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Proposal for a sustainable development index for rural municipalities

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ABSTRACT

Depopulation is a major challenge for many rural inland areas, as is the case in a considerable number of rural municipalities in Galicia (north-western Spain). The pandemic had a considerable impact on internal migration in 2020, but it was far from being anywhere near high enough to reverse the ongoing trend of population decline, highlighting the need for further action. Thus, this paper has a twofold objective: firstly, to propose an index of rural sustainable development for the rural Galician municipalities, and secondly, to identify the factors related to it. In so doing, a composite index stemming from the Benefit of the Doubt methodology has been proposed in the first stage, an index built from four-dimension factors– economic, demographic, social, and environmental. The empirical evidence of this index has been compared with three additional ones (namely, common weights, super-efficiency, and geometric mean and logistic normalization models). In the second stage, the relationship between the composite index and a set of exogenous variables that affect rural development has been analyzed, the data confirming that the rates of female immigration and occupancy in the hospitality sector favors sustainable development, whereas the distance from the provincial capital hinders it. This paper paves the way for an assessment of the potentialities of each territory, and the evidence found allows actions to be supported that generate sustainable progress in rural Galician municipalities and that are useful for tackling this complex problem.

1. Introduction

Depopulation of rural areas is a widespread phenomenon that has been affecting most developed economies since the second half of the twentieth century (Alados et al., 2014). According to Eurostat (2020), in 2018, rural areas accounted for 29.1% of the European Union's population, but this percentage is expected to experience a sharp decline of up to 7.9 million inhabitants by 2050 (ESPON, 2017).

The reasons behind this rural exodus, as Casini et al. (2021) have stated, are numerous: rural 'push factors' such as agricultural mechanization, the scant growth of industries in rural territories, land pressure, and natural disasters; urban 'pull factors' such as pay raises, and urban-biased governmental policies. Therefore, rural residents struggle to access technology, services, and infrastructure, and have fewer labor opportunities, causing ever-increasing rural desertification (ESPON, 2017; Esteban-Salvador et al., 2020), leading to poorer tax revenue and infrastructure (Hospers and Reverda, 2015).

In addition, many of these "migrants" are productive youths of child-bearing age, leaving behind an aging rural population and a decrease in birth rates. Therefore, population decline has a major impact on demographics, economic growth, and social well-being, but it also threatens environmental sustainability and culture.

In Europe the industrialization and urbanization that have taken place throughout the last two centuries has led to a rural depopulation process, even though its pace and strength varies noticeably from one territory to another (Delgado, 2019). The Nordic countries, Finland and Sweden, Germany (an outlier in northern Europe), and the Iberian countries, Portugal and Spain, contain a high number of shrinking regions (ESPON, 2017). In Spain, this socio-demographic process started to become commonplace in the 1950s, but despite the delay compared with other European countries, the process has been more intense and has lasted longer, developing at an unstoppable rate (Miranda-García et al., 2019). It cannot be ignored that Spain has some of the most underpopulated rural areas in Europe (Delgado, 2019), where there are territories with less than 3 inhabitants per square kilometer. In 2021, among the 8131 Spanish municipalities, almost half of them (49.1%)

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had less than 500 inhabitants, making up just 1.5% of the Spanish population, and almost one fifth (17%) had less than 100 inhabitants (Instituto Nacional de Estadística [INE], 2021).

Inland Spain has been hardest hit by rural depopulation, especially mountainous areas, Aragon and Castile and León being two of the regions which have suffered the most in the last few decades (Pinilla and Sáez, 2021). In the most intense period of depopulation (1950–1991) the rural depopulation rate of both regions was almost double the Spanish average (Pinilla and Sáez, 2021), far exceeding it in the subsequent few years, except in the period 2000–2008, which witnessed a reverse in the trend. In the north of Spain the situation is not more optimistic, particularly in Asturias and Cantabria (Delgado, 2019; Nieto-Masot et al., 2020) as well as in Galicia (Ónega-López et al., 2010), the focus of this paper, nor are the perspectives for the coming decades (López-Iglesias et al., 2018).

The Galician government was pioneer in passing a law (5/2021, February 2nd, 2021) on the demographic revival of this territory, but neither this nor the recent return of villagers, especially during the current COVID-19 pandemic, has been anywhere near enough to reverse the downward trend (Fernández-Martínez et al., 2020; González-Leonardo et al., 2022). The figures on population density reflect the ongoing depopulation process, with 31.4% of the 315 Galician municipalities at less than 30 inhabitants per square kilometer in 2000 rising to 43.5% in 2020 (Instituto Galego de Estatística [IGE or Galician Statistics Institute]) 2020).

Rural development, defined by Abreu et al. (2019) as the set of actions aimed at trying to compensate the imbalances between rural and urban areas and improve life quality and economic welfare of rural areas seems crucial to reverse this population shrinkage. Nonetheless, this is "a complex and sometimes vague concept" [Abreu et al. (2019), p. 1108], so we should start by approaching and assessing the term "rural development", especially when it comes to whether it is sustainable. However, despite there being many development indices, most of them are not specifically intended for the assessment of rural areas (Abreu et al., 2019).

Therefore, the objective of this paper is twofold: (a) to propose and define a Rural Sustainable Development Index (RSDI) for rural Galician municipalities; and (b) to determine which exogenous factors influence it. The index has been constructed based on four dimensions -demographic, social, economic, and environmental-, using the Benefit of the Doubt (BoD) methodology, which is modeled on the Data Envelopment Analysis (DEA).

Composite indices which assess the development of territories are widespread, but not for rural areas; to our knowledge, only one paper has used DEA-BoD to calculate sustainable rural development, while we have opted for the bootstrap CCR. Besides this, no reference in the literature has attempted to conduct a two-stage analysis for the truncated regression aimed at analyzing the relationship between the exogenous variables and the previously-constructed composite index. This methodology even allows continuous application by introducing variables from the second stage in future refinements to make a more comprehensive composite index (Dutta et al., 2020).

Ours is the first RSDI focusing on Galicia, which has needed other indicators to be significantly adapted; this is due to particularities like isolation and geographical conditions compared with other Spanish territories, resulting in populations composed of smallholders in scattered small rural communities (López-González et al. 2004). Therefore, a methodology that deals with specific features in Galicia is necessary, to design a strategic plan aimed at reducing imbalances, not only between urban and rural areas, but also within rural areas themselves.

The remainder of the paper is organized as follows: the second section reviews the theoretical framework regarding development indices and identifies the driving forces behind sustainable rural development by specifying the research hypotheses, the third section defines the methodology and the variables, and the fourth section presents and discusses the outcome of the empirical analyses. The fifth section presents the concluding remarks.

2. Theoretical framework

2.1. The creation of rural sustainable development indices

Different indices aimed at assessing regional development have emerged throughout history, but it is the Gross Domestic Product (World Bank, 1997) which has long been considered the main indicator for measuring this. However, as Abreu et al. (2019) have recognized, this index is solely focused on economic growth, thus presenting some notable drawbacks when assessing rural development, which goes beyond the economic scope.

In response to these downsides, various authors have advocated the need to consider a wider set of indicators when measuring regional development. Indeed, back in the 1950s, William Kapp had already warned of the risk that unregulated economic development might cause serious damage to social and natural environments (Luzzati, 2009). Therefore, the concept of sustainable development, with its three interconnected domains (i.e., economic, social, and environmental), has been increasingly acknowledged by governments and worldwide institutions (Floridi et al., 2011), being integrated into political agendas (Lemke and Bastini, 2020).

Sustainable development, which, according to 1987's Brundtland report, means meeting the needs of the present generation without compromising the ability of future generations to meet their own needs, was assessed from an empirical perspective, mainly using composite indices (CIs [Floridi et al., 2011; Salvati and Carlucci, 2014]). These constituted an appropriate assessment, offering an integral approach that allowed indicators to be included by proxying for all dimensions of sustainable development (Singh et al., 2012). The Index of Sustainable Economic Welfare (Cobb, 1989), and the United Nations Human Development Index (UNDP, 2016) are examples of CIs of a multidimensional nature, although they have not been tailored to assess rural areas.

International organizations such as the World Bank and the OECD have proposed several indicators aimed at assessing the sustainable development of rural areas. Similarly, Castellani and Sala (2010) have put forward a sustainable performance index designed to develop sustainable tourism policies, while Salvati and Carlucci (2014) have constructed an index of sustainable development for Italian municipalities.

Rural development, understood as "the set of activities and actions of diverse actors -individuals, organizations, groups-that taken together leads to progress in rural areas" (Shepherd, 1998, p. 1), has evolved over time in response to the development and implementation of the concept of sustainability (Fernández-Martínez et al., 2020). Nonetheless, not only has the concept of sustainable development in rural territories evolved, but so has the focus of policies on these areas. Thus, from a focus initially centered on the agricultural sector, it has shifted toward a more holistic and inclusive approach that incorporates other economic sectors as well as the environment.

Despite there being numerous indices on sustainable development, there are few references especially designed to assess rural areas, as Abreu et al. (2019) and Martínez-Vega et al. (2020) have recognized. However, some authors have attempted to measure the sustainable development of rural areas. Martínez-Vega et al. (2009) have defined a global index of sustainability which integrates economic, social, and environmental dimensions for a rural mountain area in Cuenca (Spain). More recently, Abreu et al. (2019) have designed a rural development index for Portuguese municipalities based on four dimensions (i.e., population, social, economic, and environmental), while Fernández-Martínez et al. (2020), focusing on 10 regions in Huesca (Spain), have created an RSDI based on several indicators stemming from the three sustainability dimensions (social, economic, and environmental) and using a DEA-BoD model.

