ACCSCIENCE PUBLISHING

International Journal of Population Studies

RESEARCH ARTICLE

Local population changes as a spatial varying multiscale process: The Italian case

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Abstract

The population dynamics in Italy show a strong spatial heterogeneity within a framework of persistent demographic territorial disparities. From a local point of view, it is necessary to understand what demographic determinants govern this process. In the paper, we model the population change according to a local (i.e., spatial varying coefficients) multiscale approach. To this aim, local demographic growth rates of each Italian municipality for the period 2011 – 2019 were estimated and modeled by means of a classic a-spatial global model (i.e., ordinary least-square), and a multiscale geographically weighted regression. The multiscale dimensions of local population changes are therefore analyzed by means of three sub-dimensions: Level of influence, scalability, and specificity. The results show that the determinants of local population changes are not spatially constant and that they vary in their effect at different geographical scales.

Keywords: Spatial demography; Local approach; Spatial varying coefficients; Multiscale geographically weighted regression model; Italy

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Citation: Benassi, F., Mucciardi, M., & Gallo, G. (2023), Local population changes as a spatial varying multiscale process: The Italian case. *International Journal of Population Studies.*
https://doi.org/10.36922/ijps.393

Received: October 13, 2023

Accepted: February 8, 2023

Published Online: February 27, 2023

1. Introduction

In Italy, demographic changes present a strong spatial heterogeneity (Billari & Tomassini, 2021). Fertility and mortality, on the one hand, are affected by local and global spatial autocorrelation (Salvati *et al.,* 2020) and by spatial diffusion (Benassi & Carella, 2022; Vitali & Billari, 2017). On the other hand, migrations – internal and international – are affected by "classic" spatial variations, like the north–south divide, urban–rural divide, and new ones (for example the ones related to inner areas) (Benassi *et al.,* 2019; Bonifazi *et al.,* 2021; Lamonica & Zagaglia, 2013; Strozza *et al.*, 2016). The result of these processes is a dual demographic spatial landscape in which some spatial contexts grow, and some others shrink, with several (negative) effects on territorial cohesion and social sustainability (Reynaud *et al.,* 2020).

It is crucial to understand demographic components that act as drivers of that process considering spatial dependence and scale heterogeneity. Although studies that approach the process of demographic change in Italy from a spatial perspective already exist, they usually address a rather large geographic scale. A few studies that have referred to a local scale (i.e., at municipality level) have used mainly explorative approaches. The rare cases that have used a regression approach are mainly based on a-spatial models or, at most, spatial global models (i.e., spatial autoregressive models). In other words, there is a lack of local multiscale approach in studying demographic changes in Italy.

To fill this gap, and based on these premises, this paper proposes a study on population change at the local level (municipality) using a multiscale approach: Multiscale geographically weighted regression (MGWR hereafter) recently proposed by Oshan *et al.* (2019). This class of model has been recently used in several studies regarding different issues like COVID-19 fully vaccinated rates (Yang *et al.*, 2022a), opioid use disorders in older populations (Yang *et al.*, 2022b), and mortality (Cupido *et al.*, 2021; Song *et al.*, 2021) and has proved to be extremely useful to grasp the multiscale nature of population spatial processes. However, quite surprisingly, to the best of our knowledge, no application to Italy has been made. This is paradoxical if we bear in mind that the demographic and socio-economic processes in Italy are deeply interested in spatial divides and spatial dependence processes (Benassi & Naccarato, 2017; Reynaud & Miccoli, 2018; Reynaud *et al.*, 2018; Caltabiano *et al.*, 2019; Zambon *et al.*, 2020). Indeed, on a local scale, the heterogeneity of demographic dynamics increases significantly, especially with regards to the drivers of changes. Migrations (both internal and international) play a key role in such changes since the natural growth is negative (or at most equal to zero) almost everywhere. The determinants of the capacity of a municipality to attract people (both from other Italian municipalities and/or abroad) are many: Spanning from the opportunity of finding a job, which is typically higher in urban areas located in the north and the center part of Italy, to the level of accessibility to services and infrastructures, which remains nowadays very low in many areas of the country, especially, mountainous and inland areas, and from many other factors related for example the presence of certain services (in particular primary school) that had proven to be crucial to counteract depopulation processes (Benassi *et al.*, 2021; 2023).

