



Testing Density-Dependent and Path-Dependent Population Dynamics in Greece with Spatial Quantile and Geographically Weighted Regressions

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Abstract

Regional variability in the spatial distribution of resident population and across-country density divides have consolidated heterogeneous demographic patterns at the base of modern urban systems in Europe. Although economic, historical, institutional, and cultural factors have demonstrated to affect the spatial distribution of resident population, density-dependence and path-dependence are mechanisms persistently shaping demographic dynamics at both local and regional scale. Analysis of density-dependent patterns of population growth (and decline) over sufficiently long time intervals allows a refined comprehension of socioeconomic processes underlying demographic divides. Despite a long settlement history, empirical investigation of the role of density-dependence in the long-term evolution of human populations along urban–rural gradients is relatively scarce especially in Mediterranean countries. The present study performs a comparative analysis of population distribution in 1033 Greek municipalities identifying (and testing the significance of) density-dependent and path-dependent mechanisms of population growth between 1961 and 2011, using spatially implicit and explicit econometric approaches. Results highlight a positive impact of density on population growth where settlements are concentrated. Assuming goodness of fit of the tested models as a proxy of density-dependence, the empirical findings clarify how density-dependent mechanisms were not significant all over the study period, being instead associated with specific phases of the city life cycle—basically urbanization with population concentrating in central locations. Density-dependence was less intense with suburbanization and counter-urbanization—when population sprawled over larger areas at medium–low density. An improved understanding of density-dependent and path-dependent mechanisms of population growth contributes to rethink spatial planning, regional development strategies, and socio-demographic policies adapting to heterogeneous (and rapidly changing) local contexts.

Keywords Territorial divides · Population density · Local development · Spatially explicit models · Europe

1 Introduction

Unbalanced demographic dynamics and spatial inequalities in economic performances are intimately interconnected in social systems and determine an asymmetric path of local development (Sato & Yamamoto, 2005; Scheuer et al., 2016; Zhang, 2002). Despite the inherent role in developmental studies (e.g. Johnson et al., 2005; Mc Guirk & Argent, 2011; Tapia et al., 2018), comparative analyses of population dynamics over long time intervals are relatively scarce for advanced economies (Montgomery, 2008; Rees et al., 2012; Taylor et al., 2010). In this direction, investigating local-scale demographic trends in a continent such as Europe—where individual countries exhibit distinctive characteristics deriving from their intrinsic socioeconomic structure, history, and political/cultural background—provides significant insights in the analysis of regional growth (Coleman, 2005; Gardiner et al., 2011; Haase et al., 2010; Lutz et al., 2003).

A wealth of factors has reported to affect the spatial distribution of resident population in Europe (Adveev et al., 2011; Arapoglou, 2012; Bocquier & Brée, 2018; Brombach et al., 2017), including (1) globalization, (2) structural change of economic systems, and (3) international migration (Champion, 2001; Cheshire, 1995; Haase et al., 2016; Oueslati et al., 2015). However, density-dependent mechanisms of population growth remain an important driver of demographic dynamics at regional scale (Lee, 1987; Lima & Berryman, 2011; Lutz et al., 2006). With this perspective in mind, local-scale population density is a pertinent variable whose investigation may clarify the recent evolution of European regions (Alados et al., 2014; Ciommi et al., 2018; Gavalas et al., 2014). Analysis may specifically decompose path-dependent socioeconomic transformations from density-dependent mechanisms of population growth along a complete metropolitan cycle (Benassi et al., 2020; Salvia et al., 2021; Zambon et al., 2017).

Complex cycles have been observed in Europe since World War II (Lerch, 2014; Reher, 2004; Salvati et al., 2018). While compact urbanization driven by internal migration was associated with settlement concentration and medium–high population density, dispersed urbanization stimulated residential mobility to suburban areas (Bayona-i-Carrasco et al., 2014; Gkartziros, 2013; Kabisch & Haase, 2011). Suburbanization in turn affected metropolitan structures and socioeconomic functions, determining a huge decline of central cities together with other impacts (Carlucci et al., 2018; Duvernoy et al., 2018; Henrie & Plane, 2008). In such contexts, analysis of demographic dynamics at disaggregated spatial scales may outline latent trends toward short-haul mobility and preference for large dwellings in peri-urban locations (Allen et al., 2004; Cuadrado-Ciuraneta et al., 2017; Gutiérrez-Posada et al., 2017).

Assuming that Mediterranean countries share comparable demographic outcomes at the regional scale and over long time periods (Carlucci et al., 2017), the results of global and local (econometric) models may contribute to define internal and external factors shaping local-scale population dynamics (Lande et al., 2017; Larramona, 2013; Leichenko, 2001). With this perspective in mind, density-dependent regulation of population dynamics was tested at municipal scale in Greece over a time interval encompassing a metropolitan cycle with sequential waves from urbanization to re-urbanization (Egidi et al., 2020). More specifically, the time interval investigated here was divided in four sub-periods reflecting urbanization, suburbanization, counter-urbanization, and re-urbanization dynamics (Morelli et al., 2014). The econometric specification was intended to distinguish density-dependent from path-dependent processes of demographic growth, controlling for agglomeration, scale, and spatial effects (Salvati, 2020). Population growth rates at the decade $t +$

$2/t + 1$ (the dependent variable) was specified as a function of population growth rates at the decade $t + 1/t$, population size (log) at time t , demographic density at time t , and perimeter-to-area ratio (a control variable assessing size and morphology of each municipality and indirectly testing the possible influence of scale). To evaluate the role of territorial dynamics, both spatially implicit and spatially explicit techniques were adopted here (Lanfredi et al., 2022). By integrating basic indicators of demographic change and fluctuations in population density, comparative approaches based on global (e.g. quantile) and local (e.g. geographically weighted) regressions, may provide a basic knowledge of intensity and spatial direction of urban growth, reflecting trans-scalar dynamics over time (Benassi et al., 2020; Salvati et al., 2019; Serra et al., 2014).

Integrated results of both parametric (spatially implicit Ordinary Least Squares, OLS, and spatial autoregressive) models and non-parametric techniques (quantile regressions) may better delineate the influence of different socioeconomic contexts (Nickayin et al., 2022) and the importance of spatial heterogeneity in local-scale population dynamics (Beeson et al., 2001; Crescenzi et al., 2016; Salvati & Carlucci, 2016). These findings contribute to regional science with a more complete understanding of the metropolitan cycle—an issue of vital importance when assessing long-term city metabolism and (rapidly changing) urban–rural relationships (e.g. Cecchini et al., 2019; Chen, 2009; Grafeneder-Weissteiner & Prettnner, 2013). To accommodate such considerations, the present study was structured in six chapters as follows. Section 2 provides a brief literature review. Section 3 describes the methodology and input data adopted in this study. Section 4 illustrates the empirical results of the study. Section 5 discusses the novel contribution of the study with respect to recent literature, and Sect. 6 concludes the paper with indications for future research.

2 Literature

Earlier studies have demonstrated the validity of the hypothesis of density-dependent regulation of population size for human populations (Åström et al., 1996; Baldini, 2015; Bell, 2015). However, these studies have also highlighted some important differences with density-dependent mechanisms typical of biological (non-human) populations (e.g. Cayuela et al., 2019; Duncan et al., 2001; Salvati, 2020). An evident divergence with animal ecology is intrinsically grounded in the fact that density-dependent regulation can explain only a part of the overall variability of population growth rates in the human species (Cohen, 2003), being in turn mediated by individual choices/preferences, cultural, ethnic and religious factors, the socioeconomic context at large, and exogenous processes of a stochastic nature, not always identifiable and easily modeled (Getz, 1996; Mathur et al., 1988; Millward, 2008). Elements in common with the broad literature dealing with animal ecology are (1) the intrinsic stochasticity (Fauteux et al., 2021) associated with density-dependent mechanisms (i.e. the prevalence of positive, neutral, or negative impacts of density on short-term population growth rates), (2) temporal volatility (Nowicki et al., 2009), and (3) spatial heterogeneity underlying the complex mosaic of growth and decline typical of human populations (Ciommi et al., 2020). These factors are observed under demographic conditions of dynamic equilibrium (Lesthaeghe, 2014; Rees et al., 2017; Reher, 2011), i.e. along sufficiently long time ranges and in geographical areas large enough to be representative of short and medium-range movements of a given population (e.g. a country or a large region).

