formulated by the Tagliacarne institute (Rinaldi 2002), this value includes all of the goods and services purchased by households, even those paid by instalments or those kept in stock to extent their consumption over a specific period of time. In addition to the actual rents of the rental properties, these expenses include the figurative costs of the houses directly used by the owners. Moreover, it also includes the self-consumption of agricultural and food products, the value of the goods and services paid by employers to their employees in the form of remuneration in kind. the services produced in the family with the help of third parties such as domestic workers, drivers, etc·

Secondly, for the year 2017, data from Italian income tax return was available at municipal level (7983 municipalities based on the changes and municipal mergers carried out from 2016) regarding taxable per capita income expressed in Euros, extracted from the open data archive of the Italian Ministry of Finance.

4.2 Preliminary Explorative Spatial Analyses

Since the spatial distribution of observations and the autocorrelation structure of the two variables are essential when using spatial predictors and Kriging and CK estimator, we carried out explorative spatial analyses using the open GeoDa software developed by Anselin (2003).

[5] The estimates at provincial level are available in the G. Tagliacarne website section "Numbers and Territory". It is worth noting that the data available from Tagliacarne institute—for the year from 2012 to 2017—refer for all the years to the Italian partition in 110 provinces. For these reasons in the text we specified the existence of n = 110 provinces.

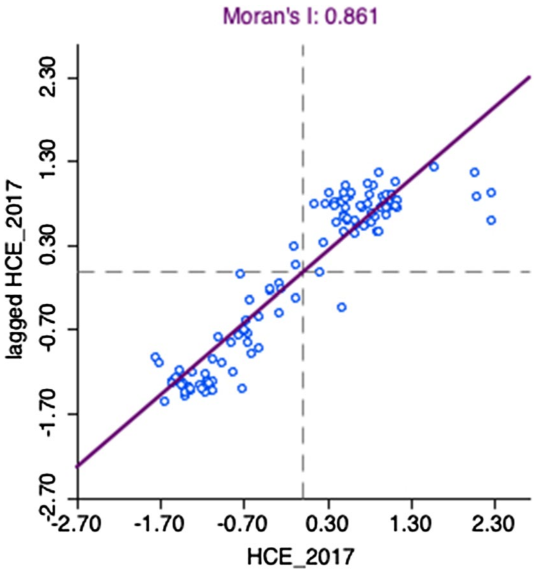


Fig. 2 Moran index of spatial autocorrelation for HCE at provincial level

Figure 1 shows the HCE distribution (in Euros) for the 110 Italian provinces combined with its empirical distribution. It is observed that the lowest value of consumption expenditure was registered for the provinces of Caserta (Campania) and Crotone (Calabria) while the highest values were found for the provinces of Milano (Lombardy), Aosta (Valle d'Aosta Region) and Bologna (Emilia Romagna). The median HCE observed value at provincial level was equal to approximately 18.3 thousand Euros with an interquartile range equal to 5225 Euros, thus demonstrating the variability of the central part of the distribution.

Moreover, Fig. 2 shows the results of the Moran scatter plot which confirms the existence of spatial autocorrelation with the value of the Moran's I equal to 0.861 and statistically significant (p-value < 0.01) showing therefore the existence of a positive autocorrelation.

Figure 3 shows the empirical distribution of taxable income in terms of both spatial distribution at municipal level—which confirms also for the per capita taxable income the existence of a general North–South gap, even if a moderate level of heterogeneity can be seen within Piemonte and Emilia Romagna regions as well as in central regions such as Tuscany.

Figure 4 illustrates the observed spatial autocorrelation at municipality level measured by the Moran index of spatial autocorrelation whose value equal to 0.806 and statistically significant (p-value < 0.01) confirms the existence of a positive autocorrelation.

5 Estimating HCE At Municipal (LAU-2) Level

5.1 The Specified Geostatistical Model

With the aim of introducing our CK approach for estimating HCE at municipal level, it is firstly important to distinguish between the two different levels for which the HCE