The main goals of the paper are straightforward: (i) Identifying what demographic determinants govern the process of local population change in Italy; (ii) verifying if these determinants are spatially constant or not; and (iii) if their effects vary at different geographical scale.

The paper is structured as follows: In the next section, data and methods are described, and then results are shown. The final section draws some conclusions and future developments.

2. Data and methods

In the paper, we modeled the yearly average total population growth rate (TOTPGR) by means of MGWR in function of a set of pure demographic determinants (independent variables).

These are:

- Yearly average natural population growth rate (NATPGR),
- Yearly average internal migratory population growth rate (MIGPGR),
- Yearly average international migratory population growth rate (INTPGR),
- Yearly average of Italian population growth rate (ITAPGR), and
- Yearly average of foreign population growth rate (FORPGR).

The variables refer to the Italian municipalities (7,904 cases) and cover the period 2011 – 2019. They have been standardized to a Z distribution so that their mean is equal to zero ($\mu = 0$) and their standard deviation is equal to one ($\sigma = 1$).

In the analysis and the interpretation of the multiscale regression results, we follow the approach of Yang *et al.* (2022a; 2022b) in which three multiscale dimensions of spatial process are defined:

- Level of influence, the percentage of population affected by a certain determinant across the entire area;
- Scalability, the spatial process of a determinant into global, regional, and local process; and
- Specificity, the determinant that has the strongest association with the yearly average total population growth rate.

These dimensions are evaluated in relation to each independent variable (Key findings section).

Population data used are based on the intercensal reconstruction of resident population and are provided by the Italian National Institute of Statistics (Istat). Basically, they refer to stocks (resident population at a given time) and flows (births, deaths, emigrations, and immigrations occurred in a given period) of resident population (Italians and foreigners). The period refers to 2011 – 2019.

The local dimension of the study lies both in the regression approach used (MGWR, that is a local regression approach) and, therefore, in the statistical units adopted. Indeed, our statistical units are the Italian municipalities. Municipalities, local administrative units

(LAUs) based on the Eurostat definition, are the basic spatial units adopted in this study. LAUs are defined with the aim to dividing the territory of the European Union for the purpose of providing statistics at local levels. They are low-level administrative divisions of a country below province, region, or state. LAUs may refer to a range of different administrative units, including municipalities, communes, parishes, or wards. In Italy, they correspond to municipalities.

For each municipality, we computed the rates following the approach proposed in Preston *et al.* (2001) and applied, among others, by Strozza *et al.* (2016). In such approach, the idea is that TOTPGR is the instantaneous growth rate (from one year to another) and can be expressed as the ratio between population change during time interval 0-*t* and the number of persons for that period *t* $(P_t-P_0)/ln\ (P_t/P_0)$ (Preston *et al.*, 2001). We computed all the other rates in the same way. These rates, standardized to a Z distribution, act as dependent (TOTPGR) and independent variables (NATPGR, MIGPGR, INTPGR, ITAPGR and FORPGR) in a MGWR model. As known, scale is a fundamental concept in spatial and regional demography (Howell *et al.,* 2016; Lloyd, 2016). This is currently discussed in the considerable and diverse literature that investigates the various roles that scale plays in different social processes (Fotheringham *et al.*, 2017). It is generally accepted that different processes can operate at different spatial scales, and we often make a distinction between micro and macro, or between local and global processes, but in real-world scenarios, data are often generated from spatial processes operating at different spatial scales (Wolf *et al.*, 2017). If we consider a less restrictive assumption that all spatially variable processes in a model operate at the same spatial scale, we can think of a more flexible model. Local models such as geographically weighted regression (GWR) (Fotheringham *et al.*, 2002) can capture process heterogeneities but do not adequately incorporate the multiscale properties of processes into modeling. Indeed, the bandwidth of the latter is closely related to the spatial scale of the processes examined, and bandwidths for each independent variable are assumed to be the same. In this respect, the semiparametric geographically weighted regression (SGWR) model (Nakaya, 2015; Nakaya *et al.*, 2005) provides, even if in a strictly rigid or extreme form, a first response to the multiscale problem by distinguishing between factors that play a role at a local and the global levels. Demographic research is often based on individual and contextual level data over a wide range of spatial scales, and therefore, the corresponding variables, which involve correlated social and economic aspects, require a deep understanding of the spatial context (Mucciardi, 2021). To overcome this problem, the development of the GWR/SGWR model, called MGWR, removes the single bandwidth assumption, and allows covariate-specific bandwidths to be optimized (Oshan *et al.*, 2019).