To fulfill our first objective, namely, defining an RSDI, we needed to choose a set of indicators for the sustainable development of Galician rural municipalities. Therefore, based on a comprehensive literature review and data availability at a municipality level, different variables have been selected to elaborate the RSDI. In the economic dimension, information on active population and disposable income has been included; in the demographic dimension, following Abreu et al. (2019) and Fernández-Martínez et al. (2020), an attempt has been made to capture the population dynamics and density; in the social dimension, measures on the likelihood of receiving non-university education, medical care, and home help services have been included; finally, the environmental dimension includes forest, actively cultivated areas, and protected areas, because as Ónega-López et al. (2010) have highlighted, land-based economic activities can contribute to sustainable development. All these indicators represent variables over which public authorities have scope for action (i.e., they can be affected by public policies), by prior identification of municipalities that are in the best and worst situations.

2.2. Exogenous variables in the assessment of rural development. Hypothesis proposals

A literature review reveals the existence of references that have attempted to analyze the driving forces of sustainable rural development using other methodologies such as Structural Equation Models (e.g., Casini et al., 2021) and regression models (e.g., Sánchez-Zamora et al., 2014). Connected to our second objective and based on the previous literature review, after the RSDI was created, we tried to analyze the effect of underlying forces upon it. In so doing, different research hypotheses, detailed below, have been proposed.

Regarding the economic dimension, Sánchez-Zamora et al. (2014), in their analysis of successful territorial dynamics in rural areas of Andalusia (Spain), have considered economic indicators to be the number of overnight bookings and economically active establishments, whereas Salvati and Carlucci (2014) have opted for the number of beds in hotels or similar establishments and rural hospitality occupancy level. Similarly, Fernández-Martínez et al. (2020) have considered the area of retail trade to assess the sustainability of rural development in Huesca (Spain). These aspects have led us to propose the following research hypotheses:

H1. Occupancy in the hospitality sector positively affects the level of the RSDI.

H2. Real estate properties for commercial use positively affect the level of the RSDI.

H3. Properties for tourists positively affect the level of the RSDI.

The Bank of Spain's Annual Report 2020 (BdE, 2021) recommends tackling the unequal distribution of the Spanish population, by highlighting the advantages of making investments to provide internet coverage to rural municipalities and make them more competitive to overcome digitization challenges. These recommendations require

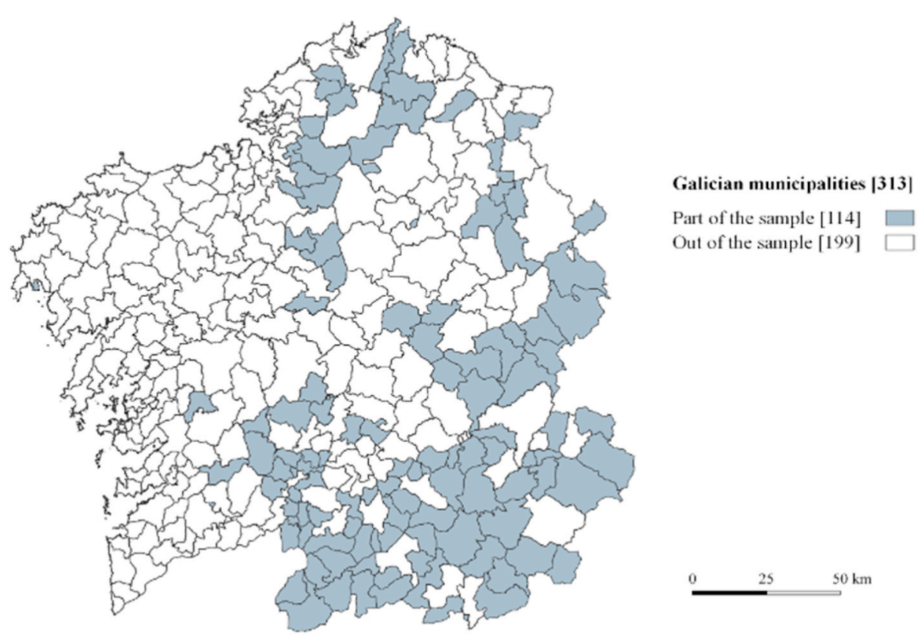

Fig. 1. Map of Galicia and its municipalities
Source: own elaboration using the Quantum Geographic Information System (QGIS).[1]

[1] The base maps shown in this article have been downloaded from http://mapas.xunta.gal/ideg.

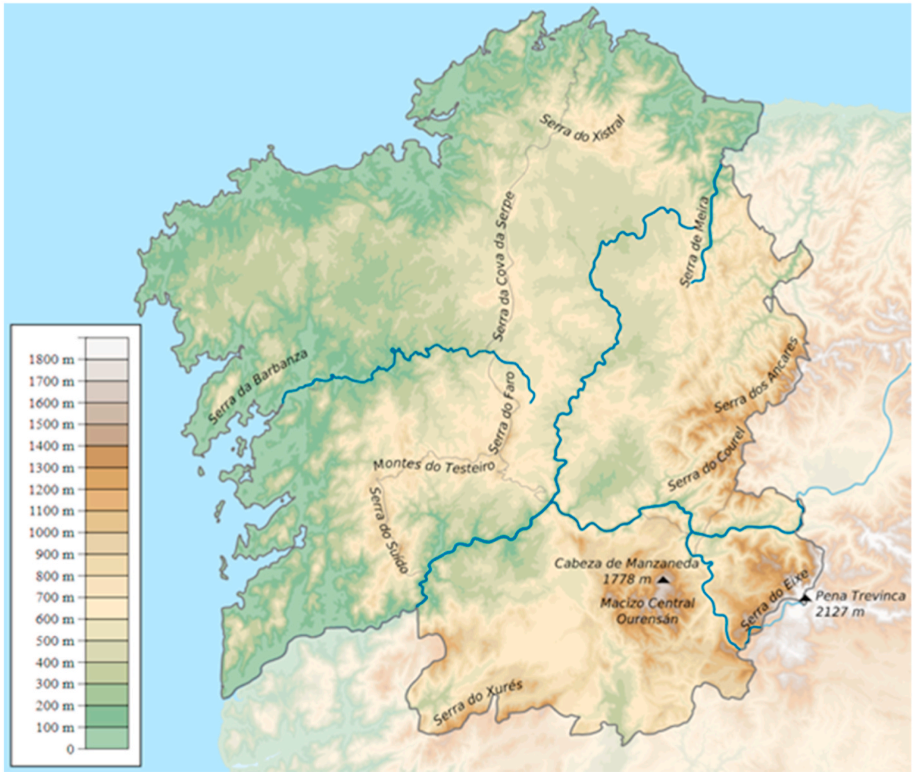

Fig. 2. Topographical map of Galicia with mountain names Source Edoarado (2010).

support and training to facilitate telecommuting, e-commerce, and digital services. Floridi et al. (2011) have incorporated internet diffusion per household to assess the sustainability of Italian regions. With all this in mind, we have proposed the following hypothesis in the social dimension:

H4. Internet coverage positively affects the level of the RSDI

Altitude in meters and distance from the provincial capital have already been considered by Sánchez-Zamora et al. (2014) as environmental variables reflecting the peripherality and remoteness of rural areas. López-González et al. (2004) have also used distance from the capital to assess the accessibility of rural territories in Galicia. Therefore, we have proposed the following hypotheses in the environmental dimension:

H5. Altitude negatively affects the level of the RSDI

H6. Distance from the capital negatively affects the level of the RSDI

Floridi et al. (2011) and Abreu et al. (2019), in their assessment of the development of Portuguese and Italian municipalities, respectively, have considered net migration a reflection of the territory's capacity to appeal to inhabitants, whereas Valiente (2019) has used female emigration as a proxy variable to measure the ability for residents to settle in the territory with the intention of starting a family. Consequently, we have opted to use female immigration due to its reproductive potential as a variable within the demographic dimension. Our proposed hypothesis is as follows:

H7. Female immigration positively affects the level of the RSDI

3. Methodology and variables

This section describes the sample and the methodology applied in the empirical section, as well as the variables used.

3.1. Sample

Galicia is composed of different population entities, but the unit of analysis in this paper is the municipality as it is the one that displays the most scope for improvement in terms of taking and promoting decisions. Galicia has a total of 313 municipalities, our sample being made up of rural municipalities, which according to the INE's classification (INE, 2021a) are those with population figures of under 2000 inhabitants. 114 municipalities can be defined as rural in Galicia according to population figures for the year 2021. Fig. 1 shows the map of Galicia with the sampled municipalities highlighted. The list of specific municipalities can be seen in Table A3 (Appendix).

Among the municipalities in the sample, 59.6% of them are concentrated in Ourense province (in the southeast) and 23.7% in Lugo province (in the northeast). Only two of the municipalities have a coastline; most of the remaining ones correspond to the highest areas of the Galician massif (Fig. 2).

A total of 83 municipalities in our sample are in the category that Iglesias-Casal et al. (2020) have defined as "deprived municipalities or municipalities in need of revitalization" due to their serious demographic situations that require immediate action to alleviate the population's decline[2]. These municipalities belong to the high mountain areas of Ourense and Lugo provinces (52 and 21, respectively), A Coruña (9), and Pontevedra (1).

3.2. Methodology

With the aim of determining the variables that can influence sustainable development in rural Galician municipalities, we have followed a two-stage methodology: in the first stage we have built the composite index, and in the second we have analyzed the index's relationship with a set of exogenous variables.

3.2.1. First stage: composite index

The DEA offers an alternative way of obtaining partial indicator weights in the construction of composite indicators, namely, the BoD approach,[3] which can be applied in the creation of a Sustainable Rural Development Index.