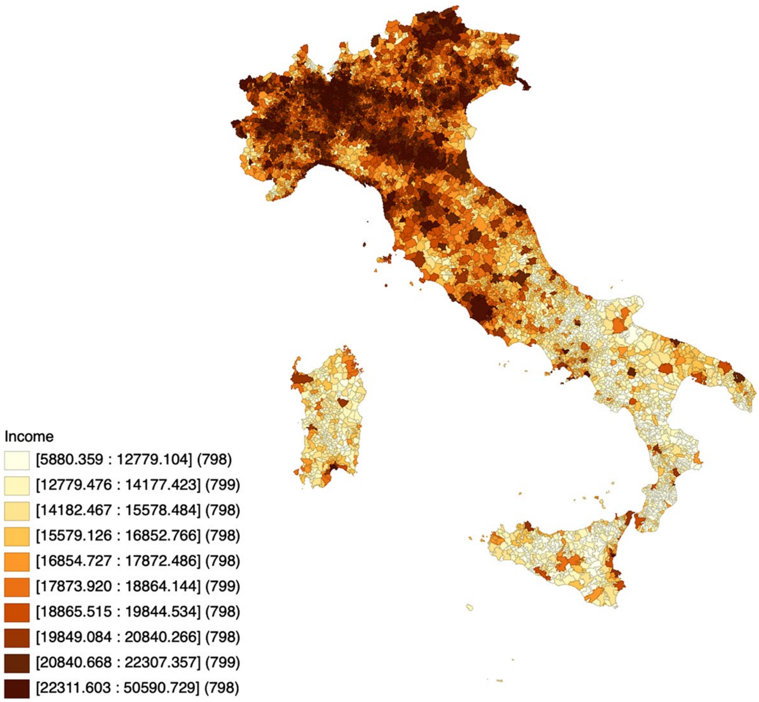
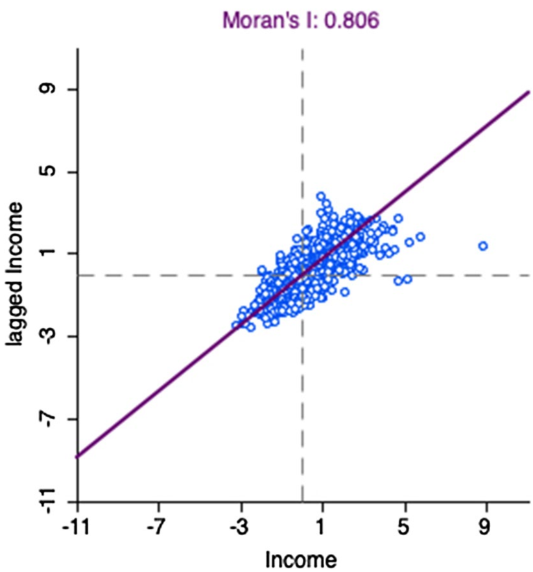


Fig. 3 Taxable income (in Euros—year 2017) distribution at municipal level

Fig. 4 Moran index of spatial autocorrelation for taxable income



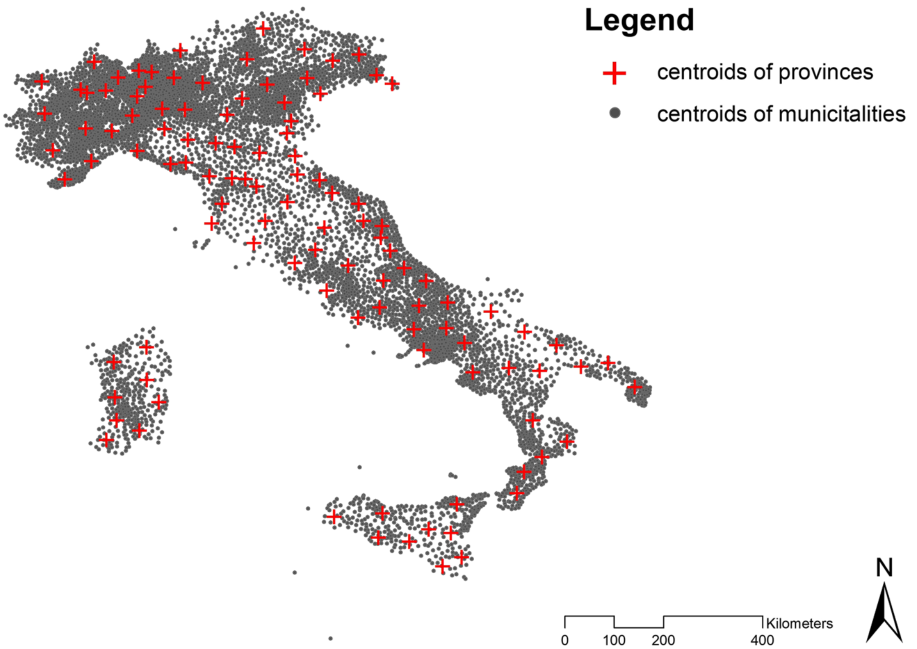


Fig. 5 Geographical location of the available information (red points) and the estimates obtained (grey dots)

information was available, at provincial level, and the more disaggregated level for which the estimates aims to be obtained, represented by the municipal level.