The scale of a spatial non-stationarity relationship may vary for each predictor variable. The MGWR model has the ability to differentiate local, regional, and global processes by optimizing a different bandwidth for each covariate (Li & Fotheringham, 2020). The following equation gives the specification of MGWR:

$$y_i = \sum_{j=0}^{m} \beta_{bwj}\left(u_i, u_j\right) x_{ij} + \varepsilon_i \quad (1)$$

Where β_{bwj} represents the coefficient of the bandwidth with the spatial weighting kernel used for estimating the *j*-th predictor variable x_{ij} at local site (i.e., municipality) *i*, ε_i is the error term, and y_i is the response variable. As pointed out by Oshan (Oshan *et al.,* 2019), MGWR provides an extension that allows each variable to be associated with a distinct bandwidth by recasting GWR as a generalized additive model such that:

$$y_i = \sum_{j=1}^{k} f_j + \varepsilon_i \quad (2)$$

Where f_j is a smoothing function applied to the *j*-th explanatory variable at location *i* that may be characterized by distinct bandwidth parameter and ε_i the error term of the model. Hence, a key advantage of MGWR over GWR is that it can more accurately capture the spatial heterogeneity within and across spatial processes, minimize overfitting, mitigate concurvity (i.e., collinearity due to similar functional transformations), and reduce bias in the parameter estimates (Oshan *et al.*, 2020). The MGWR model is calibrated using a "back-fitting" algorithm which maximizes the expected log likelihood, and the criteria for selecting the bandwidths are derived from the same procedure used in the conventional GWR framework using the corrected Akaike information criteria corrected (AICc) for finite samples (Burnham & Anderson, 2004). The calibration process concerns the method and the criterion of choosing the bandwidth. In our empirical estimation, we used an adaptive (bi-square) kernel because it is more favorable when dealing with non-uniform spatial distributions of observations (i.e., municipalities in our case) and it is also able to better handle irregularly shaped study areas. We recall that, although the fixed kernel could be used in the MGWR model, a limitation of this approach is that there may have calibration issues when there are sparsely populated regions of a study area (Oshan *et al.*, 2019). Furthermore, to compare each of the bandwidths obtained from an MGWR model, it is necessary to standardize the dependent and independent variables so that they are zero-centered and based on the same range of variation. Consequently, the bandwidths are unconstrained from the scale and the variation of the explanatory variables, helping the relative comparison of bandwidths (Oshan *et al.*, 2020). In the first phase, we built a classic ordinary least square (OLS) model (which assumes processes to be constant across the study area) as a benchmark for evaluation of the MGWR model and report comparison. Before moving to the presentation of the results, it should be noted one limitation of the present study. The independent variables used (demographic rates obtained by a decomposition approach) can interact with each other. The estimation done cannot grasp this (possible) effect of interaction between independent variables. Nevertheless, our primary goal here is not to understand the "net" effect of the independent variables on the dependent one nor to explain the variance of this latter. Our primary goal is to prove that the local demographic change in Italy is a local multiscale process (i.e., it varies across spaces and across scales).