This approach is used to construct a composite indicator (CI) for a Decision Making Unit (DMU) in which a dummy input variable equals one for each unit. The BoD model consists of the aggregation of individual outputs into a compound output, endogenously obtaining the weights of the outputs that maximize the CI value for a DMU with respect to the others. This gives the following mathematical formulation of a DMU j:

$$CI_j = \max_{\lambda_i} \sum_{i=1}^{m} \lambda_i y_{ij}$$

$$s.t.: \sum_{i=1}^{m} \lambda_i y_{ij} \leq 1 \; j = 1, \ldots, n \tag{1}$$

$$\lambda_i \geq 0 \quad i = 1, \ldots, m$$

where n is the number of DMUs (i.e., municipalities), m is the number of partial indicators, CI is the composite indicator score, and λ is the weighting.

One of the weaknesses of the DEA methodology is that it tends to generate biased estimates of the CI value. Therefore, we have opted for the bootstrap-DEA method, proposed by Simar and Wilson (1998, 2002), to correct the bias of estimators and to provide the confidence interval of the composite indicator.

In traditional DEAs, DMUs are allowed to use the most favorable weighting to maximize their score for the composite indicator. Normally there is more than one "best-practice"[4] DMU, and therefore, the traditional models do not allow for discriminations among groups of "best-practice" units. The bootstrap solves not only these problems but also two other alternative models that we have proposed, namely, the DEA model with common weights and the super-efficiency model, both of which are effective methods for putting the "best-practice" units or municipalities in a hierarchical order.

Table 1
Indicator synthesis for the first-stage analysis.

Dimension	Initials	Indicator	Year
Economic	AR	Activity Rate: percentage of active population over total population (i.e., aged 16 or over).	2001
	GDIPC	Gross Disposable Income per Capita, in euros.	2011
Demographic	PG	Population Growth.	2018
	PD	Population Density: measured as inhabitants per square kilometer.	2018
Social	NUTC	Non-University Teaching Centers.	2018
	NPCP	Number of Primary Care Physicians.	2018
	HHS	Home Help Service: number of hours of home help service offered in municipality (Source: primary data collected via online and over-the-phone questionnaires).	2019
Environmental	AOW	Area of Woodland: percentage of forest area over the total area of the municipality.	2018
	AL	Arable Land: percentage of actively cultivated land over the cultivated area and meadow.	2009
	PLA	Protected Land Area: percentage of protected areas within the Natura 2000 network with respect to the total land area of the municipality.	2018

The exogenous variables used for the second part of our analysis are detailed in Table 2.

The common weights model (Wu et al., 2016) can deal with the full flexibility of traditional DEA model weights by introducing a single common set of weights to evaluate all DMUs, so that they can be compared with the same benchmark in calculating the CI.

In this model, we first calculate the upper and lower CI value of the DMUs to find the unique set of common weights. Based on this set of optimal weights, the satisfaction degrees of the DMUs can be calculated as

$$\psi_j = \frac{CI_j^{Common} - CI_j^{min}}{CI_j^{max} - CI_j^{min}} \; \forall j$$

where CI_j^{max} is calculated with the most favorable weights, i.e., the highest-possible score that a DMU can achieve, meaning that maximum CI is equal to CCR CI value. The minimum score of a DMU appears when trying to select the most favorable set of BoD weights for another DMU, in particular the one that makes its performance the smallest. CI_j^{Common} is obtained with the set of optimal weights.

The super-efficiency model based on global efficiency measures is a tool designed to improve the likelihood of gaining a hierarchical and objective order.

Andersen and Petersen (1993) have proposed modifying the DEA model so that the unit is evaluated against a linear combination of the remaining DMUs, excluding the DMU itself. The main drawback of this proposal arises from a problem with infeasibility and the fact that CI scores can be greater than one. Tone (2002) put forward a model based on Slack Based Measure (SBM) in which all the sources of inefficiency are collected, and which tries to minimize the weighted distance between a "best-practice" DMU and the set of possibilities excluding the DMU itself. The model directly incorporates all slack and its fractional formulation admits a standard transformation with a linear objective function. The model returns an optimal coefficient, $0 < \rho \leq 1$, being equal to 1 if and only if the unit under analysis is a "best-practice" DMU.

Finally, we have proposed a naïve method that combines logistic normalization with geometric mean as a way to perform aggregations. Geometric mean is suitable for decision makers who do not accept full compensation between indicators and want to penalize the alternatives that perform poorly even on only one indicator.

3.2.2. Second stage: truncated regression

Next, we have applied the Simar and Wilson (2007) truncated regression model, Algorithm II, developed to determine the explanatory

[2] Based on four variables: i) A population of up to 2000 inhabitants, ii) A density of less than half the average density of the Autonomous Region, i.e., 20 inhabitants/km^2, iii) A population aging rate (greater than 200%), and iv) Recent population decline. Iglesias-Casal et al. (2020) have established a classification for the Galician rural municipalities. The analysis has found that 83 municipalities were considered disadvantaged or in need of revitalization (municipalities that met three out of the four criteria mentioned), 26 were intermediate (i.e., those that met two of the criteria), and 5 were dynamic (i.e., meeting just one criterion).

[3] According to Despotis (2005), this model is formally equivalent to constant-returns-to-scale (CCR) DEA model proposed by Charnes et al. (1978).

[4] The municipalities obtaining the maximum score for the composite indicator will be referred to as 'best-practice' municipalities.

Table 2
Indicator synthesis for the second-stage analysis.

Dimension	Initials	Indicator	Year
Economic	ORHS	Occupancy Rate in the Hospitality Sector: percentage of employed population in the hospitality sector over the total employed population.	2011
	RECU	Real Estate for Commercial Use: number of real estate properties for commercial use over total number of urban real estate properties.	2020
	NPT	Number of Properties for Tourists: number of hotels, *pensiones* (guesthouses), hostels, or *casas rurales* (countryside guesthouses) for tourist use.	2018
Demographic	FI	Female Immigration: number of female immigrants in a municipality.	2018
Social	IC	Internet Coverage: average coverage, weighted by population, and considering the following features: faster than 30 Mbps, fixed networks faster than 100 Mbps, 3G HSPA, and 4GLTE (Source: Ministry of Economic Affairs and Digital Transformation, 2021).	2019
	NVSC	Number of Vacancies in Social Centers.	2018
Environmental	ALT	Altitude in meters.	2020
	DC	Distance from provincial capital in kilometers, self-calculated based on routes obtained on Google Maps.	2020

character that certain exogenous variables have over the CI.

The second stage regression is given by:

$$\widehat{\widehat{CI}}_i = \beta Z_i + \varepsilon_i \quad i = 1, 2, \ldots\ldots, n \tag{2}$$

where $\widehat{\widehat{\mathrm{CI}}}_\mathrm{i}$ is the dependent variable, i.e., the bootstrapped bias-corrected CCR CI for Municipality$_\mathrm{i}$; Z_i is a vector of exogenous variables which is expected to explain the CI variations; β is a vector of parameters to be estimated in the second stage that establishes the relationship between the independent variables and the CI; ε_i is an independent error term that follows the Normal distribution with a zero mean and σ_ε^2 variance $N(0, \sigma_\varepsilon^2)$ with left-tail truncation (1-$\widehat{\beta}$ Z$_\mathrm{i}$).

Simar and Wilson (2007) have demonstrated, however, that this approach leads to inconsistent and biased estimates of the parameters. As a remedy, they have proposed the estimation of the regression model using the double bootstrap procedure.

3.3. Variables

The selection of variables was based on a range of premises, similarly to the method employed by Martínez-Vega et al. (2020), such as the following: the availability of data at the municipal level, the low statistical correlation between the variables, their coherence with established international frameworks for sustainable development, the balance between the different dimensions of sustainability, and their relevance and adequacy to Galician life.

Thus, based on previous literature, we selected four dimensions aimed at constructing a comprehensive index to assess the sustainable development of rural Galician municipalities. We then selected different indicators or variables using the interplay of theoretical considerations and data availability as a guide. The need to use data at the municipal level has meant that preparing our database has been challenging. Data at this level is rather scarce, and in some cases, it is not up to date, which has left us no option other than to reject some indicators. Most of the indicators have been collated from the IGE database using the latest data available. A few of the indicators have been taken from other databases (i.e., secondary data from other sources, and primary data obtained via online and telephone questionnaires).

The indicators for each dimension, which have been used as outputs in DEA-BoD, are detailed in Table 1. Data source is specified only when it is not from the IGE (2020a).

Table A1 displays a summary of the descriptive statistics of the variables used.

4. Results and discussion

Our first task has been to carry out a correlation analysis for the set of selected indicators. The matrix of correlation coefficients is displayed in

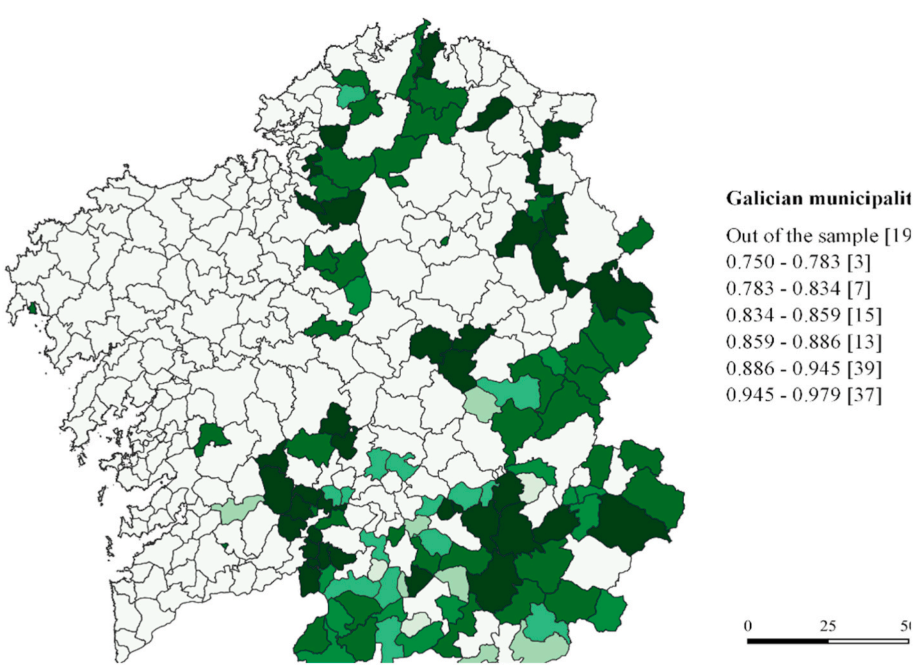

Fig. 3. Galician municipalities: Bootstrap CCR index
Source: Own elaboration using QGIS.