As highlighted in Fig. 5, a hierarchical relationship composed of two territorial levels was defined: the level-2 units (the lowest LAU-2 level, formerly identified by Eurostat as NUTS-5 units) represented by the municipalities which can be nested in level 1 units (upper LAU level), represented by the provinces.

Figure 5 shows the longitude and latitude centroids both for each of the 110 Italian provinces and the 7983 municipalities, as illustrated in the ISTAT cartographic shape files (the most recent version can be found in ISTAT, 2020).

Without loss of generality, let us assume the total spatial locations—each of them identified with the spatial centroids—N = 8093 can be divided into two territorial levels composed by (N–n) spatial locations (i.e. municipalities) at the lowest administrative level which can be grouped into n = 110 higher administrative level units, represented by the provinces. Specifically, for the n spatial locations the HCE is known while there are *(N–n)* unsampled points for which the HCE must be estimated, represented by the 7983 Italian municipalities, according to the 2017 ISTAT territorial bases. Therefore, bearing in mind this territorial partition and the available information as previously discussed, we specified the CK spatial predictors described by [2] as:

$$\hat{y}_j = \sum_{i=1}^{n} \lambda_{ji} y_i + \sum_{h=1}^{N} \delta_{jh} x_h \tag{8}$$

where $\hat{y}_j$ is the predicted HCE at the unsampled municipality j, y_i is the observed HCE value for each of the n = 110 Italian provinces used together with λ_{jh} representing the kriging weights of the adjacent measured points estimated using the variogram parameters.

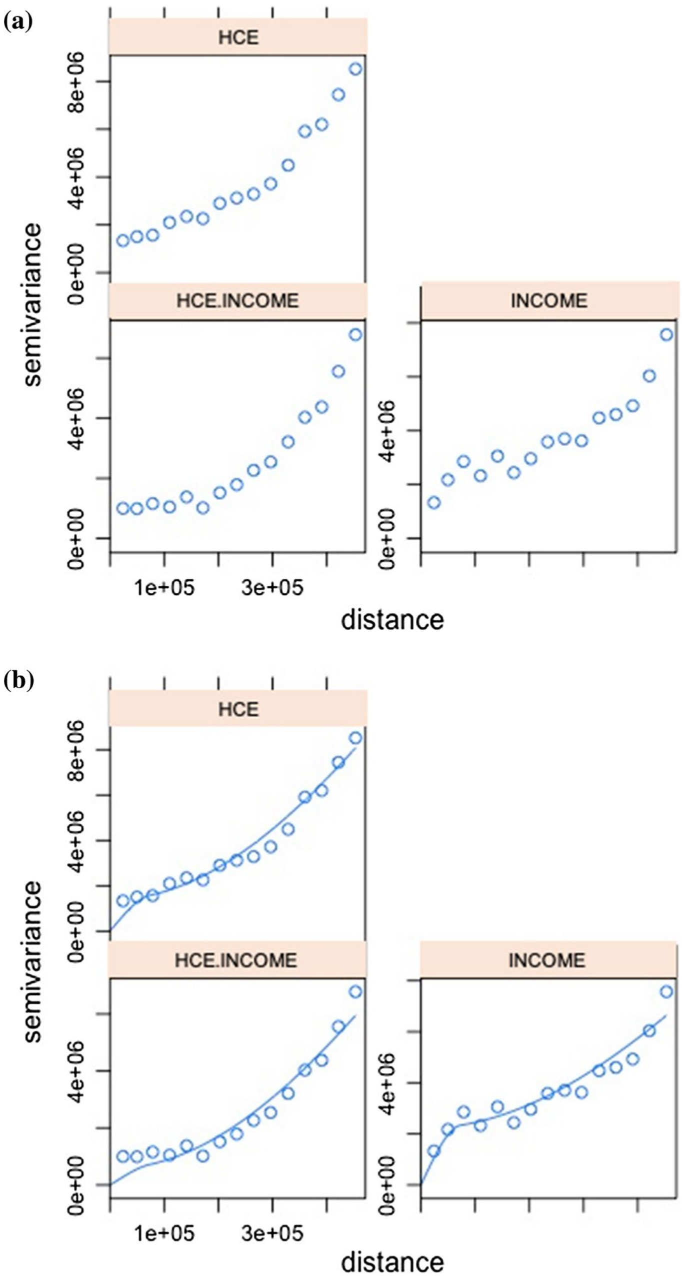


Fig. 6 **a** Empirical (experimental) variogram and cross-variograms; **b** Simple and cross variograms

Moreover, the x_h values represent the observed taxable per capita income available for all spatial locations while δ_{jh} s are the kriging weights estimated from the covariogram parameters.