3. Key Findings

From 2011 (January 1) to 2019 (January 1), the resident population in Italy passed from 59,948,497 to 59,816,673 (a decline by −2.2‰). Those changes present a strong spatial variation as clearly shown in Figure 1. The right panel map clearly shows a sort of "broken" space that divides local contexts that recorded an increase of resident population during 2011 – 2019 from the other. The positive growth areas are most of the cases represented by urban areas and big cities mainly located in the center and northern Italy (like Milan, Bologna, Florence, Rome) while the negative growth areas are represented by inner contexts but also by some important medium and medium-large cities mainly located in the southern part of the country. It is important to underline that, if we refer to the Italian population only (i.e., people with Italian citizenship), the decrease was even sharper, from 55,847,162 million residents to 54,820,515 (a total decline by −18.3‰), proving the growth of the foreign population counterpart, from 4,101,335 to 4,966,158 (a total increase by +210.9‰).

The results of global (OLS) and local (MGWR) regression models are clear (Table 1). The first important finding is that, based on the Monte Carlo randomization significance test for spatial variability, all the variables introduced in the model are affected by spatial variability so that it would be misleading to treat them as constant in space (like in the OLS model). Moreover, they are supposed to be not correlated because the variance inflation factor (VIF) value is always lower than 10.

MGWR outperforms the OLS model: AICc is lower, Adj-R-square is higher, and the distribution of residuals is not spatially autocorrelated (see the not significant value of the $I_{\_MGWR\_res}$ respect to the significant value of the $I_{\_OLS\_res}$ in Table 1). OLS results tell us that all the independent variables are statistically significant. The net effect on the dependent variable is always positive. NATPGR has a higher net impact, followed by MIGPGR.

What is important, in our view, in addition to the spatial variability of the local coefficients, is the variation of the scale (i.e., the bandwidth) for each regression coefficient. In the case of adaptive kernel, the bandwidth represents the number of nearest neighbors from the regression point which receives a non-zero weight in the local regressions (i.e., the ones which are considered as neighbors to *i*). The selection of the optimal bandwidth parameters is based on statistical optimization criteria like Akaike Information

Table 1. OLS and MGWR models for the growth rate of the total population in 2011-2019 by municipality, Italy

Parameters	OLS	MGWR					
		Min	Median	Mean	Max	S.D.	Bandwidth[(b)]
Intercept[(a)]	0.000	-0.162	-0.007	-0.032	0.083	0.061	361
NATPGR[(a)]	0.477***	0.093	0.342	0.355	0.649	0.133	161
MIGPGR[(a)]	0.455***	0.082	0.323	0.327	0.668	0.120	170
INTPGR[(a)]	0.227***	0.025	0.171	0.165	0.343	0.057	105
ITAPGR[(a)]	0.281***	0.011	0.477	0.458	0.848	0.179	78
FORPGR[(a)]	0.099***	0.034	0.155	0.159	0.302	0.067	202

Note: **OLS model results:** AICc = -5691.82; Adj-R-square=0.972; Moran $I_{\_OLS\_res}$=0.034***
VIF: NATPGR=4.154; MIGPGR=4.165; INTPGR=1.800; ITAPGR=7.582; FORPGR=1.628
MGWR model results: AICc = -9779.45; Adj-R-square=0.985; Moran $I_{\_MGWR\_res}$ = -0.002 (n.s.)
Spatial kernel=adaptive bi-square
(a) Monte Carlo randomization significance test for spatial variability $p<0.001$ (Monte Carlo tests are based on 1,000 randomizations of the data)
(b) The bandwidth is determined with the number of nearest neighbors for each location
OLS: Ordinary least square. MGWR: Multiscale geographically weighted regression.
Dependent variable is TOTPGR 2011–2019.
*$p<0.05$; **$p<0.01$, ***$p<0.001$ n.s.: Not significant.