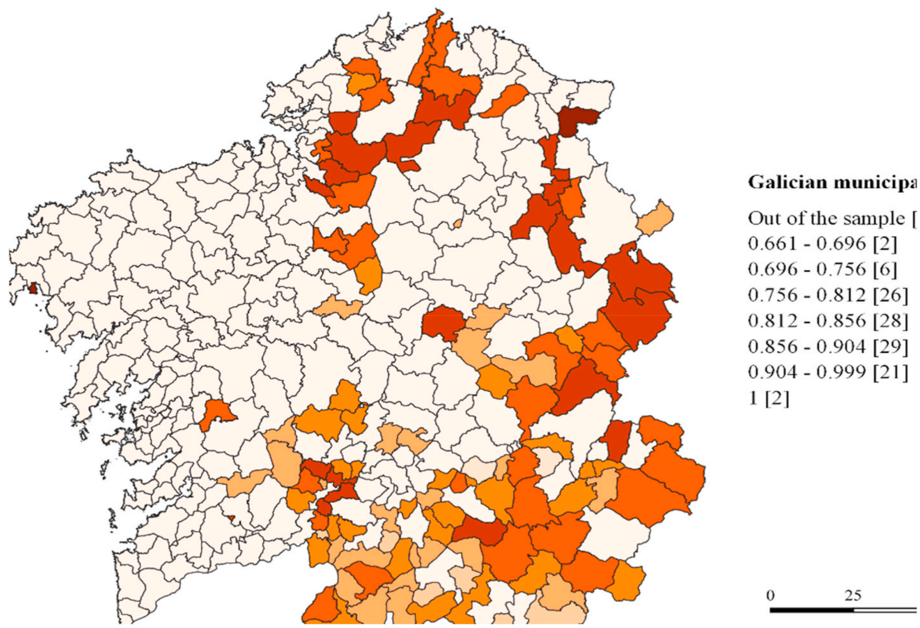

Fig. 4. Galician municipalities: Common weights index
Source: Own elaboration using QGIS.

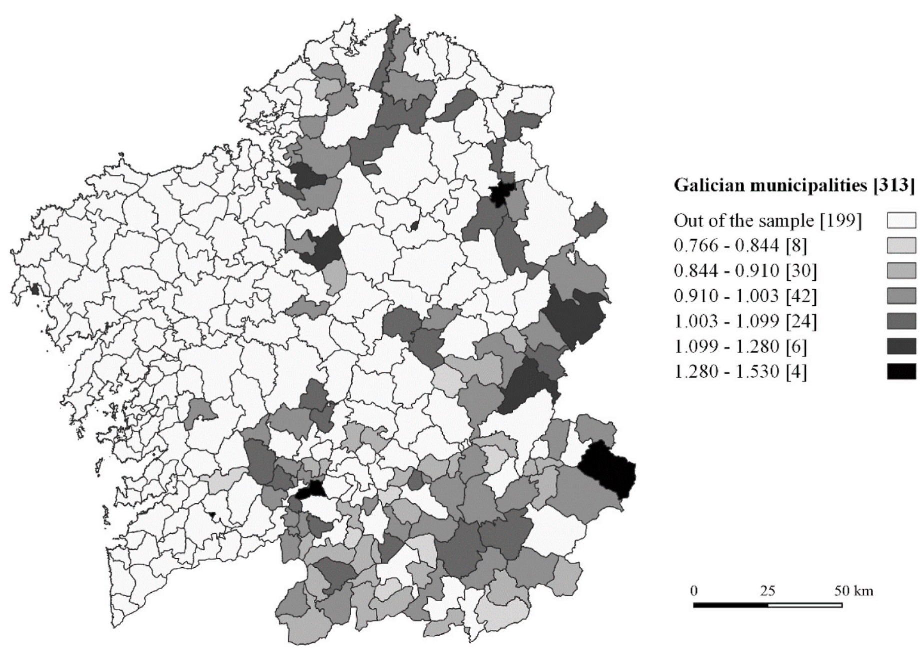

Fig. 5. Galician municipalities: Super-efficiency index
Source: Own elaboration using QGIS.

Table A2, where it can be observed that all coefficients are below 0.5.

4.1. First stage: construction of the CI

We have applied the BoD methodology to calculate the RSDI for the 114 existing rural municipalities in Galicia. Table A3 displays the scores of the different models for each municipality, ordered by the bootstrap CCR RSDI score, as well as the ranking of our composite indicator in comparison to the median rankings of the other alternative models. As can be seen, the higher the score, the better the situation for the municipality.

The municipalities of Ourense province are those that display the lowest RSDI values, followed by the municipalities of Lugo province (Table A3).

Figs. 3–6 graphically display the results for the different indices; the darker the color of the municipality on the map, the greater the value of each calculated indicator and, therefore, the better the situation of the municipality considering the four dimensions. Overall, we can observe

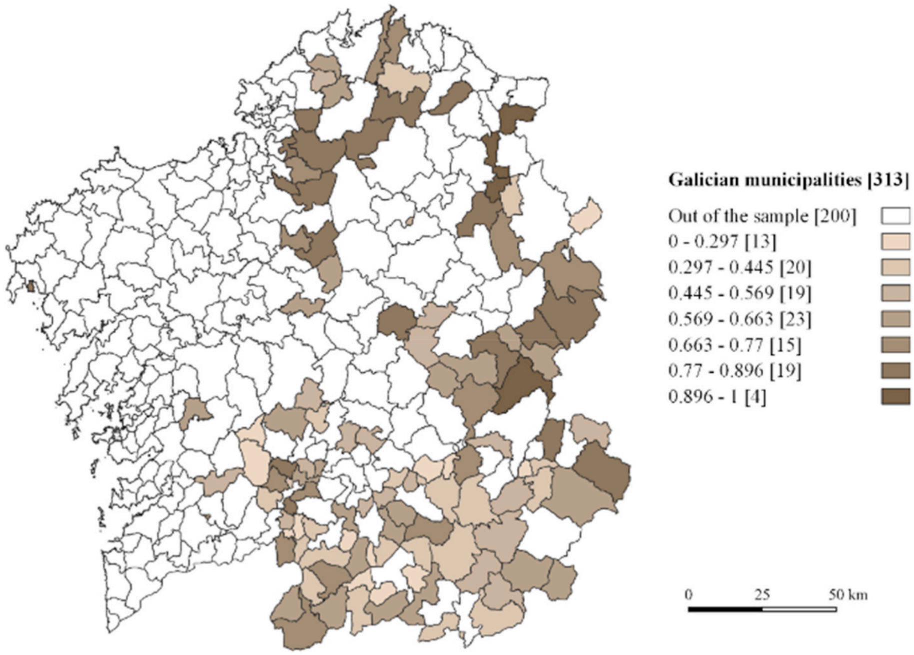

Fig. 6. Galician municipalities: Geometric-logistic index
Source: Own elaboration using QGIS.

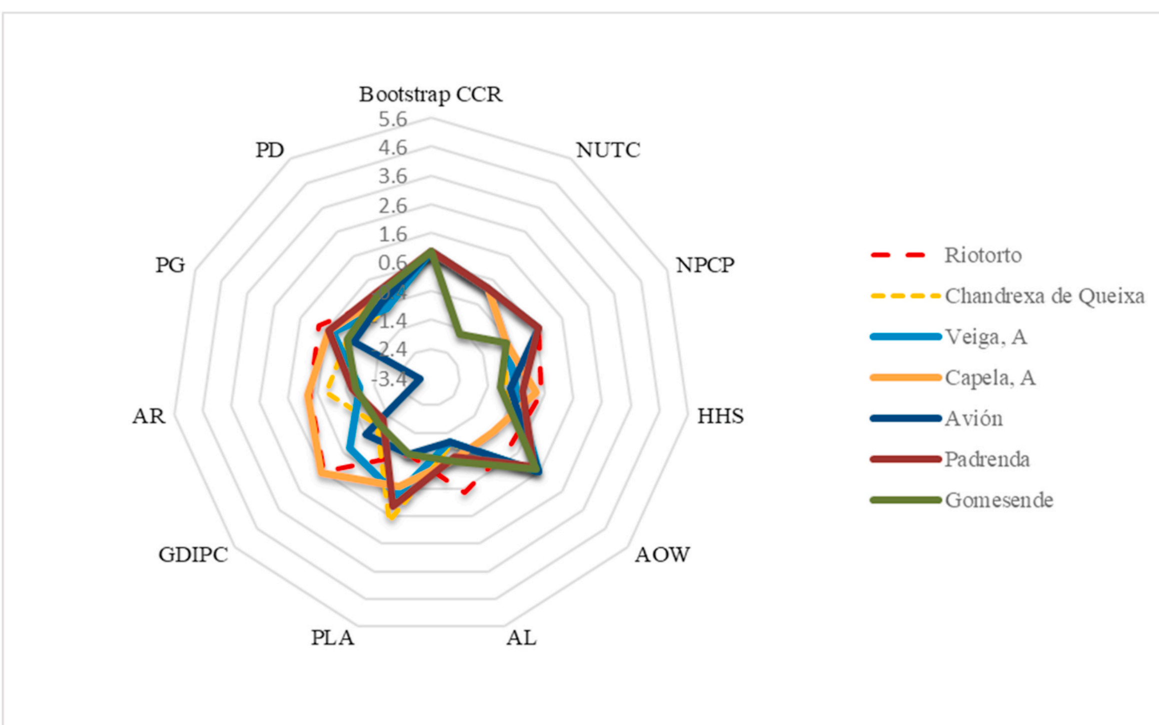

Fig. 7. Bootstrap CCR score and outputs for the best performing municipalities
Source: Own elaboration.