Density-dependent regulation of population growth proved to be interconnected with other socioeconomic processes (Hamilton et al., 2009). As an indirect proof of such dynamics, density-dependent impacts on human population growth were demonstrated to be significant only in certain contexts, e.g. at specific times and spaces, and mostly in correspondence with other economic phenomena that accelerate or limit their action (Benassi et al., 2020; Gross, 1954; Turchin, 2009). Nonetheless, a comparative analysis of the (positive or negative) feedback mechanisms at the basis of population dynamics appears indispensable for regional demography, applied economics, and urban studies, considering together various socioeconomic aspects of population growth and decline (Ciommi et al., 2022), and controlling for the role of space (e.g. Salvati & Carlucci, 2017; Soutullo et al., 2006; Turchin, 1990). To investigate the intrinsic impact of distinctive background contexts, such analyses should be run over sufficiently long time intervals (Ciommi et al., 2018; Salvati & Serra, 2016; Salvia et al., 2021).

Based on these premises, the sequential phases of a metropolitan cycle represent the appropriate background influencing density-dependent and path-dependent mechanisms of population growth (Salvati & Gargiulo, 2014). To our knowledge, the present study empirically tested—for the first time in the literature—the working hypothesis that distinctive phases of the city life cycle (urbanization, suburbanization, counter-urbanization, and reurbanization) may differently shape population dynamics, distinguishing density-dependent from density-independent regulation processes (Vinci et al., 2022). In this perspective, databases including representative data and variables at disaggregated spatial scales are still scarce and require refined procedures of standardization, validation, and control (Kroll & Kabisch, 2012; Osterhage, 2018; Partridge et al., 2009).

Despite the inherent complexity of metropolitan transformations, density-dependent population dynamics have been occasionally investigated along a complete metropolitan cycle in Europe. In regions with homogeneous settlement configurations (Allen et al., 2004), intense within-country variability in the spatial distribution of resident population and across-country differences in population density have resulted in heterogeneous socio-demographic patterns (e.g. Salvati & Carlucci, 2017). In Mediterranean Europe, such trends have reflected intense economic downturns leading to urbanization-suburbanization-reurbanization sequences accelerated by a rapid demographic transition toward low fertility and childbearing postponement, higher life expectancy, and rising immigration (Bayona-Carrasco et al., 2014; Cuadrado-Ciuraneta et al., 2017; López-Gay, 2014). This region has represented a paradigmatic example of urban expansion all over Europe, with resident population growing steadily from 89 million inhabitants (1950) to 258 million inhabitants (1995), being estimated to reach 416 million inhabitants in 2030. Urbanization rates in 1995 were ranging between 59% (Greece) and 77% (Spain), and are predicted to increase (more or less) markedly by the year 2030 (Carlucci et al., 2017; Oueslati et al., 2015; Zambon et al., 2018). Together with Spain, Portugal and Italy, the recent history of Greece is representative of heterogeneous demographic dynamics at local scale, although with different population size in respect with other countries (e.g. Gavalas et al., 2014). The densest locations coincided with central cities and the associated metropolitan areas including urban centers that attract economic activities and host key social functions (Zambon et al., 2019).

Testing density-dependent population dynamics in Europe may benefit from the operational definition of Territorial Statistical Units (the so called NUTS nomenclature system) provided by Eurostat, the Statistical Office of the European Commission. Considering municipalities as the elementary analysis' unit (e.g. Salvati & Carlucci, 2017), a relatively vast amount of data, variables, and indicators was made available in the last decade,

allowing a proper between-country comparison as far as basic socioeconomic phenomena are concerned (Kabisch & Haase, 2011). The present study exploited a specific dataset recently released by Eurostat and derived from national censuses (Ciommi et al., 2018) with the aim at testing the existence of density-dependent growth processes at a local scale in Greece, in turn distinguishing the impact of path-dependence, agglomeration, and spatial heterogeneity over a long time period encompassing the last half century (1961–2011). A quantitative approach based on non-parametric techniques (quantile regression) and local models (geographically weighted regression) was proposed to achieve this goal (Salvati et al., 2019). Indicators deriving from the empirical results of such models provided an integrated assessment of the importance of the regulatory mechanisms of population dynamics over time and space.

3 Methodology

3.1 Study Area

The investigated area extends the whole of Greece (131,982 km²). Municipalities ('dimoi' and 'koinotites' in Greek) corresponding to the NUTS-5 (Nomenclature of Territorial Statistical Units) level adopted by Eurostat, the Statistical Office of European Union, were chosen as the elementary spatial unit in this study (Rontos et al., 2016). Municipalities in Greece (n=1033) were considered a suitable analysis' unit when investigating spatial patterns of population and economic activities, possibly as a function of basic geographical gradients (Morelli et al., 2014). Municipalities illustrate the geography of Greece identifying (1) the major urban areas in the country (e.g. Athens, Thessaloniki, Heraklion), (2) dynamic (non-urban) coastal areas and islands in both Ionian and Aegean Sea attracting tourists and resident population, and (3) internal, rural areas exposed to depopulation and economic marginality (Zambon et al., 2019). Urban primacy was evident in Greece, since the Athens' metropolitan region concentrated more than 30% of total country population since 1951 (Cecchini et al., 2019), a characteristic of other Mediterranean countries, such as Portugal, and large European nations, such as France (Ciommi et al., 2018).

3.2 Data and Variables

Taken as a basic element of European NUTS classification that includes territorial units representative of local communities, Local Administrative Units (LAU) have a key role in official statistics because of data availability from national censuses and relevance for implementation of local policy (Di Feliciano & Salvati, 2015). The present study made use of a collection of total population data disseminated by Eurostat (the statistical office of European Commission) and derived from homogeneous national censuses carried out every 10 years at each LAU-2 unit for 6 time points (1961, 1971, 1981, 1991, 2001, and 2011). Since LAUs were subjected to minor changes over long observation times, Eurostat disseminated a homogenized list of spatial units and boundaries for cross-region and cross-country comparisons (Salvia et al., 2021). Four variables were elaborated from total population data: (1) per cent annual change in resident population over specific inter-census decades (i.e. 1961–1971, 1971–1981, 1981–1991, 1991–2001, 2001–2011), (2) demographic density, i.e. the ratio of resident population in total municipal area (km², log), (3) population size, i.e. the absolute number of inhabitants in each municipality at a given time (log),

and (4) perimeter-to-area ratio, an indicator derived from landscape ecology and assessing the overall configuration and spatial form of local administrative units in Greece, being computed from a shapefile of municipal boundaries released by Eurostat (Benassi et al., 2020). Variables (1) and (2) allow an explicit test of path-dependent and density-dependent regulation of population dynamics (Salvati, 2020). Variable (3) was used to document the importance of agglomeration, as measured by population concentration (Carlucci et al., 2018) and variable (4), intended as an internal control, provides in turn an indirect verification of the non-significant role of administrative size (i.e. municipal area) in population dynamics (Morelli et al., 2014).

3.3 Statistical Analysis

Data analysis was carried out mixing descriptive statistics and non-parametric correlations with spatially implicit and explicit (cross-section) models specifying population growth rates as a function of previous (i.e. lag-1) growth rates, demographic density, population size, and perimeter-to-area ratio of each municipality.