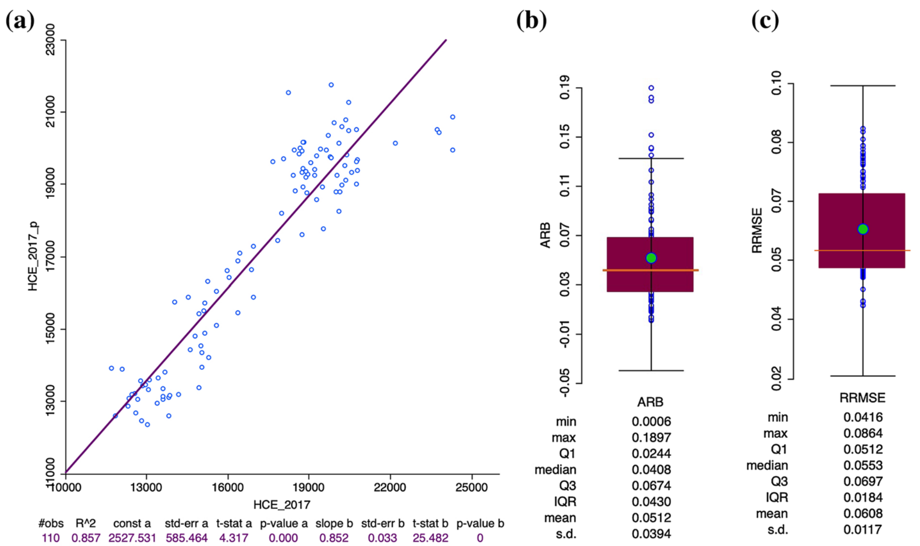


Fig. 7 **a** Scatter plot of the observed HCEs (x-axis) and predicted HCEs (y-axis) at provincial level; **b** box-plot of the empirical ARB; **c** box-plot of the RRMSE

In order to accurately and completely describe the underlying structure of spatial variability in the data, we selected the functions describing simple and cross variograms by specifying different functional forms and the best fit for the (partial) sill, range and kappa parameters. The best fitted models proved to be the spherical and Gaussian models for simple variograms related to taxable income and consumption, respectively, while the Matern semivariogram model (Matern 1960) with kappa = 1.6 was more able to characterize variability for short distances (Pardo-Iguzquisza and Chica-Olmo, 2008) regarding HCE and income cross-variograms Figs. 6.a (on the left) and 6.b (on the right) show the experimental and fitted variograms, respectively.

All of the geostatistical analyses were carried out using the R software and specifically the *gstat* package (Pebesma et al.2020).

5.2 The HCE Spatial Estimates

Before focusing on the obtained estimates, we present the performance of the CK estimation approach assessed using the LCV method, which applies the estimated spatial model for comparing the estimated values and the observed values for the Italian provinces (Fig. 7) and computing the MSE, the RRMSE and the ARB indexes.

Both the scatterplot and the computed indexes confirm the validity of our estimates and the fitted model. Indeed, the Bravais-Pearson correlation coefficient ($\rho = 0.926$) and the coefficient of determination ($R^2 = 0.857$) highlight the very high level of fit between observed and predicted values.

As a further validation tool, the ARB empirical distribution (Fig. 7b) shows that the median absolute relative bias is equal to 4.08% and only a quarter of the fitted values are predicted with a relative bias greater than 6.7%. As regards the accuracy of the estimated