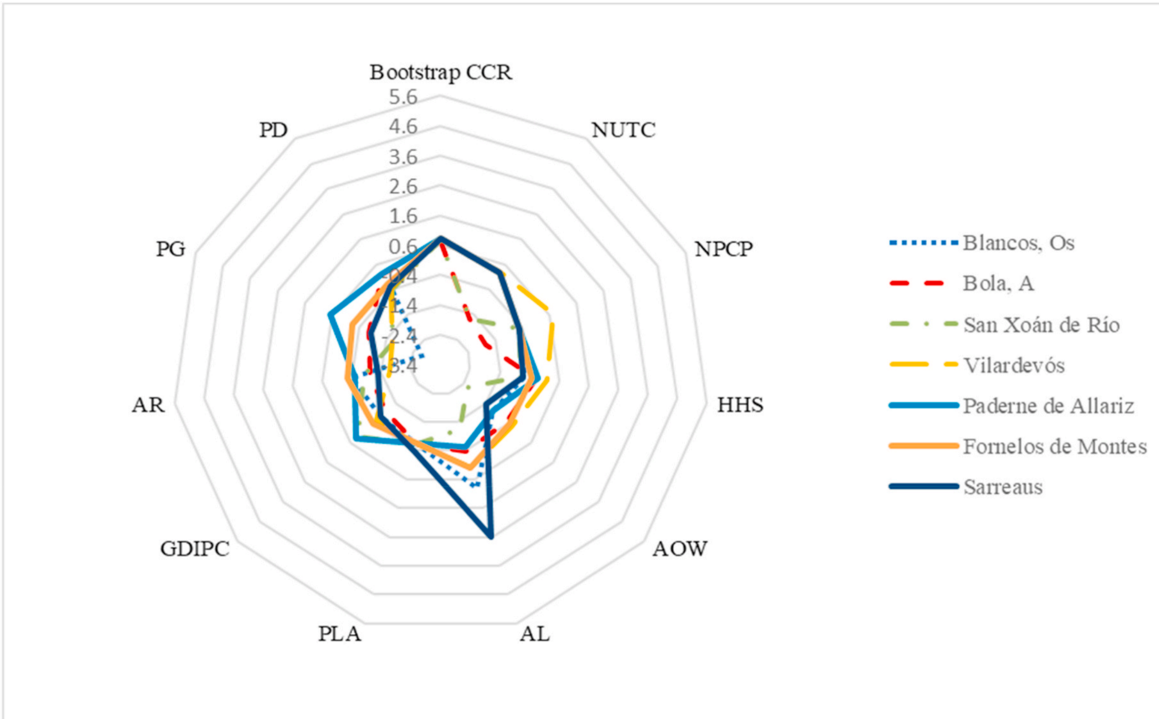

Fig. 8. Bootstrap CCR score and outputs for the worst performing municipalities
Source: Own elaboration.

that the areas surrounding the Central massif of Ourense are those with the lowest performance.

In order to balance or contrast the methodological biases and increase the overall robustness of the results, the different uncertainties that, according to Nardo et al. (2005), there could be in developing composite indicators have been analyzed. Specifically, a variety of scenarios, such as type of normalization for the sub-indicators, choice of aggregation system, assignment of the sub-indicators' weights, and elimination of outliers, have been considered and compared with the results of the BoD, to thus reinforce its accuracy.

The most important element for the robustness analysis is to analyze the variability of the ranking. Table A3 shows, as previously stated, the differences between the ranking of the bootstrap-CCR RSDI and the median of the other rankings, reflecting that the highest divergences correspond to the municipalities of Avión, Pontedeva, and Beariz. Overall though, the difference between the ranking of the bootstrap CCR and the median of the other rankings is very little. Indeed, in the case of the lowest rated or worst-performing municipalities, the ranking of the different indices is practically coincident. Therefore, empirical evidence suggests that, by and large, municipalities scoring highly (badly) in the bootstrap-CCR RSDI also obtain high (low) scores in alternative scenarios or models.

Table A4 shows the quartiles for the median of the four indices, placing the municipalities with the best situation in the first quartile (Q1) and those with the worst median score of the RSDIs in the fourth one (Q4). Municipalities belonging to Q1 display the highest values for social aspects, most noticeably, the non-university teaching centers (NUTC) and home help service (HHS) variables, whose values are twice as high as those for the municipalities in Q4. Overall, the variables within the environmental dimension score similarly regardless of which quartile the municipality is in, but those belonging to Q2, on average, have the highest values for protected land and areas of woodland. The environmental variables take similar values irrespective of the quartile. Arable land (AL) takes high values in the most disadvantaged municipalities (Q4) whereas protected land areas (PLA) takes low values, half the amount of the ones which the municipalities scored in Q1. Therefore, agriculture seems to constitute a source of resilience in rural areas in troubled times, but it can also be an obstacle for change or evolution in these regions (Lebel et al. 2006; Schouten et al. 2012).

Rodríguez-Rodríguez et al. (2021) have found that Spanish rural municipalities in special protection areas and biosphere reserves experience more serious depopulation, excepting in some cases, such as in Galicia and Asturias. Municipalities within these two regions have lower depopulation figures in protected areas, thus reinforcing the evidence found in our paper.

As has been pointed out by several authors (e.g., Black and Henderson, 1999; Abreu et al. 2019), economic activity creates the driver of economic growth in urban areas and of development in rural ones. In this regard, in the economic dimension, it can be seen that activity rate and income per capita display lower values the lower the score. The drop in the activity rate in the most disadvantaged municipalities is the sharpest, likely due to the effect of high rates of aging. Abreu et al. (2019) relate agriculture with low employment rate and the aging process. Similar results have been found by Mitrică et al. (2017), specifically that the socio-economic development of rural areas seems to be negative owing to aging populations. The evolution of demographic variables is consistent and proportional to the quartile to which the municipality belongs. By and large, the differences between the municipalities regarding the RSDI are largely due to social variables.

Figs. 7 and 8 show the bootstrap-CCR RSDI and the outputs[5] of some of the municipalities with the highest and the lowest scores. The municipalities in Fig. 7 show the upper 0.97 of the RSDI, as well as the AR, the PG, and the AOW and the PLA in particular are also quite high in these municipalities. Chandrexa de Queixa is one of many examples

[5] The outputs in Figs. 7 and 8 needed normalization (in this case, by subtracting the mean of the output and dividing the result by its standard deviation) so that the graph could be rendered useful. Otherwise, outputs would have taken very different values and the information would not have been able to be displayed in the same graph.

Table 3
Results: Truncated regression.

Variables	Model 1			Model 2		
	Beta	LL	UL	Beta	LL	UL
Intercept	0.46286	0.03817	0.88260	0.44510	0.03541	0.87936
IC	1.17622	0.56030	1.77751	1.22222	0.60442	1.80548
ALT	−0.00016	−0.00029	−0.00002	−0.00017	−0.00030	−0.00003
DC	0.00117	0.00009	0.00228	0.00122	0.00020	0.00239
ORHS	−0.23113	−0.43709	−0.04076	−0.25377	−0.46338	−0.05839
RECU	−0.21269	−4.83060	4.98796			
NPT	−0.00010	−0.00449	0.00506	−0.00018	−0.00444	0.00566
FI	−0.00335	−0.00575	−0.00057	−0.00349	−0.00588	−0.00064
Sigma	0.11468	0.09182	0.14491	0.11721	0.09130	0.14728

Notes: significance level α = 0.05; LL: lower level; UL: upper level.

Table 4
Results: Truncated regression. RSDI without PD.

Variables	Beta	LL	UL
Intercept	0.89260	0.41763	1.42014
IC	0.44603	−0.26910	1.06447
NVSC	−0.00010	−0.00098	0.00106
ALT	−0.00018	−0.00036	−0.00001
DC	0.00159	0.00014	0.00300
ORHS	−0.06909	−0.32783	0.17230
RECU	0.80407	−5.09299	7.93290
NPT	0.00129	−0.00394	0.00763
FI	−0.00359	−0.00724	−0.00010
Sigma	0.14728	0.11629	0.18773

Notes: significance level α = 0.05; LL: lower level; UL: upper level.

which has one of the highest RSDIs, peak AOW and PLA values, and even a high AR. This municipality is the most emblematic of Galicia's natural and beautiful landscapes, with a large hydroelectric reservoir and access to the "O Invernadoiro" natural park, not to mention an exceptional place for stargazing. Chandrexa de Queixa is a paradoxical case; it has been able to combat population decline by taking advantage of its unique environmental situation to pave the way for a sustainable rural development. In the municipality of A Capela, close to the city of Ferrol, and the highly-populated villages of Pontedeume and As Pontes de García Rodríguez, is found As Fragas do Eume, a natural park and a Site of Community Importance (SCI) which is considered the best preserved European Atlantic Forest. It stands out for its economic indicators, GDPC and AR, thanks to the implementation of measures to promote business entrepreneurship, such as the opening of a co-working center connected to the Green-Coworking network of As Pontes. Avión, a municipality surrounded by mountains, many of whose inhabitants emigrated to Mexico, amassed huge fortunes there and, on their return, built large mansions, which are located alongside traditional rustic houses. As a consequence, and as reflected in our indicators, this municipality displays is highly varied. A Veiga, located in the high mountains of Ourense, boasts the highest peak in Galicia (namely, the Pena Trevinca, which can be found at an altitude of 2124 m), as well as impressive landscapes which have attempted to fight against depopulation for many years via funding for restoration, subsidies to promote self-employment, and the revival of jobs such as honey production and bean growing. Unsurprisingly, therefore, this municipality has won an award from the Galician regional government for its work in geographical revitalization.