3.3.1 Descriptive Statistics

The statistical distribution of annual population growth rates across Greek municipalities ($n=1033$) was analyzed using metrics of (1) central tendency/dispersion (average, standard error, minimum and maximum) and (2) ranking/form (median, skewness, kurtosis, 25th and 75th percentile), calculated separately for each decade (1961–1971, 1971–1981, 1981–1991, 1991–2001, 2001–2011). These metrics provide a preliminary description of the target variable and were enriched with a graphical approach based on Box-Wisher plot (Di Feliciano et al., 2018) illustrating the spatio-temporal pattern of the same variable through the use of minimum and maximum values (whiskers), 25th and 75th percentiles (box), and the 50th percentile (the line within the box). The same variable was finally mapped for each Greek municipality using a shapefile provided by Eurostat (GISCO). Assuming that spatial variation in population growth rates is dependent on local contexts (Salvati & Serra, 2016), the relationship between population growth rates and demographic density was initially quantified using a pair-wise correlation analysis that compares parametric (Pearson product-moment) and non-parametric (Spearman rank) coefficients with the aim at testing linearity (or non-linearity) of the relationship between these two variables (Taylor & Demaster, 1993). Both coefficients range between 1 (the highest positive correlation between two variables) and -1 (the highest negative correlation between the two variables) with 0 indicating uncorrelated variables. Significant pair-wise correlations were tested at $p < 0.05$ after Bonferroni's correction for multiple comparisons (Ciommi et al., 2019). The absolute ratio of Spearman to Pearson coefficients by year and country outlines the main type of relationship (prevalently linear or non-linear). A particularly high ratio (Spearman higher than Pearson coefficient) indicates a non-linear relationship between demographic density and population growth (Duvernoy et al., 2018).

3.3.2 Econometric Models

In line with earlier literature (e.g. Salvati, 2020), our work assumed different spatial regimes of population dynamics associated with each phase of the metropolitan cycle (sensu Zambon et al., 2019), modelling the variability in population growth rates (PG_1) as

a function of (1) population growth rate (PG_0) in the previous (i.e. $lag_{(-1)}$) time period, (2) population density (PD_0), and (3) the overall size of the resident population as a proxy of agglomeration (PS_0). The analysis has also considered (4) spatial dimension and configuration of municipalities—estimated as the perimeter-to-area ratio (PA), a landscape ecology metric adopted as a proxy of scale (Kazemzadew-Zow et al., 2017) and, together, intended as a control variable under the assumption that the administrative size of municipalities does not influence population dynamics (Salvati et al., 2019). All variables were standardized prior to analysis (Di Felicianantonio et al., 2018). Use of these variables in econometric models testing density-dependent regulation of human population dynamics was earlier discussed in Benassi et al. (2020). Model specification was summarized as follows:

$$PG_1 = a + b_1PG_0 + b_2PD_0 + b_3PS_0 + b_4PA + e \quad (1)$$

where a is the regression constant and e is the stochastic error of the model. Models were run controlling for time (i.e. distinguishing the impact of the four phases of the metropolitan cycle mentioned above) and space (i.e. using global and spatially explicit econometric specifications and comparing results with those from spatially implicit, global specifications and from local specifications). These specifications allow distinguishing the role of density-dependent regulation of population growth from the more general path-dependency of local population dynamics (Cohen, 2003), highlighting the importance of direct spatial effects, and separating them from the indirect ones (i.e. spillovers). The time schedule of the four phases of the metropolitan cycle in Greece was defined according with Morelli et al. (2014) as follows: urbanization (1971–1981), suburbanization (1981–1991), counter-urbanization (1991–2001), and re-urbanization (2001–2011). Cross-section regressions were run for each time interval mentioned above, assuming each phase of the metropolitan cycle as representative of distinctive socioeconomic contexts and demographic dynamics at the local scale (Di Felicianantonio & Salvati, 2015). A Variance Inflation Factor (VIF) was finally calculated for each time interval. Values systematically below 10 for all variables delineate a non-redundant structure of predictors' matrix (Duvernoy et al., 2018).

3.3.2.1 Spatially Implicit, Global Models Assuming linear changes over time in population distribution across urban and rural areas, the relationship between population growth rates as the dependent variable and selected predictors (see above) was initially tested adopting a linear specification of standardized input variables separately for each year through the use of global regressions based on Ordinary Least Squares (OLS). The models' goodness of fit was checked by way of adjusted R^2 coefficients. Inference on regression results (i.e. Fisher-Snedecor F tests and Student t tests respectively on the overall regression fit and on individual coefficients, testing against the null hypothesis of zero coefficients with $p < 0.001$) provided an additional criterion for model's evaluation (Zambon et al., 2018). To verify violations in the basic assumptions of a general linear model, a Durbin–Watson (DW) statistic checking for serial correlation, a Breusch–Pagan (BP) index for heteroscedasticity, and a Moran (M) spatial autocorrelation coefficient for spatial dependence of residuals were run for each model, testing for significance at $p < 0.05$ against the null hypothesis of no serial correlation, no heteroscedasticity, and no spatial autocorrelation structure, respectively.

A non-parametric (quantile) regression was run to model the same relationship illustrated above (4 predictors and four percentiles of population growth rate as the dependent variable) in a framework of non-linear dependence among variables and deviation from normality. This regression technique estimates changes in a specified percentile of the dependent variable produced by a given change in the predictors, without imposing

stringent parametric assumptions. Model's outcomes include slope coefficient estimates and the associated significance level (testing for the null-hypothesis of non-significant regression coefficient) based on Student t statistics at $p < 0.05$. Goodness-of-fit of each model was assessed using pseudo R^2 and tested for significance (against the null hypothesis of non-significant model) through a Fisher–Snedecor F test with $p < 0.001$. A statistic assessing slope equality was finally provided to verify significant differences among regression coefficients against the null hypothesis of equal coefficients across quantile models.

3.3.2.2 Spatially Explicit, Global Models The relationship between population growth rates and the four predictors mentioned above was further assessed using global models that make spatial relations explicit using a linear distance matrix (W) among elementary units (i.e. municipalities). Separate regressions were run for each phase of the metropolitan cycle (Egidi et al., 2020), considering together the results of different statistical techniques that use the same specification to model the spatial distribution of decadal population growth rates across Greek municipalities. To delineate the most significant variables influencing population dynamics in local systems (Ali et al., 2007), a comparative approach based on the use of different regression techniques modelling the joint impact of predictors, allows an indirect assessment of stability in model's outcomes (Salvati et al., 2019). While presenting a variable goodness-of-fit, consistent regression outputs (i.e. the same significant predictors with comparable intensity and sign) may identify a statistically stable (and conceptually relevant) relationship between population growth rates and the selected predictors (Benassi et al., 2020), under a specific background context (i.e. a given phase of the metropolitan cycle).

By investigating the dependence of a given variable's value on the values of the same variable recorded at neighboring locations, spatial regressions were intended here as an extension of linear regressions (Fotheringham et al., 2003). Spatial autocorrelation assumes outcome in one area to be affected by outcomes, covariates or errors in nearby areas, meaning that models may contain spatial lags of the outcome variable, spatial lag of covariates, and autoregressive errors, respectively (Partridge et al., 2009). The lag operator becomes a $N \times N$ matrix W describing the spatial arrangement of the N units computed using planar coordinates where each entry $w_{ij} \in W$ represents the spatial weight associated to units i and j (Ali et al., 2007). In order to exclude self-neighbors, the diagonal elements w_{ii} are conventionally set equal to zero. Overall, our analysis run a cross-sectional Spatial Durbin Model (SDM) and, to assess the stability of model's results over time, two additional models were tested using the same specification and input variables: a Spatial Autoregressive Model (SAR), and a spatial autoregressive error term (SEM). Both direct and indirect (spillover) effects between municipalities were detected. Best-fit estimation of the proposed models using empirical data was evaluated using pseudo R^2 . Since the results of SAR and SEM are completely aligned with those from SDM, these results were not explicitly published, remaining fully available from the authors.

As in the case of spatially implicit global models illustrated above (Sect. 2.3.3.1), a non-parametric (quantile) regression was run to model the same relationship illustrated above (4 predictors and four percentiles of population growth rate as the dependent variable) in a framework of (1) deviation from normality, (2) non-linear dependence, and (3) spatial relations among variables. This technique estimates changes in a specified percentile of the dependent variable produced by a given change in the predictors, without imposing stringent parametric assumptions and adopting W as the spatial weighting matrix (see above). Model's outcomes include slope coefficient estimates and the associated significance level

(testing for the null-hypothesis of non-significant regression coefficient) based on Student t statistics at $p < 0.05$.