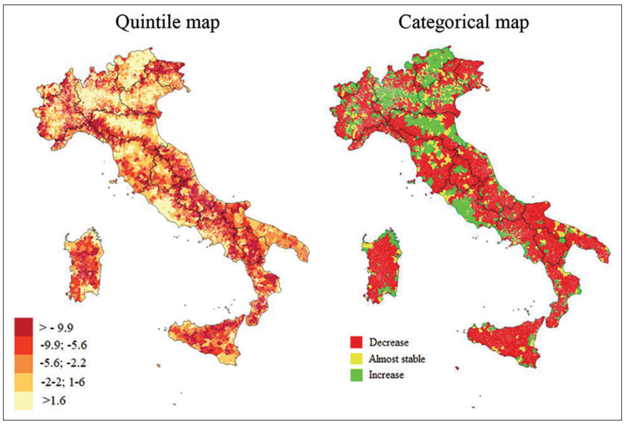

Figure 1. Yearly average total population growth rate per 1000 (TOTPGR) 2011 – 2019, Italian municipality
Note: TOTPGR: Yearly average total population growth rate.
Source: Author's elaboration on Istat data.

Table 2. Three dimensions of multiscale spatial process for each independent variable based on the MGWR models

Variable (bandwidth)	Level of influence[(a)]	Scalability[(b)]	Specificity[(c)]
NATPGR (361)	Primary (7,527)	Local	2,511 (31.8%)
MIGPGR (161)	Primary (7,527)	Local	326 (4.1%)
INTPGR (170)	Primary (7,423)	Local	0 (0.0%)
ITAPGR (78)	Primary (7,783)	Local	5,067 (64.1%)
FORPGR (202)	Primary (7,800)	Local	0 (0.0%)

Note: The model was adapted from Yang *et al.,* (2022a, 2022b).
NATPGR (yearly average natural population growth rate), MIGPGR (yearly average internal migratory population growth rate), INTPGR (yearly average international migratory population growth rate), ITAPGR (yearly average of Italian population growth rate), FORPGR (yearly average of foreign population growth rate).
[(a)] If the variable affects more than 50% the total population it is a primary influencer; otherwise (≤50%) it is a secondary influencer. The percentage of municipalities affected by a factor is included in the parentheses.
[(b)] If the bandwidth of a variable is larger than 75% of the global bandwidth, it is a global determinant; if the bandwidth is smaller than 25% of the global bandwidth, it is a local determinant; if the bandwidth is between 75% and 25% of the global bandwidth, it is a regional determinant. Global bandwidth is the total number of municipalities (7,904).
[(c)] The number and percentage of municipalities that the focal variable has the strongest significant impact on the dependent variable (i.e., the largest absolute value of the standardized coefficients that are).

Criteria (Fotheringham *et al.*, 2002; Yu *et al.,* 2020). From a spatial perspective, the bandwidth is an indicator of the spatial scale over which the processes under observation operate. It is interesting to note that the higher bandwidth is recorded by FORPGR (202) while the lower one by ITAPGR (78). This means that the spatial scale over which the effect of FORPGR operates on the dependent variable (TOTPGR) is higher, although it is relatively small in geographical sense (the total bandwidth, i.e., the total number of municipalities is equal to 7904). Results of Table 1 provide evidence that the TOTPGR is greatly influenced by local determinants that have different effects at different scales.