Among the worst-performing municipalities Fig. 8, the high AL values stand out, both when comparing them with those of the rest of the outputs in these municipalities, and with the AL values for the best-performing municipalities in Fig. 7. All these municipalities have minimum PLA indicators.

4.2. Second stage: truncated regression

The results of the truncated regression are shown in Table 3. Empirical evidence reveals that female immigration positively and significantly affects rural sustainable development, confirming our H7. Sánchez-Zamora et al. (2014) have pointed out that foreign immigrants are usually young people of childbearing age who come from countries with high birth rates and who therefore usually play a part in population growth. The ORHS is also significant and with the expected sign (H1); the higher the occupancy rate, the higher the RSDI.

Distance from the provincial capital contributes to explaining rural sustainable development, i.e., the greater the distance, the more fragile that development is (H6). This result can be related to the fact that the greater the distance from the town or city of reference, the harder it is to access certain services. Therefore, due to many healthcare services being concentrated in towns or cities, they deter rural inhabitants from making use of them (Eurostat, 2017). Additionally, running a business in a rural area tends to lead to higher transport costs than running one in an urban area, thus hindering potential workers from settling in rural areas. This statistically significant effect might also motivate public agents to improve mobility alternatives, fostering collective means of transportation.

The number of tourist accommodation facilities is not significant for rural development, even though, as Hernández-Maestro and González-Benito (2014) have stated, many public funds have been devoted to rural tourism, seeking to drive the development of poor rural areas by supporting retail growth, creating employment opportunities, and contributing to the preservation of nature and architecture. Conversely, Sánchez-Zamora et al. (2014) have found that an increase in the overnight lodging capacity of hotels leads to an improvement in sustainable rural development. This result is in line with Abreu et al. (2019) in that tourism in rural areas has been seen as an opportunity for development.

Real estate for commercial use is not significant. Conversely, the variable on internet coverage is, albeit with a negative sign, thus contradicting what was expected, especially when, because of the current COVID-19 pandemic, we have been witnessing a tendency to move to rural areas owing to the push towards telecommuting, which is directly associated with internet coverage. However, as the data on this variable refers to the year 2018, it might not be an accurate reflection of the current situation; broadband coverage is advancing rapidly, and in the near future almost all areas in Galicia should have it, thus favoring and promoting rural development.

Due to the paradoxical result regarding internet coverage, an additional regression removing the population density indicator (the one which has the highest correlations with internet coverage) as an output in the estimation of the CI has been presented (Table 4). In this case, the variable on internet coverage fails to be statistically significant. Besides this, different combinations have been made in the explanatory variables of the truncated regression, none of which have shown a significant positive relationship between the CI and internet coverage. Coverage indicators have even been used without weighting by population, but the results have not provided any evidence that it positively and significantly has an effect.

5. Conclusions

Many rural areas in Europe are at high risk of depopulation, which highlights the need to take further action. Galicia, a northwestern Spanish region sparsely populated by many villages is not immune to this demographic challenge. Hence, this paper has a twofold aim: (a) to propose and define an index of sustainable development for rural municipalities, and (b) to identify the exogenous factors that may influence it to learn more about the rural depopulation process in Galicia, thus helping design corrective programs.

Taking factors from four dimensions, namely, demographic, economic, social, and environmental, this paper outlines the proposal of a rural sustainable development index (RSDI) using different non-parametric methodologies, i.e., Benefit of the Doubt, common weights, super-efficiency, and logistic-geometric. Additional exogenous RSDI factors have been considered through truncated regression.

The comparative RSDI analysis has allowed the situation of each rural Galician municipality to be assessed, revealing that, overall, the poorest performers are in inland mountain areas, mainly located in Ourense province. Social variables (i.e., non-university teaching centers, number of primary care physicians, and home help service hours) are, by and large, responsible for the greatest differences in the RSDI of the sampled municipalities and, therefore, social dimension is the area that requires the most corrective action. Providing services and infrastructure (e.g., health, education, home help support and transport) to rural inhabitants not only benefits them but also creates employment opportunities via, for instance, the development of the silver economy. Furthermore, taking into account that female immigration has a positive effect on the RSDI, public policies fostering population settlements should attract young immigrants and enable a turnaround.

The values for environmental aspects are high, with similar values to each other, in all the municipalities; those with the worst situations have the lowest values except for arable land, which stands out, implying certain dependence on the agricultural sector in rural Galician areas. Not in vain, there are paradoxical examples of municipalities (e.g., Chandrexa de Queixa) that from a very unfavorable situation have been able to substantially develop by taking advantage of their environmental features.

Despite its contributions, this paper presents some minor limitations, such as variables integrating the composite index referring to different periods of time due to data at the municipality level being rather scarce. Furthermore, the selection of said variables is a process that, even though done rigorously, can be subjective. In spite of these limitations though, this study clearly adds to the literature on the topic by proposing, for the first time, a tailor-made rural sustainable development index for Galician municipalities, which could be extrapolated to other areas. This allows for the detection of variables requiring improvement. Additionally, other variables have been identified that influence the index and that should be considered in any public policy aimed at reducing depopulation in rural areas.

CRediT authorship contribution statement

M. Celia López-Penabad: Conceptualization, Methodology, Data curation, Writing – original draft, preparation, Supervision, Visualization, Formal analysis, Software. **Ana Iglesias-Casal:** Conceptualization, Methodology, Formal analysis, Data curation, Supervision, Validation, Writing – review & editing. **Lucía Rey-Ares:** Conceptualization, Methodology, Data curation, Formal analysis, Supervision, Validation, Writing – original draft, preparation and, Editing.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix

Table A.1
Descriptive statistical analysis

	NUTC	NPCP	HHS	IC	AOW	AL	PLA	ALT	DC	GDIPC	AR	ORHS	RECU	NPT	PG	PD	FI
Mean	0.85	1.41	1184.42	0.70	70.44	23.61	15.60	492.36	56.54	10843.32	39.73	0.52	0.01	5.04	4.43	26.33	28.11
Median	1.00	1.00	901.10	0.71	71.51	19.19	3.15	493.31	52.25	10829.00	40.25	0.53	0.01	3.00	4.34	16.30	26.00
Standard deviation	0.54	0.82	1202.97	0.07	12.91	17.23	24.33	234.08	28.17	1593.92	5.96	0.15	0.01	6.55	1.55	42.00	14.92
Minimum	0.00	0.00	0.10	0.50	34.31	0.48	0.01	12.05	13.00	5638.00	21.80	0.00	0.00	0.00	0.10	2.70	5.00
Maximum	3.00	6.00	6855.10	0.89	93.69	99.14	98.01	1110.92	141.00	14431.00	53.00	0.84	0.04	42.00	9.46	290.40	84.00
No. obs.	114	114	102	114	114	114	114	114	114	114	114	114	114	114	114	114	114

Table A.2
Pearson correlation matrix

	NUTC	NPCP	HHS	IC	NVSC	AOW	AL	PLA	ALT	DC	GDIPC	AR	ORHS	RECU	NPT	PG	PD	FI
NUTC	1																	
PCP	0.4240*	1																
HHS	0.1324	0.1291	1															
IC	0.2906*	0.1138	−0.1233	1														
NVSC	0.1720	0.1579	−0.1650	0.1363	1													
AOW	−0.0677	−0.0501	−0.0439	−0.2784*	0.1008	1												
AL	−0.1154	0.0094	0.0318	0.1587	−0.0247	−0.3027*	1											
PLA	−0.0176	−0.0167	−0.1383	−0.3486*	−0.1606	0.2350*	−0.2610*	1										
ALT	−0.1977*	−0.0031	−0.2346	−0.2210*	−0.0017	−0.0565	−0.0703	0.2903*	1									
DC	0.1332	−0.0669	0.0460	−0.2622*	0.0703	0.2964*	−0.2723*	0.3305*	0.0974	1								
GDIPC	0.3523*	0.3181*	0.2549*	0.1276	−0.1257	−0.2406*	−0.0373	−0.1765	−0.3104*	−0.0145	1							
AR	0.3399*	0.1794	0.1976*	0.0111	−0.0299	−0.2780*	−0.1051	0.0728	−0.1154	0.0305	0.3145*	1						
ORHS	0.1855*	0.0641	−0.1350	0.2829*	−0.0282	0.0525	0.0525	−0.1052	−0.0350	−0.0561	0.1213	−0.1723	1					
RECU	0.3000*	0.3570*	−0.0761	0.2822*	0.1242	−0.0513	−0.0836	−0.0769	0.0817	−0.0734	0.0806	0.0410	0.2251*	1				
NPT	0.1304	0.1733	0.1861*	−0.1892*	0.1303	0.0162	−0.1529	0.2886*	−0.0246	0.1856*	0.2997*	0.2946*	−0.0259	0.1237	1			
PG	0.1041	−0.1173	−0.0462	0.1115	−0.1183	−0.0067	−0.0739	−0.0196	−0.1917*	−0.0965	0.0944	0.2297*	−0.0335	0.1721	0.0242	1		
PD	0.2503*	−0.0929	−0.0619	0.4642*	0.2093	−0.2817*	−0.0619	−0.2265*	−0.3667*	−0.1718	0.2300*	0.2306*	0.2488*	0.3796*	0.0088	0.2822*	1	
FI	0.3439*	0.2132*	−0.0096	0.3404*	0.0081*	−0.0025	−0.0020	−0.2298*	−0.1507	−0.1430	0.0469	−0.1020	0.1812	0.3992*	−0.0759	0.3943*	0.2777*	1

Note: Any variables displaying significantly high correlations have been rejected beforehand. * 5% significance level.