3.3.2.3 Spatially Explicit, Local Models To predict the intrinsic variability of population growth rates across Greece, the empirical results of global models were refined with a spatially explicit (local estimation) strategy based on Geographically Weighted Regressions (GWRs) adopting the specification presented in Eq. 1. Originally proposed by Fotheringham et al. (2003), GWRs estimate regression parameters at each location using weighted least squares, implying that each coefficient in the model is a function of space (s), and thus giving rise to a distribution of local estimated parameters (Partridge et al., 2009). The weights for the estimation of local regression models were derived from a bi-square nearest neighbor kernel function, a common specification placing more weight on the observations closer to the location s (Ali et al., 2007). Regressions were estimated separately for each phase of the metropolitan cycle (Zambon et al., 2019). Model's goodness of fit was assessed using (global and local) R^2 coefficients. A t -statistic testing for significant regression coefficients at $p < 0.01$ was considered an additional criterion for model evaluation. Maps with the spatial distribution of local parameters were provided for intercept, predictors' coefficients, R^2 value, and the standardized residuals of each model (Carlucci et al., 2018).

4 Results

4.1 Descriptive Statistics

The statistical distribution of annual population growth rates over time was explored using descriptive metrics of central tendency and dispersion (Table 1). By computation on the municipal rates of population growth ($n = 1033$), both mean and median values were found slightly negative for the first (1961–1971) and the last (2001–2011) decades and positive for the remaining three decades, with moderate standard errors. Minimum and maximum rates indicate a substantial heterogeneity in population dynamics, with accelerations during 1961–1971 and 1981–1991, and a weak deceleration

Table 1 Indicators of the statistical distribution of population growth rates (%) across Greek municipalities by decade

Metric	1961–1971	1971–1981	1981–1991	1991–2001	2001–2011
<i>Central tendency and dispersion</i>					
Minimum	− 0.60	− 0.56	− 0.48	− 0.37	− 0.75
Maximum	2.46	1.94	2.56	2.49	1.80
Mean	− 0.054	0.067	0.095	0.094	− 0.072
Std. error	0.009	0.009	0.008	0.007	0.008
<i>Ranking and distribution form</i>					
Median	− 0.12	0.01	0.05	0.04	− 0.10
25th perc	− 0.21	− 0.09	− 0.05	− 0.04	− 0.22
75th perc	0.00	0.14	0.16	0.15	0.04
Skewness	3.08	2.16	3.03	2.97	1.77
Kurtosis	15.0	7.9	17.5	16.8	7.6

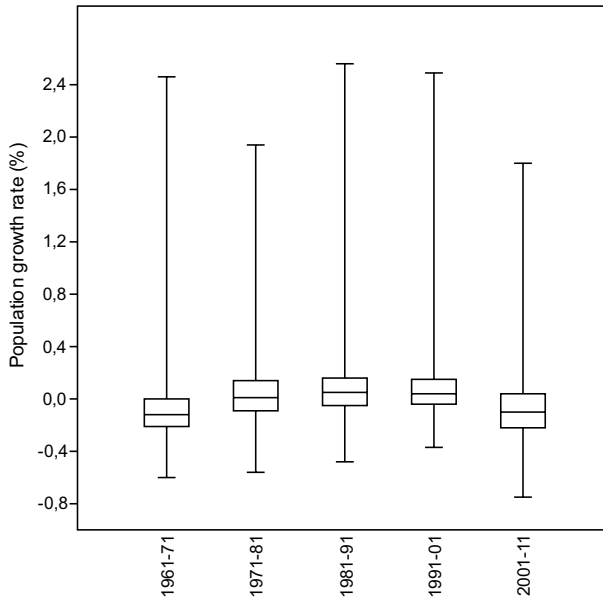


Fig. 1 Box-Wisher plot illustrating the statistical distribution of population growth rates (%) across Greek municipalities by decade

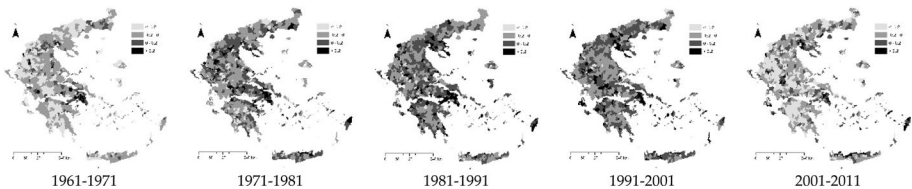


Fig. 2 Spatial distribution of population growth (per cent annual rates) in Greek municipalities by decade

during 2001–2011. Skewness was intense with positive population growth rates, and the reverse pattern was observed with demographic decline. Kurtosis followed a slightly different trend, reaching the highest values between 1981 and 2001 and declining since 2001. A Box-Wisher plot (Fig. 1) reflects a particularly heterogeneous distribution of population growth rates with a long tail including positive values in urban and peri-urban contexts. Less heterogeneous distributions were observed in two decades reflecting distinctive demographic contexts (high fertility and medium–low mortality rates, 1971–1981; low fertility and medium–high mortality rates, 2001–2011). The statistical distribution of population growth rates follows a spatial gradient from urban areas to rural districts (Fig. 2). The highest growth rates were observed in the metropolitan regions of Athens and Thessaloniki, the two largest agglomerations in Greece. Positive growth rates were also observed in Crete, Rhodes, Peloponnese (in correspondence with Patra’s agglomeration), and Central Greece (in correspondence with Ioannina urban area). Inland municipalities experienced intense population decline as a consequence of a continuous rural–urban exodus.

Results of a preliminary correlation analysis exploring path-dependent and density-dependent population growth in Greek municipalities were illustrated in Table 2. To discriminate linear from non-linear pair-wise relationships, results of parametric (Pearson) and non-parametric (Spearman and Kendall) coefficients were analyzed together. More specifically, path-dependent growth was tested correlating the statistical distribution of population growth rates over a given decade with the same variable's distribution over the previous decade. Density-dependent growth was instead tested correlating the statistical distribution of population growth rates over a given decade with the statistical distribution of population density at the beginning of the same decade. Path-dependent population growth was significant and linear for all decades, being more intense at the beginning and the end of the study period. Positive (and linear) density-dependence was observed only for the initial and final decade in Greece. The strength of non-linear correlation coefficients (both Spearman and Kendall) increased in correspondence with a weak demographic recovery (2001–2011) after a continuous fertility decline starting in the mid-1970s. In all cases, the absolute value of coefficients and the associated probability values testing for significance of the null hypothesis (absence of a pair-wise correlation between the studied variables) were not particularly intense, justifying a refined econometric analysis that considers spatial issues explicitly.

4.2 Global Regression Models

Results of global econometric approaches (both spatially implicit and explicit) regressing population growth rates at a given decade with (1) population growth rates at the previous decade, (2) population size and, (3) demographic density—both measured at the beginning of the previous decade, as well as (4) a control variable quantifying municipal form (perimeter-to-area ratio) were illustrated in Table 3.