As known, one of the major strong points of local regression models is that we can map the local coefficients (Matthews & Yang, 2012). From Figure 2**,** we can understand how space matters. In particular, we can observe how the strength of the net effect of each local coefficient varies across space - where it is statistically significant, in MGWR model a "specific" adjusted alpha-value and critical t-value are computed for each of the independent variables (Oshan *et al.*, 2020)- and the different magnitude of local R-squares. The historical north–south geographical contrast of Italy only partially explains the spatial patterns of local coefficients underlying the relevance of local scale dimension in measuring the demographic process (Salvati *et al.,* 2020). The geographical distributions of the local parameters of NATPGR and MIGPGR draw similar patterns: higher values are recorded in the north and in particular in the north-east part of the country. It seems to indicate that local context that act as attractors for internal migration flow are the ones where the natural growth is, comparatively, higher. If we bear in mind that, usually, the internal mobility of foreigners is higher than the one of Italians (Benassi *et al.,* 2019) and it follows a south to north axis, we can infer how relevant is the contribution of foreign population to the local population changes (Strozza *et al.,* 2016). The map of the local estimation of INTPGR is quite different in terms of intensity from that of NATPGR and of MIGPGR. The north still remain the part of Italy with higher values (the majority of the municipalities located in the north part of the country are classified in the last two classes of the legend, i.e., >0.300), but the intensity of the local coefficients is lower than the one of the first two maps. Interesting to note that among all of these first three maps the Sardinia Island does not present any statistically significant local estimation. The geographies of the local regression coefficients related to the ITAPGR and FORPGR variables appear partially mirrored each other and, to some extent, help to better understand what has emerged so far. The effects are generally more intense for the ITAPGR variable than for FORPGR. However, in both cases, the largest effects occur in central and southern Italy, where the effects (i.e., local coefficients) of the NATPGR, MIGPGR, and INTPGR were smaller. In contrast to the Italian component, in the case of foreigners, FORPGR, particularly small effects are also registered in the north-east and, albeit to a lesser extent, in the north-west as well as in some specific areas of the south including the islands.