Table A.3
Composite Indices: score and ranking by municipality and province, using different methodologies

Municipality	Bootstrap CCR	Common weights	Super-efficiency	Geometric - Logistic	Bootstrap CCR Rk	Median of ranks	Difference in Rank	Median of scores
Chandrexa de Queixa	0.9795	0.8744	0.9984	0.3952	1	44	-43	0.8744
Capela, A	0.9771	0.9192	0.9974	0.8076	2	20	-18	0.9192
Veiga, A	0.9751	0.8921	0.9976	0.5941	3	39	-36	0.8921
Avión	0.9745	0.7723	1.0150	0.2600	4	103	-99	0.7723
Riotorto	0.9737	0.9817	1.0098	0.9931	5	5	0	0.9931
Padrenda	0.9733	0.8508	1.0028	0.7119	6	35	-29	0.8508
Gomesende	0.9705	0.8352	0.9852	0.2884	7	67	-60	0.8352
Navia de Suarna	0.9698	0.9231	0.9984	0.7202	8	31	-23	0.9231
Vicedo, O	0.9693	0.8988	0.9870	0.6777	9	37	-28	0.8988
Manzaneda	0.9687	0.8400	1.0023	0.5546	10	63	-53	0.8400
Baleira	0.9681	0.9447	1.0306	0.7558	11	25	-14	0.9447
Xunqueira de Espadanedo	0.9668	0.8948	1.0106	0.5147	12	33	-21	0.8948
Pol	0.9664	0.9241	1.0247	0.8384	13	16	-3	0.9241
Ramirás	0.9639	0.8202	1.0169	0.4431	14	76	-62	0.8202
Vilarmaior	0.9635	0.8925	0.9930	0.7925	15	31	-16	0.8925
Trabada	0.9635	1.0000	1.0266	1.0000	16	1	15	1.0000
Dozón	0.9622	0.8211	1.0232	0.5550	17	67	-50	0.8211
Laza	0.9621	0.8710	1.0447	0.4071	18	46	-28	0.8710
Coirós	0.9615	0.9464	1.0248	0.8659	19	11	8	0.9464
Beariz	0.9613	0.7839	0.9795	0.2970	20	99	-79	0.7839
Paradela	0.9596	0.7775	1.0295	0.5220	21	74	-53	0.7775
Castro Caldelas	0.9592	0.8714	0.9889	0.6720	22	42	-20	0.8714
Cenlle	0.9589	0.9387	0.9834	0.6564	23	40	-17	0.9387
Cortegada	0.9583	0.8939	0.9766	0.5497	24	51	-27	0.8939
Melón	0.9574	0.8267	0.9770	0.3694	25	70	-45	0.8267
Pontedeva	0.9557	0.7559	0.9760	0.0183	26	107	-81	0.7559
Leiro	0.9546	0.9460	0.9831	0.7889	27	22	5	0.9460
Sandiás	0.9541	0.7901	1.0450	0.4454	28	81	-53	0.7901
Páramo, O	0.9536	0.8014	0.9771	0.5409	29	71	-42	0.8014
Carballeda de Avia	0.9531	0.8675	1.0540	0.6882	30	36	-6	0.8675
Ribeira de Piquín	0.9525	0.8877	0.9710	0.4204	31	53	-22	0.8877
Portomarín	0.9517	0.9610	1.0773	0.8684	32	10	22	0.9610
Montederramo	0.9500	0.8563	0.9660	0.3120	33	57	-24	0.8563
Aranga	0.9493	0.8939	0.9827	0.8314	34	30	4	0.8939
Piñor	0.9477	0.8534	1.0646	0.4390	35	54	-19	0.8534
Alfoz	0.9476	0.9018	1.0624	0.8223	36	21	15	0.9018
Arnoia, A	0.9474	0.9886	1.0942	0.7987	37	13	24	0.9886
Vilariño de Conso	0.9448	0.8769	1.0702	0.5577	38	42	-4	0.8769
Vilasantar	0.9446	0.8915	0.9708	0.6941	39	34	5	0.8915
Irixo, O	0.9431	0.8507	0.9633	0.5928	40	59	-19	0.8507
Samos	0.9426	0.8818	0.9707	0.8876	41	39	2	0.8876
Muras	0.9420	0.9673	1.0801	0.8961	42	7	35	0.9673
Pedrafita do Cebreiro	0.9417	0.8663	1.0857	0.6085	43	50	-7	0.8663
Mañón	0.9417	0.8853	1.0861	0.7340	44	28	16	0.8853
Xermade	0.9417	0.9526	1.0957	0.8768	45	10	35	0.9526
Negueira de Muñiz	0.9416	0.7829	1.0780	0.1416	46	101	-55	0.7829
Ourol	0.9392	0.8698	0.9585	0.4330	47	61	-14	0.8698
Bande	0.9391	0.8853	1.0991	0.7523	48	26	22	0.8853
Vilamartín de Valdeorras	0.9389	0.9238	0.9637	0.8455	49	17	32	0.9238
Gudiña, A	0.9374	0.8599	0.9560	0.6061	50	52	-2	0.8599
Nogais, As	0.9368	0.9043	0.9589	0.8000	51	24	27	0.9043
Corcubión	0.9359	1.0000	1.1506	0.8790	52	8	44	1.0000
Muíños	0.9358	0.8071	0.9662	0.6304	53	56	-3	0.8071
Cerdido	0.9348	0.8879	0.9521	0.6425	54	45	9	0.8879
Castrelo de Miño	0.9332	0.9910	1.4751	0.7243	55	3	52	0.9910
Sobrado	0.9325	0.8787	1.2801	0.7886	56	23	33	0.8787

Municipality	Bootstrap CCR	Common weights	Super-efficiency	Geometric - Logistic	Bootstrap CCR Rk	Median of ranks	Difference in Rank	Median of scores
Rábade	0.9322	0.7968	1.2386	0.5587	57	65	-8	0.7968
Carballeda de Valdeorras	0.9321	0.8754	1.5000	0.7944	58	20	38	0.8754
Mondariz-Balneario	0.9321	0.9206	1.3895	0.7702	59	19	40	0.9206
Cervantes	0.9319	0.9165	1.2125	0.8132	60	16	44	0.9165
Meira	0.9315	0.9371	1.5298	0.9928	61	3	58	0.9928
Irixoa	0.9309	0.9591	1.1957	0.7172	62	9	53	0.9591
Folgoso do Courel	0.9304	0.9740	1.2610	0.9801	63	6	57	0.9801
Pobra do Brollón, A	0.9278	0.8870	0.9442	0.7487	64	36	28	0.8870
Somozas, As	0.9275	0.8963	0.9478	0.6506	65	43	22	0.8963
Campo Lameiro	0.9259	0.8702	0.9439	0.6182	66	48	18	0.8702
Monfero	0.9243	0.9118	0.9452	0.8958	67	22	45	0.9118
Vilar de Barrio	0.9229	0.9087	0.9420	0.6887	68	35	33	0.9087
Xunqueira de Ambía	0.9198	0.8249	0.9441	0.6082	69	68	1	0.8249
Beade	0.9188	0.7767	0.9472	0.3511	70	95	-25	0.7767
Castrelo do Val	0.9179	0.8409	0.9381	0.5044	71	72	-1	0.8409
Rubiá	0.9178	0.8801	0.9329	0.5654	72	64	8	0.8801
Cualedro	0.9136	0.8301	0.9356	0.6629	73	69	4	0.8301
Entrimo	0.9117	0.8685	0.9393	0.6561	74	49	25	0.8685
Taboadela	0.9071	0.8260	0.9294	0.5688	75	71	4	0.8260
Santiso	0.9070	0.8019	0.9284	0.5931	76	76	0	0.8019
Trasmiras*	0.8863	0.7253	0.9047	0.1618	77	109	-32	0.7253
Mezquita, A	0.8821	0.8353	0.9072	0.6270	78	66	12	0.8353
Porqueira*	0.8808	0.8055	0.9100	0.2446	79	88	-9	0.8055
Toques	0.8807	0.8433	0.8999	0.6472	80	60	20	0.8433
Ribas de Sil	0.8800	0.8229	0.8961	0.4714	81	80	1	0.8229
Triacastela	0.8799	0.8194	0.8977	0.5962	82	77	5	0.8194
Petín	0.8797	0.8446	0.8920	0.3891	83	88	-5	0.8446
Bolo, O*	0.8797	0.7908	0.8988	0.4056	84	89	-5	0.7908
Lobios	0.8776	0.8523	0.9051	0.7337	85	55	30	0.8523
Larouco	0.8773	0.8408	0.8927	0.2429	86	87	-1	0.8408
Baltar	0.8762	0.8447	0.8974	0.6009	87	58	29	0.8447
Quintela de Leirado*	0.8726	0.7995	0.8952	0.3473	88	91	-3	0.7995
Lobeira*	0.8659	0.8068	0.8883	0.3972	89	89	0	0.8068
San Amaro*	0.8590	0.8192	0.8834	0.5490	90	78	12	0.8192
Riós*	0.8584	0.7977	0.8738	0.5309	91	92	-1	0.7977
Parada de Sil*	0.8569	0.6964	0.8724	0.0318	92	112	-20	0.6964
Baños de Molgas*	0.8568	0.8247	0.8703	0.5883	93	73	20	0.8247
Verea*	0.8561	0.8087	0.8803	0.3411	94	91	3	0.8087
Punxín	0.8554	0.8384	0.8716	0.6096	95	64	31	0.8384
Teixeira, A*	0.8538	0.7908	0.8685	0.2455	96	97	-1	0.7908
Moeche*	0.8516	0.8164	0.8689	0.5668	97	80	17	0.8164
Incio, O*	0.8514	0.8109	0.8658	0.5958	98	82	16	0.8109
Rairiz de Veiga*	0.8511	0.8316	0.8667	0.5826	99	68	31	0.8316
Esgos*	0.8511	0.8375	0.8663	0.4186	100	86	14	0.8375
Calvos de Randín*	0.8503	0.8115	0.8677	0.3446	101	97	4	0.8115
Vilamarín*	0.8414	0.7988	0.8595	0.4789	102	92	10	0.7988
Peroxa, A*	0.8411	0.7878	0.8623	0.5360	103	98	5	0.7878
Merca, A*	0.8366	0.8095	0.8567	0.6023	104	83	21	0.8095
Vilar de Santos*	0.8342	0.7740	0.8573	0.2588	105	104	1	0.7740
Oímbra*	0.8256	0.7469	0.8491	0.4155	106	106	0	0.7469
Bóveda*	0.8231	0.8170	0.8404	0.6549	107	79	28	0.8170
Sarreaus*	0.8182	0.7800	0.8440	0.3175	108	102	6	0.7800
Fornelos de Montes*	0.8172	0.8072	0.8316	0.5126	109	85	24	0.8072
Paderne de Allariz*	0.8126	0.7838	0.8299	0.5209	110	100	10	0.7838
Vilardevós*	0.8122	0.7508	0.8289	0.3529	111	109	2	0.7508
Blancos, Os*	0.7832	0.7519	0.8034	0.2017	112	108	4	0.7519
San Xoán de Río*	0.7694	0.6612	0.7816	0.0000	113	114	-1	0.6612
Bola, A*	0.7505	0.7303	0.7659	0.1233	114	111	3	0.7303