4.2.1 Spatially Implicit Regression Models

Ordinary Least Square (OLS) regressions were run as a baseline. Computing on standardized input variables, OLS regressions delineated a positive impact of both path-dependence

Table 2 Pair-wise correlation coefficients between (left) population growth rate at decade $t+2/t+1$ and decade $t+1/t$ and (right) population growth rate at decade $t+1/t$ and population density at time t (parametric Pearson coefficients indicate linear correlations; non-parametric Spearman and Kendall coefficients indicate non-linear correlations)

Variable	Pearson		Spearman		Kendall	
	Growth	Density	Growth	Density	Growth	Density
1961–1971	–	0.47**	–	0.44**	–	0.31**
1971–1981	0.55**	0.34**	0.57**	0.36**	0.42**	0.25*
1981–1991	0.41**	0.11*	0.18*	0.20*	0.12*	0.14*
1991–2001	0.41**	0.12*	0.32**	0.24*	0.23*	0.17**
2001–2011	0.40**	0.36**	0.35**	0.52**	0.26*	0.37**

*Significant coefficient at $0.001 < p < 0.05$

**Significant coefficient at $p < 0.001$; significance level after Bonferroni's correction for multiple correlations

Table 3 Comparative results of global (left) spatially implicit Ordinary Least Square (OLS) and quantile (τ) regressions, and (right) a spatially explicit Durbin model (SDM, taken as baseline) and quantile (τ) regressions exploiting a W distance matrix with population growth rates between $t+2$ and $t+1$ as dependent variable and (1) population growth rates between $t+1$ and t , (2) population size (log) at time t , (3) demographic density (log) at time t , and (4) perimeter-to-area ratio as predictors (ns not significant; $*0.01 < p < 0.05$; $**p < 0.01$; VIF: Variance Inflation Factor)

Predictor	OLS	Spatially implicit quantile regression			SDM	Spatially explicit quantile regression			VIF	
		$\tau = 0.75$				$\tau = 0.75$				
		$\tau = 0.25$	$\tau = 0.5$	$\tau = 0.99$		$\tau = 0.25$	$\tau = 0.5$	$\tau = 0.99$		
<i>1971–1981</i>										
Intercept	≈ 0.0 (0.025)	- 0.448 (0.024)**	- 0.110 (0.022)**	0.323 (0.042)**	2.111 (0.210)**	0.001 (0.025)	- 0.420 (0.022)**	- 0.091 (0.024)**	0.362 (0.054)**	2.180 (0.216)**
Pop.growth	0.461 (0.030)**	0.440 (0.033)**	0.481 (0.039)**	0.612 (0.062)**	0.783 (0.174)**	†0.451 (0.031)**	0.437 (0.040)**	0.490 (0.045)**	0.640 (0.074)**	0.636 (0.168)**
Pop.size	- 0.277 (0.051)**	0.037 (0.034)	- 0.098 (0.039)*	- 0.294 (0.069)**	- 0.878 (0.434)*	- 0.268 (0.052)**	0.055 (0.043)	- 0.107 (0.044)*	- 0.318 (0.091)**	- 0.891 (0.344)**
Dem.density	0.232 (0.068)**	0.074 (0.041)	0.103 (0.053)*	0.151 (0.097)	0.307 (0.591)	0.214 (0.068)**	0.017 (0.066)	0.123 (0.060)*	0.175 (0.099)	0.330 (0.531)
Per-area ratio	- 0.035 (0.052)	- 0.054 (0.045)	- 0.030 (0.044)	0.003 (0.127)	0.291 (0.770)	- 0.037 (0.052)	- 0.034 (0.055)	- 0.046 (0.064)	- 0.052 (0.118)	0.278 (0.617)
Breusch-Pagan	95.88**					§72.0**				
Durbin-Wats	1.68**									
Slope equality		25.7**					**	ns	ns	ns
Moran's $I(z)$	5.09*									
W sp. Matrix										
Adjusted R^2	0.336	0.156	0.185	0.239	0.477	0.345				
<i>1981–1991</i>										
Intercept	≈ 0.0 (0.027)	- 0.539 (0.024)**	- 0.099 (0.031)**	0.407 (0.039)**	2.299 (0.525)**	- 0.006 (0.028)	- 0.537 (0.028)**	- 0.110 (0.039)*	0.416 (0.046)**	2.625 (0.476)**
Pop.growth	0.353 (0.030)**	0.128 (0.036)**	0.295 (0.044)**	0.419 (0.055)**	0.636 (0.672)	0.342 (0.030)**	0.128 (0.056)*	0.298 (0.060)**	0.413 (0.060)**	0.572 (0.147)*

Table 3 (continued)

Predictor	OLS		Spatially implicit quantile regression				Spatially explicit quantile regression				VIF	
			$\tau=0.25$	$\tau=0.5$	$\tau=0.75$	$\tau=0.99$	SDM	$\tau=0.25$	$\tau=0.5$	$\tau=0.75$		$\tau=0.99$
Pop.size	-0.431 (0.057)**		-0.056 (0.045)	-0.259 (0.049)**	-0.500 (0.065)**	-1.282 (0.752)	-0.416 (0.058)**	-0.059 (0.052)	-2.576 (0.064)**	-0.491 (0.071)**	-1.201 (0.260)**	4.51
Dem.density	0.317 (0.076)**		0.147 (0.058)*	0.206 (0.062)**	0.270 (0.081)**	0.597 (0.939)	0.285 (0.076)**	0.148 (0.068)*	0.213 (0.067)*	0.265 (0.010)*	0.513 (0.311)	6.87
Per-area ratio	-0.141 (0.055)		-0.095 (0.051)	-0.143 (0.053)**	-0.138 (0.065)*	-0.332 (0.582)	-0.144 (0.056)	-0.096 (0.053)	-0.139 (0.049)	-0.134 (0.082)	-0.338 (0.284)	4.20
Breusch-Pagan	163.0**						§32.8**					
Durbin-Wats	1.82**											
Slope equality		28.8**										
Moran's I(z)	2.75*							ns	ns	ns	ns	
W sp. matrix												
Adjusted R ²	0.230		0.025	0.057	0.159	0.407	0.240					
1991-2001												
Intercept	≈ 0.0 (0.027)		-0.503 (0.026)**	-0.156 (0.030)**	0.336 (0.038)**	2.845 (0.640)**	≈ 0.0 (0.028)	-0.502 (0.031)**	-0.150 (0.032)*	0.347 (0.030)*	2.827 (0.351)*	
Pop.growth	0.325 (0.029)**		0.229 (0.039)**	0.310 (0.042)**	0.426 (0.049)**	1.085 (0.671)	0.327 (0.030)**	0.218 (0.050)**	0.316 (0.070)*	0.412 (0.047)*	0.873 (0.374)	1.14
Pop.size	-0.411 (0.061)**		-0.044 (0.046)	-0.203 (0.044)**	-0.439 (0.067)**	-1.676 (0.591)**	-0.409 (0.062)**	-0.020 (0.064)	-0.188 (0.063)*	-0.423 (0.096)*	-1.739 (0.353)*	5.05
Dem.density	0.380 (0.079)**		0.136 (0.058)	0.229 (0.059)**	0.365 (0.072)**	1.439 (0.943)	0.378 (0.081)**	0.074 (0.076)	0.187 (0.068)	0.324 (0.116)	1.504 (0.541)	7.50
Per-area ratio	-0.081 (0.056)		-0.040 (0.034)	-0.068 (0.047)	-0.116 (0.044)**	-0.505 (0.859)	-0.083 (0.056)	-0.009 (0.048)	-0.059 (0.051)	-0.134 (0.078)	-0.548 (0.366)	4.20

Table 3 (continued)

Predictor	OLS	Spatially implicit quantile regression			SDM	Spatially explicit quantile regression			VIF	
		$\tau=0.25$	$\tau=0.5$	$\tau=0.75$		$\tau=0.25$	$\tau=0.5$	$\tau=0.75$		
Breusch–Pagan	87.3**				§53.7**					
Durbin–Wats	1.74**									
Slope equality		20.2**								
Moran's I(z)	1.56									
W sp. matrix						ns		*	*	
Adjusted R ²	0.223	0.047	0.081	0.161	0.222					
2001–2011										
Intercept	≈ 0.0 (0.027)	– 0.499 (0.030)**	– 0.021 (0.029)**	0.390 (0.029)**	3.115 (0.293)**	0.002 (0.027)	– 0.454 (0.027)*	– 0.023 (0.031)	0.415 (0.027)*	2.960 (0.434)
Pop.growth	0.390 (0.029)**	0.198 (0.046)**	0.415 (0.043)**	0.588 (0.041)**	1.585 (0.326)**	0.388 (0.029)**	0.201 (0.040)*	0.401 (0.052)*	0.564 (0.053)*	0.607 (0.312) 1.14
Pop.size	0.145 (0.061)*	0.303 (0.055)**	0.235 (0.046)**	0.100 (0.050)*	0.188 (0.542)	0.155 (0.061)*	0.331 (0.062)*	0.232 (0.058)*	0.079 (0.057)	0.245 (0.447) 5.10
Dem.density	0.140 (0.080)	0.081 (0.072)	0.023 (0.057)	0.061 (0.054)	– 0.864 (0.813)	0.122 (0.081)	0.043 (0.081)	0.019 (0.081)	0.053 (0.070)	– 0.640 (0.633) 7.75
Per-area ratio	0.045 (0.055)	0.024 (0.050)	0.092 (0.048)	0.049 (0.032)	0.874 (0.679)	0.046 (0.056)	0.021 (0.056)	0.058 (0.057)	0.031 (0.050)	1.230 (0.732) 4.15
Breusch–Pagan	93.5**				§38.6**					
Durbin–Wats	1.74**									
Slope equality		26.2**								