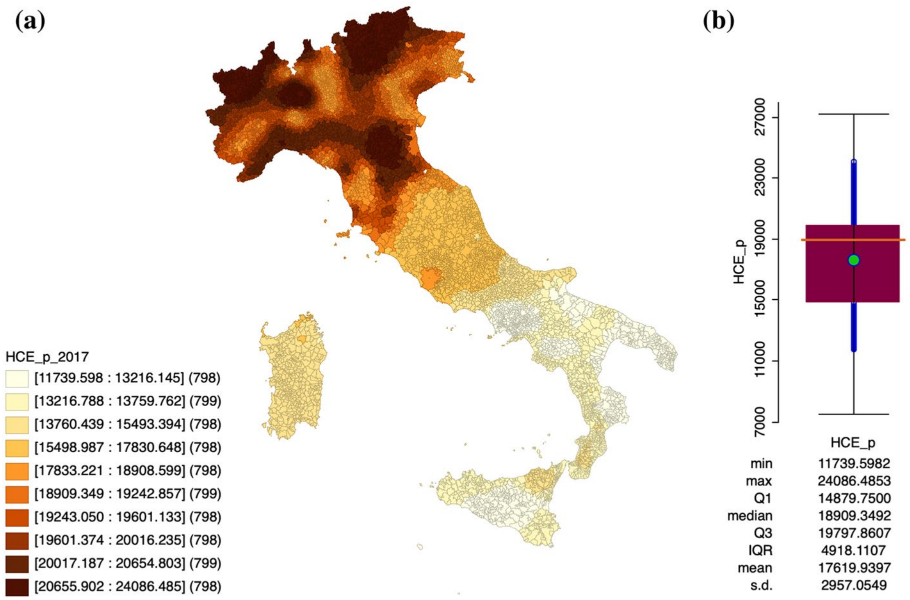


Fig. 8 **a** HCE estimates at municipal (LAU-1) level; **b** Box-plot of the estimates

values, the RRMSE empirical distribution shows that the mean RRMSE is equal to 6.08% while three quarters of the spatial locations have a relative errors lower or equal to 6.97%.

Figure 8a shows the CK estimates divided in deciles of HCEs while Fig. 8b shows a summary of the obtained estimates.

The obtained HCE values well illustrate the distribution and the existing heterogeneity in Italy and the related inequalities. As a general result, we can see that a high level of variability was found across North, Centre and South of Italy, but also within regions and provinces, this latter evidence above all for some provinces in North and South of Italy. Table 1 in the Appendix reports point estimates for the province of Bologna in the North of Italy (Emilia-Romagna region) and the province of Foggia in the South of Italy (Apulia region).[6]

As illustrated in Fig. 8a, the top-10% of the municipalities with the highest estimated values are almost all located in the Northern regions. For example, values higher than 22,000 Euros were observed within the Milan metropolitan area (i.e. municipalities of Cesano Boscone, Corsico, Settimo Milanese, Rozzano, Basiglio and also Milano), some municipalities within the Valle d'Aosta region (such as Brissogne, Saint-Christophe, Pollein and Aosta), the autonomous province of Bolzano (i.e. Villandro, Avelengo, Chiusa and Scena), the province of Bologna (some municipalities are San Lazzaro di Savena, Pianoro, Granarolo dell'Emilia, Casalecchio di Reno) and also within the province of Modena (as examples the municipalities of Zocca, Nonantola, Vignola). However, the lowest values pertaining to the first decile of the distribution, were observed within the provinces of

[6] The point estimates for all the 7983 municipalities are available on request. In assessing the results, it is important to note that estimates for the municipalities located on the administrative borders of two provinces may be affected by spatial (and economic) proximity of the provinces.

Caserta (i.e. the municipalities of Giano Vetusto, Camigliano, Capua as well as the provincial capital Caserta) and Naples in the region of Campania, Crotone in the region of Calabria and Agrigento in Sicily.

With the aim of identifying the existence of clusters across municipalities, we referred to the Local Index of Spatial Association (LISA) map (Lloyd 2010; Chun and Griffith 2013), which enabled us to identify four types of clusters: a high value surrounded by high values (High-High the red-coloured municipalities in the map); a low value surrounded by low values (Low-Low, the blue coloured municipalities in the map); a low value surrounded by high values (LH, the second quadrant of a Moran scatterplot); and high value surrounded by low values (HL, the fourth quadrant of a Moran scatterplot).

Figure 9 shows the bivariate LISA map for estimated HCE and taxable income values (together with the related significance levels) and highlights the existence of Low-Low spatial clusters especially for the Southern regions of Italy and Islands that are municipalities with low spendable and available resources surrounded by as many low-income and consumption municipalities.

The clusters reported in Fig. 9 also highlight issues that characterize the Italian subregional and sub-provincial territorial economic systems, such as the existence of a High-Low type cluster in Sardinia, above all in the North-East (i.e. the municipalities of Olbia and Loiri-Porto San Paolo), North-West part (the municipalities of Alghero and Sassari) and in Southern Italy where high consumption and income values were observed for the provincial capitals (i.e. for example, Matera in Basilicata and Taranto in Apulia) surrounded by municipalities with lower consumption and per capita income values. In the North of Italy the situation is mainly characterized by High-High type clusters indicating that most of the municipalities are characterized by estimates high HCE estimates and are almost entirely surrounded by municipalities with equally high values.

6 Concluding Remarks

It is important to acquire knowledge of individual well-being, living conditions and inequalities of the inhabitants at local level in order to enable local administrators to formulate targeted and effective intervention policies. As regards the measurement of individual material well-being and living conditions, the joint use of measures related to both income and consumption has gained consensus in recent years since it has enabled policy makers to implement effective and targeted intervention policies (Aguiar and Bils 2015; Attanasio and Pistaferri 2016; Cutillo and Scanu 2020).