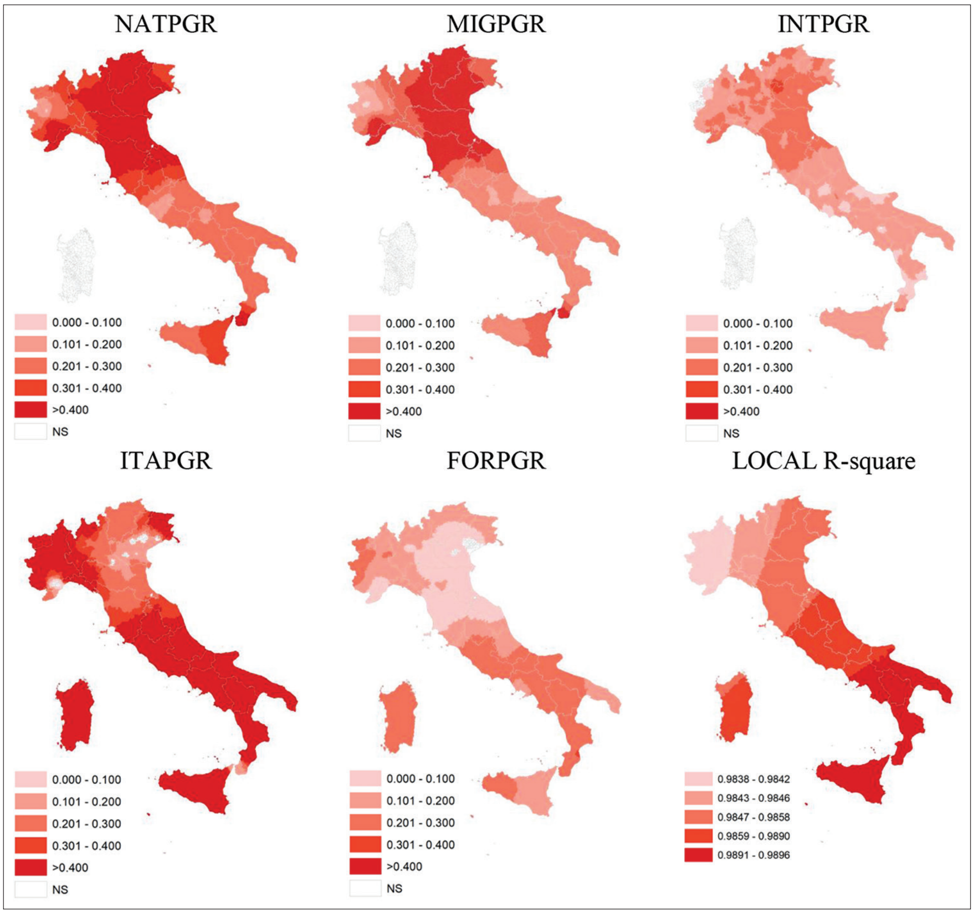

Figure 2. MGWR local coefficients and local R^2 for the growth rate of the total population 2011 – 2019 by municipality, Italy

Note: Dependent variable is TOTPGR 2011 – 2019. NATPGR: Yearly average natural population growth rate, MIGPGR: Yearly average internal migratory population growth rate, INTPGR: Yearly average international migratory population growth rate, ITAPGR: Yearly average of Italian population growth rate, and FORPGR: Yearly average of foreign population growth rate, NS: Not significant. All other parameters are statistically significant at $p<0.05$.

Source: Authors' elaboration on Istat data.

Finally, the geographical distribution of local R^2 is very peculiar. Indeed, local R^2 values are all very high although the highest values are found in southern Italy itself. The levels then tend to decrease moving northward. This means that in southern Italy the local variation in population is basically totally explained by the combination of the variables introduced in the model (local $R^2 > 0.98$).

A way to analyze these local and spatial scale varying effect has been recently proposed by Yang *et al.* (2022a; 2022b). In their approach, they proposed three dimensions of multiscale spatial process: level of influence, scalability, and specificity. Following Yang *et al.* (2022a; 2022b) based on the local estimates of an independent variable, we could identify the municipalities where the effect of this independent variable on TOTGR is statistically significant. We then divided the sum of the municipalities where the variable is statistically significant by the total number of municipalities in the entire study area. If a variable is found to influence 50% or more of the total number of municipalities, this variable will be categorized as into the primary influencer group; otherwise, (<50%) it is a secondary influencer. Scalability can be defined with the calibrated bandwidth of a variable. It has three groups: Global, regional, and local. According to Yang *et al.* (2022a; 2022b) when a calibrated bandwidth of a variable is >75% of the global bandwidth (i.e., the total number of municipalities in our case: 7,904), it can be defined as a global factor. If the bandwidth is between 75% and 25% of the global bandwidth, it is regarded as a regional factor. Finally, when the bandwidth of a variable is smaller than 25% of the global bandwidth, this variable is defined as local. Specificity is based on the standardized coefficients produced by MGWR. Each municipality has its own estimates of the independent variable and these estimates can be compared within each municipality. An independent variable may have strongest association with the dependent variable in some municipalities but not in others. Specificity is based on the number and percentage

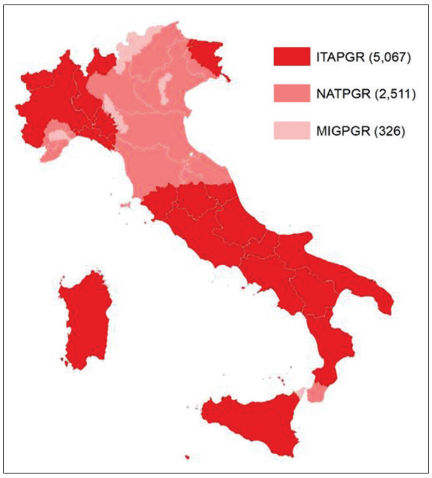

Figure 3. Specificity for ITAPGR, NATPGR, and MIGPGR[(a)]
Note: (a)In brackets the number of municipalities. ITAPGR: Yearly average of Italian population growth rate, NATPGR: Yearly average natural population growth rate, and MIGPGR: Yearly average internal migratory population growth rate.
Source: Authors' elaboration on Istat data.

of municipalities that the focal variable has the strongest significant impact on the dependent variable, TOTPGR (Yang *et al.,* 2022a; 2022b).