Table 3 (continued)

Predictor	OLS		Spatially implicit quantile regression		SDM		Spatially explicit quantile regression		VIF
	$\tau=0.25$	$\tau=0.5$	$\tau=0.75$	$\tau=0.99$	$\tau=0.25$	$\tau=0.5$	$\tau=0.75$	$\tau=0.99$	
Moran's $I(z)$		2.74*							
W sp. matrix					*	*	*	*	*
Adjusted R^2	0.150	0.167	0.202	0.232	0.237				

* Direct effects of SDM reported here; indirect (spillover) effects significant only for population growth, 1961–1971 (coeff: 0.135 ± 0.059)*

§ Breusch–Godfrey test for serial auto-correlation of order up to 3

and density-dependence and a negative impact of population size for the first decade (1971–1981) under investigation. Similar results were found for the subsequent two decades (1981–1991 and 1991–2001), with slight changes in the regression coefficients. Although positive and significant, path-dependence declined over time and the reverse pattern was observed for density-dependence. The net impact of population size (taken as a measure of demographic agglomeration) was negative and significant, with regression coefficients increasing between the first and the second decade under investigation, and then decreasing in the third decade. Model's estimation for the last decade (2001–2011) provided completely different results in comparison with the previous time intervals. The impact of path-dependence remained positive and significant; density-dependence was instead insignificant. The effect of population size become positive and moderately significant. The control variable received insignificant coefficients, confirming the absence of any indirect effect of municipal size. Variance Inflation Factor (VIF) was systematically below 10 for each variable, suggesting a non-redundant structure of predictors' matrix.

Adjusted R^2 documents how model's specification explained a variable proportion of the total variance, usually larger at the beginning of the study period (urbanization wave). Adjusted R^2 decreased from 0.34 (1971–1981) to 0.24 (2001–2011), suggesting that model's specification provided better results during urbanization in respect with the subsequent three phases of the metropolitan cycle. Intermediate values of R^2 coefficients reflect an evident heterogeneity in the municipal sample, whose interpretation justifies the use of refined econometric techniques. Results of econometric tests (Breusch–Pagan, Durbin–Watson, and Moran) further indicate that OLS estimation was (more or less) biased for all the decades under investigation. Serial correlation, heteroscedasticity, and spatial dependence tests were all significant, and suggest the adoption of more flexible models with less rigid assumptions as far as the input variables are concerned.

Results of spatially implicit quantile regressions (Table 3) outline a completely different relationship between the dependent variable and the predictors, as far as regression coefficients (slope equality tests) and goodness-of-fit (adjusted R^2) clearly document. While decreasing substantially over time and thus reflecting the pattern already observed with OLS regressions, goodness-of-fit increased systematically in homogeneous sub-samples of municipalities moving from low population growth rates ($\tau=0.25$) to higher rates ($\tau=0.99$). For all decades, path-dependence was always significant and positive, with the only exception of 0.99th percentile during suburbanization and counter-urbanization. Population size received significantly negative coefficients for both 50th, 75th and 99th percentiles during urbanization, suburbanization, and counter-urbanization. With re-urbanization, population size has displayed positive coefficients, with the exception of more dynamic municipalities ($\tau=0.99$). Density-dependence was significant and positive for the second quartile (50th) with urbanization, and for the second (50th) and third (75th) quartiles with both suburbanization and counter-urbanization, being insignificant with re-urbanization. Perimeter-to-area ratio was systematically non-significant, being only weakly significant for the second and third quartiles during suburbanization and the third quartile during counter-urbanization.

4.2.2 Spatially Explicit Regression Models

A Spatial Durbin Model (SDM) was run as a baseline for global regressions considering the spatial structure of input data explicitly (Table 3). Using the same specification, results of SDM were compared with simplified (Spatially Autoregressive, SAR, and Spatial Error,

SEM) models. Comparing models' outcomes over time revealed a satisfactory stability of regression coefficients, similar adjusted R^2 and aligned diagnostics (data not shown, available upon request from the authors). Considering direct effects, SDM regressions delineated (1) a significant, positive impact of path-dependence (with coefficients decreasing along the cycle from urbanization to counter-urbanization and then recovering under re-urbanization), (2) a negative impact of population size up to counter-urbanization (the highest coefficient observed with suburbanization) turning to a positive impact with re-urbanization, and (3) a positive density dependence with increasing coefficients from urbanization to counter-urbanization, becoming insignificant with re-urbanization. Perimeter-to-area ratio was insignificant for all investigated decades, confirming the appropriateness of the econometric specification. Indirect effects (spillovers) were systematically non-significant, with the only exception of population growth (lag-1) coefficient with urbanization. This result confirms the role of intrinsic regulations of population dynamics under specific phases of the metropolitan cycle. In line with the results of spatially implicit models, adjusted R^2 was larger with urbanization and declined afterwards. Results of a Breusch-Godfrey test indicate a weak serial autocorrelation of order up to 3, suggesting use of non-parametric spatial quantile regressions.

Despite the results of Moran's coefficients (see above), spatially explicit (quantile) regressions document the role of spatial effects only in some cases, being significant for the first quartile (25th) with urbanization and for the last two percentiles (75th and 99th) with counter-urbanization (Table 3). With suburbanization, spatial effects were not significant at all percentiles considered; conversely, spatial effects were always significant with re-urbanization. For all decades, path-dependence was always significant and positive, with the only exception of 0.99th percentile during counter-urbanization and re-urbanization. Density-dependence was significant and positive for the second quartile with urbanization, and for first, second, and third quartiles with suburbanization, becoming not significant with counter-urbanization and re-urbanization. Population size received negative coefficients for both 50th, 75th, and 99th percentiles during urbanization, suburbanization, and counter-urbanization, and positive coefficients for the first and the second quartiles under re-urbanization. Perimeter-to-area ratio was always insignificant. As expected, path-dependence coefficients increased consistently moving from 25 to 99th percentile. Density-dependence coefficients followed the same pattern, with the only exception of re-urbanization.