However as regards HCE, the available official HBS estimates provide us with reliable estimates up to regional level, while there is an increasing interest in extending this information at a more disaggregated level. From this perspective, official statistical institutes, research bodies and academics are collaborating with the aim of finding methods that enable them to obtain robust estimates of disaggregated economic and social quantities and measures, starting from the availability of official sample data.

In this study, we extended the possibility of applying the geo-statistic CK approach to economic sciences and for forecasting material well-being related measures at local level. In fact,

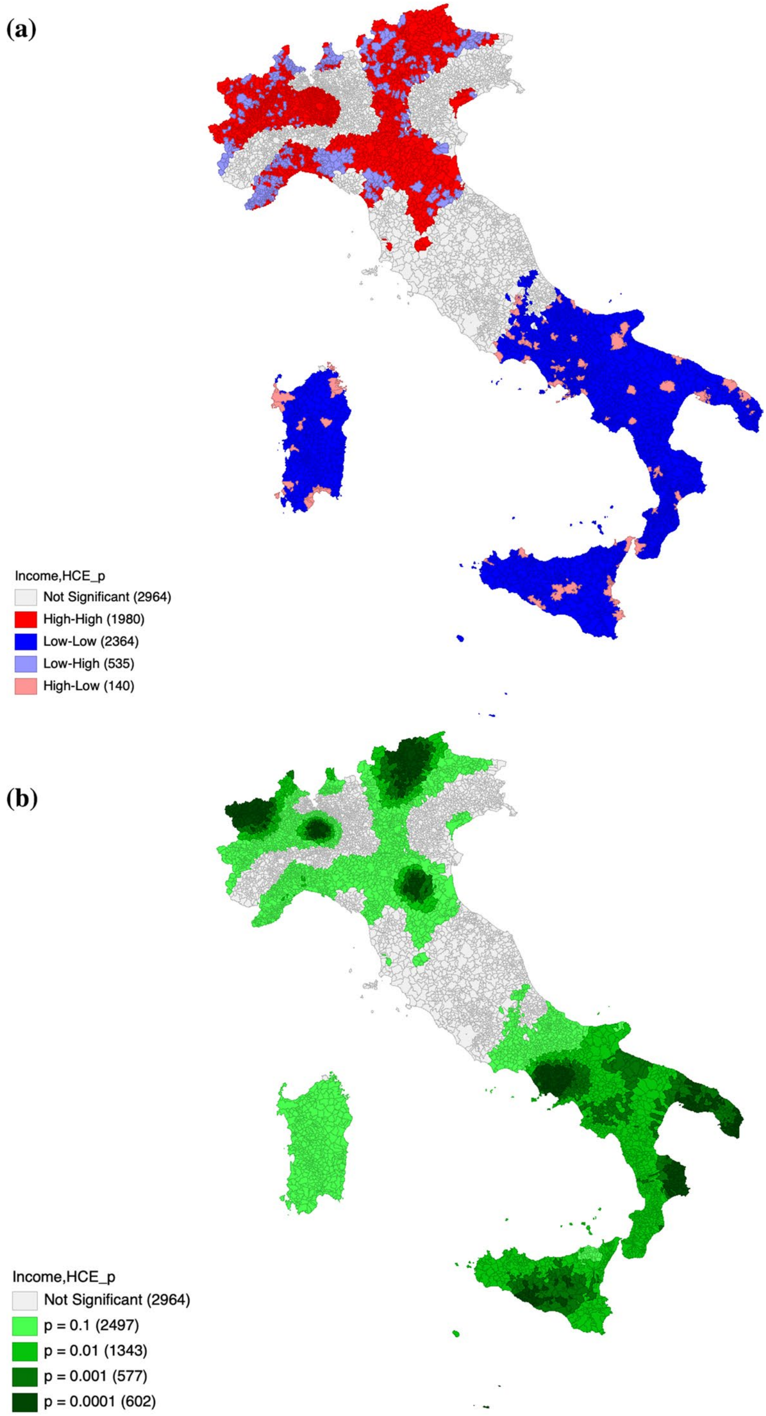


Fig. 9 Bivariate LISA map for income and consumption at LAU-2 level: **a** identified clusters; **b** significance map

spatial interpolation techniques, such as kriging and cokriging, have long been used in natural sciences (especially forestry and soil study areas) for obtaining reliable predictions of study (response) variables by exploiting spatial dependence and more abundantly sampled auxiliary information or information obtained from remote sensing.