Multiscale results with the three dimensions are presented in Table 2. They are quite interesting because they prove the relevance to modeling population growth not only as a spatial process but, most of all, as local spatial varying process. In particular, we can see – column (a) – that each independent variable plays primary level of influence on the dependent variable (TOTPGR). Therefore, the local importance of each covariate is high. Moreover, all the independent variables prove to be local determinants in terms of scalability so that their effects have to be detected at local level. In terms of specificity, we can appreciate a quite high heterogeneity between the dependent variables. ITAPGR records the highest specificity while INTPGR and FORPGR presents no specificity.

The map of specificity in Figure 3 reveals different spatial patterns for the three variables that prove to have a specificity effect, namely, ITAPGR, NATPGR, and MIGPGR. In particular, we can observe how the effect of ITAPGR involves much more municipalities than the other two. Most of them are located in the southern Italy but also in the north-east area. The NATPGR specificity cover the central part of Italy and the north-west too. Finally, the MIGPGR local specificity distribution covers few areas that are almost located in the northern part of Italy.

4. Concluding Remarks

In recent years, many papers have underlined the intrinsic spatial nature of demography (De Castro, 2007; Gu *et al*, 2020; Raymer *et al.*, 2019; Voss, 2007; Weeks, 2016) and the need to use appropriate spatial methodologies in population-based studies, i.e., considering space in the analysis (Chi & Zu, 2008; Matthews, 2019; Matthews & Parker, 2014; Weeks, 2004). In this general framework, a crucial variable is the scale of analysis (Burillo *et al.* 2020; Oshan *et al.* 2022).

In this study, we showed that this is particularly true for Italy and its local demographic dynamics but with two major additions: the spatial varying relationships and multiscale nature of these relationships. In our view, this proves the spatial complexity of demographic changes in Italy and the need for measuring demographic processes without a constant scale approach.

Indeed, it can be misleading if modeling the spatial demographic process is without considering the spatial dimension (classic OLS model), without considering local dimensions – such as, spatial global regression models like spatial lag model, spatial error model, and spatial Durbin model – or without a multiscale framework (classic GWR model).

At least, the case for Italy for the period 2011 – 2019 as this paper clearly proves it. We argue that the results achieved provide new insights into the importance of treating the population process as spatial phenomena and in particular as local and multiscale (spatial) phenomena. The achieved results also have relevance in terms of policy implications. In Italy, as in other parts of Europe, there are vast areas of land in systematic depopulation (shrinking regions) (Klingholz, 2009), a real challenge for territorial planners and policy makers. Adopting this type of model (MGWR) allows the depopulation phenomenon to be modeled locally by identifying the radius of influence of the different explanatory variables and thus enabling the territorial calibration of policies to counter it.

Acknowledgments

The authors would like to thank the two anonymous reviewers and the editor for their suggestions, which helped to improve the paper significantly.

Funding

None.

Conflict of interest

The authors declare that they have no competing interests.

Author contributions

Conceptualization: Federico Benassi and Gerardo Gallo
Investigation: Federico Benassi

Methodology: Massimo Mucciardi
Formal analysis: Massimo Mucciardi
Writing – original draft: Federico Benassi and Massimo Mucciardi
Writing – review & editing: Federico Benassi, Massimo Mucciardi, and Gerardo Gallo

Ethics approval and consent to participate

Not applicable.

Consent for publication

Not applicable.

Availability of data

Data used in the paper can be downloaded from the Italian National Statistical Institute (Istat) web site: https://www.istat.it/en

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