4.3 Local Regression Models

Results of geographically weighted regressions were illustrated as global outcomes in Table 4 and as local outcomes in Figs. 3 and 4. GWR models had a superior goodness of fit in comparison with the corresponding global models (e.g. OLS or SDM). Considering models pooling the effects of the four predictors, the adjusted R^2 was relatively high for urbanization (0.47), lower for suburbanization (0.32) and counter-urbanization (0.31), and intermediate for re-urbanization (0.40). In line with the results of spatially implicit and spatially explicit models presented in Sect. 3.2, population growth rates in the previous decade (lag-1) explained the largest variability of the dependent variable, ranging between 0.36 and 0.31 along the different phases of the metropolitan cycle. Considering the local outcomes of GWRs, local R^2 systematically above 0.4 were more frequent during urbanization, being concentrated in the Aegean side of Central Greece (Attica and the neighboring regions) and Southern Greece (e.g. Peloponnese, a region basically gravitating on Athens). During suburbanization, local R^2 systematically above 0.4 were found in Attica

Table 4 Global results (adjusted R^2) of geographically weighted regressions with population growth rate over $t+2/t+1$ time interval as dependent variable and (1) population growth rate over $t+1/t$

Time interval	Pop. Growth (lag-1)	+Demo. density (log)	+Popula- tion size (log)	+Perimeter- to-Area ratio
1961–1981	0.363	0.386	0.451	0.473
1971–1991	0.239	0.263	0.299	0.318
1981–2001	0.214	0.232	0.285	0.305
1991–2011	0.309	0.386	0.398	0.402

Moving from left to right, models were augmented with additional predictors, namely (2) demographic density at time t , (3) population size at time t , and (4) perimeter-to-area ratio

and in the surrounding regions that gravitate on Athens (e.g. Evvia, Viotia, Korinthia, Argolida). Goodness of fit of local GWR models maintained the same spatial pattern with systematically low values during counter-urbanization, evidencing the residual role of the Greek capital city. A completely different pattern was observed with re-urbanization, since the highest R^2 coefficients (systematically above 0.4) were observed in Northern Greece only (the region gravitating on Thessaloniki, the second city of Greece), while the role of Athens was progressively losing importance. A positive model's intercept was observed in the regions around Athens during both urbanization and suburbanization, confirming the accelerated demographic dynamics typical of the capital city and the surrounding area in the first two phases of the metropolitan cycle in Greece. With counter-urbanization, positive local intercepts were residually observed in a small (coastal) region East of Athens. In the last observation decade, positive intercepts concentrated in the Aegean islands (Crete, Cyclades, Dodecanese), a dynamic region from the demographic point of view. Negative intercepts were observed in more peripheral districts of Western Greece during the whole study period. High (negative or positive) model's residuals were rather scarce and sparsely distributed all over the area.

Path-dependence was positive and significant at all decades examined in this study, being more intense in (1) Central and Southern Greece during urbanization, (2) Central and South-Eastern Greece during suburbanization, (3) Eastern continental Greece during counter-urbanization, and (4) almost all over Greece during re-urbanization, with the exception of Western Peloponnese and Eastern Trace. All over the study period, density-dependence was positive and significant only in Eastern Greece, being more intense in the regions around Athens during urbanization. With counter-urbanization, a moderately positive density-dependence of population dynamics was observed in various regions gravitating on Athens and Thessaloniki. On the contrary, density-dependence was weak in Eastern Greece during suburbanization and re-urbanization, and completely absent in marginal districts of Western Greece, Trace, and Crete. Taken as a measure of agglomeration, population size received significantly negative coefficients in municipalities of the regions surrounding Athens (Evvia, Argolida, Beotia, Korinthia) during urbanization. The negative impact of this variable extended to Eastern Greece—from Macedonia to Southern Peloponnese—during suburbanization and counter-urbanization, losing strength with re-urbanization, when a moderate, positive impact was observed in marginal districts of Western Greece. Perimeter-to-area ratio, taken as a measure of scale, was insignificant during urbanization and basically insignificant during re-urbanization. During the two intermediate phases, perimeter-to-area ratio received weakly negative coefficients in Eastern Greece, especially in areas around Athens and Thessaloniki.

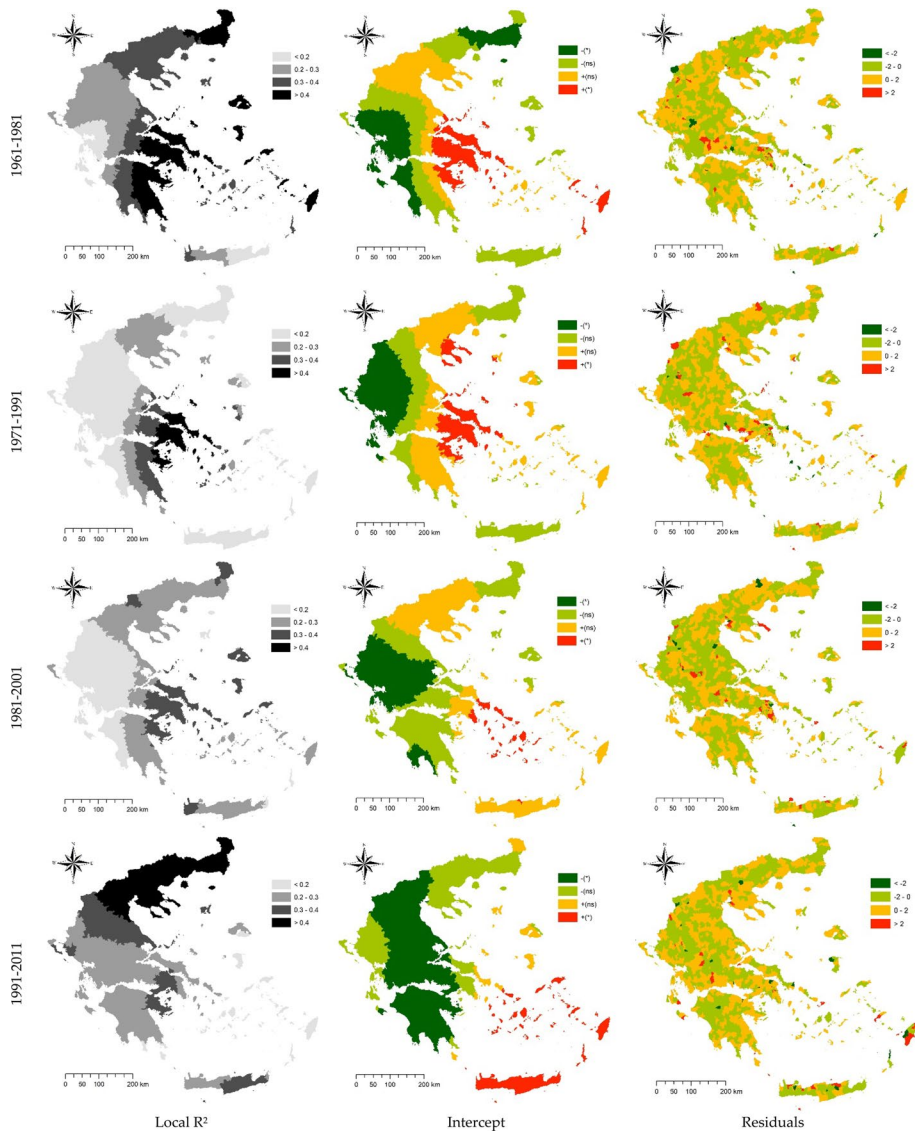


Fig. 3 Results of a Geographically Weighted Regression with population growth at time $t + 2/t + 1$ as dependent variable, population growth ($t + 1/t$), population density (\log, t), population size (\log, t), and perimeter-to-area ratio as predictors

5 Discussion

During the last century, metropolitan regions in Europe have continuously expanded at the expense of rural areas thanks to accelerated demographic dynamics amplifying socioeconomic divides (Allen et al., 2004; Arapoglou, 2012; Paulsen, 2014). To understand latent patterns of population growth, our study illustrates a diachronic analysis of demographic dynamics (1961–2011) at the municipal scale in Greece, verifying