Starting from the definition of a spatial hierarchical system—which is composed of two-level spatial dimensions of available information—adopting CK enabled us to obtain HCE estimates for all of the Italian municipalities by considering the spatial dependence between the administrative units and the availability of open-data on taxable income at a more disaggregated level (i.e. LAU-1 level), used as auxiliary and "more-abundant" variable.

The obtained estimates represent a good starting point for conducting a more detailed and in-depth analysis of the differences existing within the Italian provinces by evaluating the estimated values at municipal level.

However, the results of this study will prove useful for official statistics, applied socio-economic researchers and policy makers for different but related purposes. On one hand, the planning of sample surveys could consider estimation domains at a finer level also using spatial interpolation techniques that take advantage of the autocorrelation among spatial units as well as across hierarchical administrative borders. It is also worth emphasizing the fact that in this type of spatial analysis, the results depend on the positions of the n sampled units for estimating the remaining spatial points. In fact, the variability analysis of the estimates reveals the presence of a greater level of bias when the distance between spatial units is high and there are no other sampled points. Therefore, the design of the sample surveys could benefit from this study by considering a combination of the estimation domains: certainly the provincial level should be combined with the representativeness of the estimates for some municipalities (LAU-2) above a certain threshold of population. Moreover, the adoption of an additional intermediate level which could be represented by local labour systems—i.e. by using variables available at this level such as employment rate—could prove useful for improving estimates at a more detailed micro-territorial level.

Lastly, policy makers could help academics and applied researchers to identify the measures, quantities and indicators that better explains the individuals' situation at local level thus enabling us to determine and study individual living standards, related issues and inequalities in the best possible way.

Appendix: HCE Estimates at Municipal (LAU-2) Level

See Table 1.

Table 1 Estimated HCEs for Municipalities within the Provinces of Bologna and Foggia

Province	ID-Municipality	Municipality name	HCE (predicted value)	SD
BOLOGNA	37,062	Alto Reno Terme	19,437.78	830.11
	37,001	Anzola dell'Emilia	22,115.90	832.94
	37,002	Argelato	22,126.32	947.95
	37,003	Baricella	21,641.41	943.09
	37,005	Bentivoglio	22,143.11	951.23
	37,006	Bologna	23,199.14	622.12
	37,007	Borgo Tossignano	21,524.73	953.01
	37,008	Budrio	22,273.14	888.28
	37,009	Calderara di Reno	22,488.89	833.09
	37,010	Camugnano	20,127.66	908.93
	37,011	Casalecchio di Reno	22,995.40	613.44
	37,012	Casalfiumanese	21,925.20	914.01
	37,013	Castel d'Aiano	20,545.99	947.18
	37,014	Castel del Rio	21,482.52	989.16
	37,015	Castel di Casio	19,909.33	911.28
	37,016	Castel Guelfo di Bologna	21,811.72	876.71
	37,019	Castel Maggiore	22,643.81	839.84
	37,020	Castel San Pietro Terme	22,397.78	822.99
	37,017	Castello d'Argile	21,631.34	1022.49
	37,021	Castenaso	22,872.22	768.67
	37,022	Castiglione dei Pepoli	20,451.59	922.67
	37,024	Crevalcore	20,858.37	1077.10
	37,025	Dozza	21,821.59	884.35
	37,026	Fontanelice	21,648.13	960.59
	37,027	Gaggio Montano	20,092.00	955.11
	37,028	Galliera	21,252.83	1051.89
	37,030	Granarolo dell'Emilia	22,672.94	839.99
	37,031	Grizzana Morandi	20,902.51	932.86
	37,032	Imola	21,362.14	874.79
	37,033	Lizzano in Belvedere	19,558.34	915.98
	37,034	Loiano	21,987.41	855.20
	37,035	Malalbergo	21,645.27	981.42
	37,036	Marzabotto	21,940.67	808.58

Table 1 (continued)