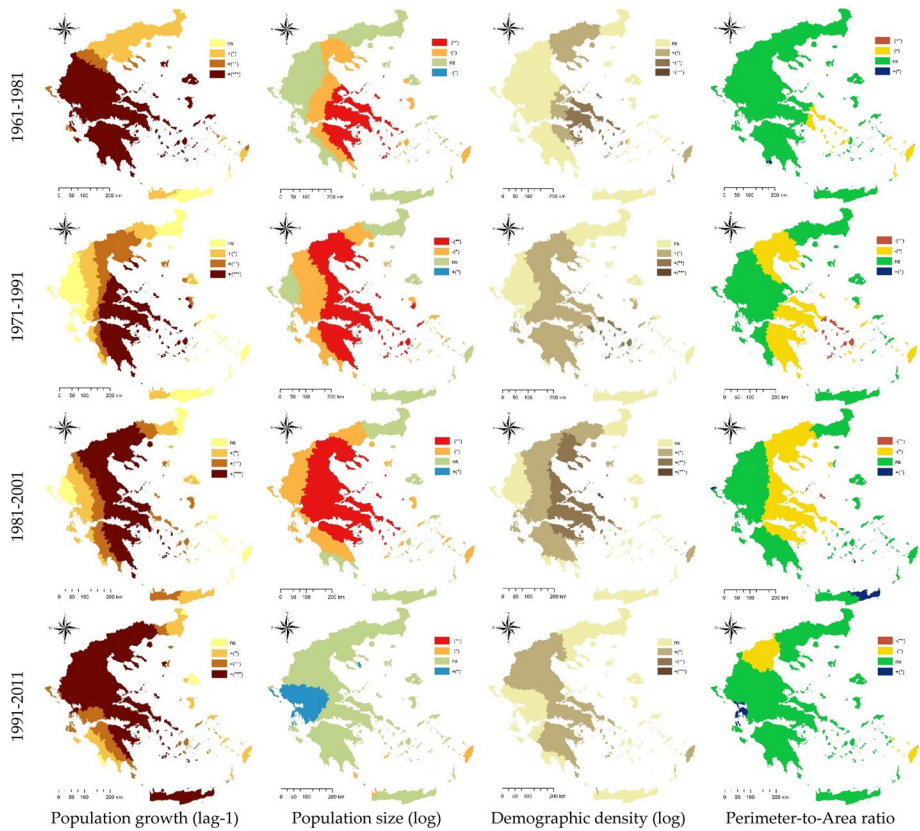


Fig. 4 Results of a Geographically Weighted Regression (local slope coefficients) with population growth at time $t + 2/t + 1$ as dependent variable, population growth ($t + 1/t$), population density (t), population size (\log, t), and perimeter-to-area ratio as predictors (in each figure legend, + or — indicates a significantly positive (or negative) coefficient; significance was tested at * $0.01 < p < 0.05$; ** $0.001 < p < 0.01$; *** $p < 0.001$; *ns* indicates an insignificant relationship)

density-dependence, path-dependence, agglomeration/scale impacts, and spatial effects over a complete metropolitan cycle from urbanization to re-urbanization (Morelli et al., 2014). Testing density-dependent population growth over time contributes to delineate mechanisms consolidating a metropolitan hierarchy representative of many other European countries (Benassi et al., 2020) and centered on large compact cities (Berliant & Wang, 2004). At the same time, density-dependence was regarded at the base of local-scale settlement evolution typical of rural areas and common to different Mediterranean countries (Salvati, 2020). Population expansion along coastal, non-urban areas and the contemporary decline of inland, marginal districts have been sometimes explained with such dynamics (Salvia et al., 2021). Assuming that demographic fluctuations reveal how people live and move around space, present population changes were modeled—together with density levels—on the base of past (lag-1) changes, population size (a proxy of agglomeration), local administrative size (a proxy of economic scale and, at the same time, a control variable), and spatial heterogeneity (Salvati, 2020).

Our study demonstrates how sequential waves of concentration and de-concentration of urban (and peri-urban) nodes were associated with density-dependent mechanisms of population growth, shaping the expansion of rural/accessible districts, and the abandonment of marginal districts (Crescenzi et al., 2016; Duncan et al., 2001; Morelli et al., 2014). While identifying distinctive (demographic) regimes at the local scale (Nickayin et al., 2022), the empirical results of our study outline the intrinsic characteristics of local contexts and the substantial differences in the relationship between population growth and density across time, corroborating the assumption that density-dependent regulation is intrinsically associated with exogenous dynamics depending on metropolitan cycles and the consequent economic downturns (Ciommi et al., 2018).

Accentuating the divide in high-density and low-density areas, the results of the (global) econometric models document how density-dependence has been observed in correspondence with urbanization, a specific phase of the metropolitan cycle (Salvia et al., 2021). This suggests the role of economic agglomeration, and highlights the importance of the internal balance (high fertility and medium–low mortality) and the inherent contribution of immigration (Bocquier & Brée, 2018). At the same time, density-dependent regulation was insignificant in both suburbanization and counter-urbanization phases, i.e. when population tends to be more dispersed across regions (e.g. Ciommi et al., 2020). In these contexts, the role of agglomeration and scale may reduce proportionally, becoming less negative and, in some cases, neutral or even positive, and density-independent factors that regulate population growth may predominate (Cohen, 2003). With re-urbanization, the positive rate of population growth observed in rural areas counterbalanced the stable (or negative) pattern observed in urban areas (Duvernoy et al., 2018), indicating a relationship with population growth that reflects congestion externalities and subtle processes of peri-urbanization intensifying in recent decades (Gkartziou, 2013).

Taken together, the results of quantile regressions—with or without incorporation of spatial effects—indicate a non-linear relationship between population growth and density for all time intervals, although with important differences as far as the impact of individual factors is concerned (Paulsen, 2014). Results of quantile regressions document a positive effect of density on population growth rates, being stronger at higher concentration levels, while declining slightly over time (Partridge et al., 2009). Such findings are in line with the documented outcomes of sequential waves of urbanization, suburbanization, and re-urbanization characterizing the post-war metropolitan cycles in Mediterranean Europe (Cuadrado-Ciuraneta et al., 2017; Salvati & Carlucci, 2017; Zambon et al., 2017). In other words, the density-growth relationship is indicative of sequential waves of the metropolitan cycle, reflecting multiple factors of change (Di Felicianantonio & Salvati, 2015). Demographic dynamics and multifaceted urbanization patterns—from compact growth to sprawl—have played a key role shaping the spatial distribution of resident population (Arapoglou, 2012). More specifically, location factors promote distinctive patterns of local development based on population density (Alados et al., 2014).

In this perspective, long-term demographic processes in Mediterranean Europe were seen as representative of more general dynamics at the continental scale (Ciommi et al., 2018). Consolidation of urban and rural poles, socioeconomic divides along the elevation gradient and a substantial density-dependent mechanism of population growth are generalized phenomena of interest for urban and regional planning (Oueslati et al., 2015; Osterhage, 2018). Moreover, a comparative analysis of local-scale population dynamics may emphasize the inherent complexity of different European contexts and the importance of a diachronic investigation of density-dependent and path-dependent regulation of demographic processes (Haase et al., 2010). Although urbanization processes tend to vary from

country to country, our results document how population growth in Mediterranean Europe was influenced by similar forces that can be better characterized in a comparative analysis of metropolitan cycles (Zambon et al., 2017). By reflecting similar regimes in the density-dependent mechanisms of population growth, these factors are more intense in demographically dynamic regions. Spatial econometric approaches monitoring such factors may provide, at least implicitly, some novel indicators of practical use in official statistics. These indicators seem to be particularly appropriate when evaluating regional paths of change and socioeconomic progress toward globalization, competitiveness, and sustainability.

6 Conclusions

Integration of basic socioeconomic indicators, including demographic growth rates and population density, allows identification of (apparent and latent) spatial divides, outlining long-term and more recent socioeconomic trends and their impact on settlement structure and urbanization patterns. In this line of thinking, a comparative analysis of population dynamics clarifies the role of local contexts when designing and implementing joint strategies for spatial planning and regional development at both country and continental scale in Europe. Population divides were easily identified at the municipal scale, being associated with density-dependent processes of urban growth, and reflect the socioeconomic divide in accessible/dynamic regions and marginal/inland districts. A refined analysis of socioeconomic contexts resulting from different demographic patterns and processes can also improve the reliability and accuracy of demographic forecasts. In this regard, geo-referenced databases with local-scale, up-to-date information encompassing long time intervals, provide the basic knowledge to identify spatial regimes of demographic growth and the influence of population density. Results of this study encourage a spatially explicit analysis of population dynamics aimed at identifying spatial regimes of urban growth under variable socioeconomic conditions and heterogeneous local contexts. Spatial econometrics proved to be a particularly appropriate tool in this research direction.

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Declarations

Competing interests None.

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