Province	ID-Municipality	Municipality name	HCE (predicted value)	SD
	37,037	Medicina	21,753.91	888.44
	37,038	Minerbio	22,131.63	932.14
	37,039	Molinella	21,465.96	888.63
	37,040	Monghidoro	21,424.25	941.27
	37,042	Monte San Pietro	21,991.87	759.95
	37,041	Monterenzio	22,209.40	850.34
	37,044	Monzuno	21,722.73	867.97
	37,045	Mordano	20,899.68	815.98
	37,046	Ozzano dell'Emilia	22,936.96	699.26
	37,047	Pianoro	23,069.67	569.18
	37,048	Pieve di Cento	21,286.84	1067.38
	37,050	Sala Bolognese	22,020.14	938.10
	37,051	San Benedetto Val di Sambro	20,982.04	941.63
	37,052	San Giorgio di Piano	21,950.46	983.94
	37,053	San Giovanni in Persiceto	21,548.74	978.53
	37,054	San Lazzaro di Savena	23,262.07	586.51
	37,055	San Pietro in Casale	21,535.10	1033.60
	37,056	Sant'Agata Bolognese	21,201.63	961.50
	37,057	Sasso Marconi	22,713.28	643.22
	37,061	Valsamoggia	21,572.53	745.29
	37,059	Vergato	20,955.03	922.57
	37,060	Zola Predosa	22,524.21	723.43
FOGGIA	71,001	Accadia	13,340.61	1070.37
	71,002	Alberona	13,522.69	1062.39
	71,003	Anzano di Puglia	13,313.09	1003.88
	71,004	Apricena	13,852.47	1072.48
	71,005	Ascoli Satriano	13,270.74	1122.65
	71,006	Biccari	13,432.12	1055.49
	71,007	Bovino	13,322.40	1078.83
	71,008	Cagnano Varano	13,977.73	1159.96
	71,009	Candela	13,406.23	1146.03
	71,010	Carapelle	12,999.45	977.26
	71,011	Carlantino	14,165.64	921.44
	71,012	Carpino	13,973.91	1185.35
	71,013	Casalnuovo Monterotaro	14,061.09	999.33

Table 1 (continued)

Province	ID-Municipality	Municipality name	HCE (predicted value)	SD
	71,014	Casalvecchio di Puglia	13,974.91	1027.48
	71,015	Castelluccio dei Sauri	13,245.58	1041.61
	71,016	Castelluccio Valmaggiore	13,362.73	1070.45
	71,017	Castelnuovo della Daunia	13,851.02	1034.13
	71,018	Celenza Valfortore	14,003.99	974.85
	71,019	Celle di San Vito	13,333.57	1068.86
	71,020	Cerignola	12,896.56	1012.00
	71,021	Chieuti	14,556.59	1142.74
	71,022	Deliceto	13,344.31	1097.65
	71,023	Faeto	13,330.41	1059.04
	71,024	Foggia	12,918.63	695.58
	71,025	Ischitella	14,129.21	1204.66
	71,026	Isole Tremiti	14,780.11	1230.65
	71,027	Lesina	14,279.41	1166.34
	71,028	Lucera	13,314.35	912.73
	71,029	Manfredonia	13,106.65	978.63
	71,031	Mattinata	13,890.80	1213.04
	71,033	Monte Sant'Angelo	13,798.16	1173.68
	71,032	Monteleone di Puglia	13,271.36	1011.41
	71,034	Motta Montecorvino	13,722.38	1044.68
	71,063	Ordona	13,128.67	1030.74
	71,035	Orsara di Puglia	13,316.34	1073.88
	71,036	Orta Nova	13,025.83	1025.09
	71,037	Panni	13,307.29	1063.21
	71,038	Peschici	14,211.33	1233.71
	71,039	Pietramontecorvino	13,741.48	1040.22
	71,040	Poggio Imperiale	14,183.80	1138.69
	71,041	Rignano Garganico	13,294.38	837.21
	71,042	Rocchetta Sant'Antonio	13,463.91	1128.87
	71,043	Rodi Garganico	14,214.19	1219.15
	71,044	Roseto Valfortore	13,407.10	1052.92
	71,046	San Giovanni Rotondo	13,356.79	974.06
	71,047	San Marco in Lamis	13,486.62	975.93
	71,048	San Marco la Catola	13,875.80	1001.34
	71,049	San Nicandro Garganico	14,001.61	1135.84
	71,050	San Paolo di Civitate	14,114.08	1094.93
	71,051	San Severo	13,478.90	909.22
	71,052	Sant'Agata di Puglia	13,390.80	1087.00

Table 1 (continued)

Province	ID-Municipality	Municipality name	HCE (predicted value)	SD
	71,053	Serracapriola	14,380.82	1117.30
	71,054	Stornara	13,001.72	1043.97
	71,055	Stornarella	13,081.70	1068.18
	71,056	Torremaggiore	13,874.94	1038.92
	71,058	Troia	13,286.45	1020.10
	71,059	Vico del Gargano	14,121.39	1221.39
	71,060	Vieste	14,111.93	1235.15
	71,061	Volturara Appula	13,696.68	1039.44
	71,062	Volturino	13,620.09	1050.34
	71,064	Zapponeta	13,028.87	1042.19

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