Note: *Rk* stands for "the position in the ranking". * is used for highlighting the municipalities that display the lowest RSDI values overall. Blue is used for municipalities belonging to the A Coruña province, green for those belonging to Pontevedra, red for those in Lugo and black for those in Ourense.

Table A.4
Municipalities by quartiles. Median score of the four indices

First quartile		Second quartile	
Municipality	Median	Municipality	Median
Trabada	1.0000	Nogais, As	0.9206
Riotorto	0.9874	Ribeira de Piquín	0.9201
Folgoso do Courel	0.9770	Monfero	0.9181
Arnoia, A	0.9680	Vilasantar	0.9181
Corcubión	0.9680	Laza	0.9166
Meira	0.9650	Vilar de Barrio	0.9158
Castrelo de Miño	0.9621	Castro Caldelas	0.9153
Baleira	0.9564	Samos	0.9151
Portomarín	0.9564	Mañón	0.9135
Muras	0.9546	Bande	0.9122
Coirós	0.9539	Padrenda	0.9120
Leiro	0.9503	Somozas, As	0.9119
Cenlle	0.9488	Cerdido	0.9114
Capela, A	0.9481	Vilariño de Conso	0.9109
Xermade	0.9471	Carballeda de Avia	0.9103
Navia de Suarna	0.9464	Pobra do Brollón, A	0.9074
Pol	0.9452	Sobrado	0.9056
Irixoa	0.9450	Ourol	0.9045
Vicedo, O	0.9340	Manzaneda	0.9044
Veiga, A	0.9336	Pedrafita do Cebreiro	0.9040
Vilamartín de Valdeorras	0.9313	Carballeda de Valdeorras	0.9038
Xunqueira de Espadanedo	0.9308	Montederramo	0.9032
Vilarmaior	0.9280	Gomesende	0.9029
Chandrexa de Queixa	0.9269	Piñor	0.9006
Mondariz-Balneario	0.9264	Rubiá	0.8989
Cortegada	0.9261	Gudiña, A	0.8986
Alfoz	0.9247	Campo Lameiro	0.8980
Cervantes	0.9242	Irixo, O	0.8969
Aranga	0.9216		
Third quartile		***Fourth quartile***	
Municipality	**Median**	**Municipality**	**Median**
Melón	0.8920	Esgos	0.8443
Ramirás	0.8920	Porqueira	0.8432
Dozón	0.8917	Rairiz de Veiga	0.8414
Entrimo	0.8901	Baños de Molgas	0.8408
Castrelo do Val	0.8794	San Amaro	0.8391
Páramo, O	0.8775	Lobeira	0.8363
Avión	0.8734	Quintela de Leirado	0.8361
Beariz	0.8726	Bolo, O	0.8352
Xunqueira de Ambía	0.8724	Moeche	0.8340
Sandiás	0.8721	Verea	0.8324
Cualedro	0.8718	Incio, O	0.8312
Muíños	0.8714	Calvos de Randín	0.8309
Paradela	0.8686	Riós	0.8280
Taboadela	0.8666	Merca, A	0.8230
Lobios	0.8649	Teixeira, A	0.8223
Rábade	0.8645	Vilamarín	0.8201
Negueira de Muñiz	0.8622	Bóveda	0.8201
Petín	0.8622	Peroxa, A	0.8144
Toques	0.8620	Fornelos de Montes	0.8122
Baltar	0.8604	Trasmiras	0.8058
Larouco	0.8591	Vilar de Santos	0.8041
Mezquita, A	0.8587	Sarreaus	0.7991
Pontedeva	0.8558	Paderne de Allariz	0.7982
Santiso	0.8545	Oímbra	0.7863
Ribas de Sil	0.8514	Vilardevós	0.7815
Triacastela	0.8496	Parada de Sil	0.7767
Beade	0.8477	Blancos, Os	0.7676
Punxín	0.8469	Bola, A	0.7404
		San Xoán de Río	0.7153

References

Abreu, I., Nunes, J.M., Mesias, F.J., 2019. Can rural development Be measured? Design and application of a synthetic index to Portuguese municipalities. Soc. Indicat. Res. 145, 1107–1123. https://doi.org/10.1007/s11205-019-02124-w.

Alados, C.L., Errea, P., Gartzia, M., Saiz, H., Escós, J., 2014. Positive and negative feedbacks and free-scale pattern distribution in rural-population dynamics. PLoS One 9 (12), e114561. https://doi.org/10.1371/journal.pone.0114561.

Andersen, P., Petersen, N.C., 1993. A procedure for ranking efficient units in data envelopment analysis. Manag. Sci. 39 (10), 1261–1264. https://www.jstor.org/stable/2632964.

BdE, Banco de España, 2021. Informe Anual 2020. Banco de España, Eurosistema.

Black, D., Henderson, J.V., 1999. A theory of urban growth. J. Polit. Econ. 107 (2), 252–284. https://doi.org/10.1086/250060.

Casini, L., Boncinelli, F., Gerini, F., Romano, C., Scozzafava, G., Contini, C., 2021. Evaluating rural viability and well-being: evidence from marginal areas in Tuscany. J. Rural Stud. 82, 64–75. https://doi.org/10.1016/j.jrurstud.2021.01.002.

Castellani, V., Sala, S., 2010. Sustainable performance index for tourism policy development. Tourism Manag. 31 (6), 871–880. https://doi.org/10.1016/j.tourman.2009.10.001.

Charnes, A., Cooper, W.W., Rhodes, E., 1978. Measuring the efficiency of decision making units. Eur. J. Oper. Res. 2 (6), 429–444. https://doi.org/10.1016/0377-2217(78)90138-8.

Cobb, J.B., 1989. The index of sustainable economic welfare. In: Daly, H.E., Cobb, J.B. (Eds.), For the Common Good. Beacon Press, Boston, pp. 401–455.

Delgado, C., 2019. Depopulation processes in European rural areas: a case study of Cantabria (Spain). Eur. Countrys. 11 (3), 341–369. https://doi.org/10.2478/euco-2019-0021.

Despotis, D.K., 2005. A reassessment of the human development index via data envelopment analysis. J. Oper. Res. Soc. 56, 969–980. https://doi.org/10.1057/palgrave.jors.2601927.

Dutta, P., Jain, A., Gupta, A., 2020. Performance analysis of non-banking finance companies using two-stage data envelopment analysis. Ann. Oper. Res. 295, 91–116. https://doi.org/10.1007/s10479-020-03705-6.

Edoarado, 2010. https://commons.wikimedia.org/wiki/File:Galicia_Topo.svg.

ESPON, 2017. Shrinking rural regions in Europe: towards smart and innovative approaches to regional development challenges in depopulating rural regions. Luxembourg Policy Brief, 10.12.20. https://www.espon.eu/rural-shrinking.

Esteban-Salvador, L., Gargallo-Castel, A.F., Pérez-Sanz, J., 2020. Environmental practices in firms located in underpopulated rural areas in Spain: the case of the province of teruel. Int. J. Environ. Res. Publ. Health 17, 8993. https://doi.org/10.3390/ijerph17238993.

Eurostat, 2017. Eurostat regional yearbook. https://doi.org/10.2785/568258, 2017.

Eurostat, 2020. Urban and rural living in the EU. https://ec.europa.eu/eurostat/web/products-eurostat-news/-/EDN-20200207-1.

Fernández-Martínez, P., de Castro-Pardon, M., Barroso, V.M., Azevedo, J.C., 2020. Assessing sustainable rural development based on ecosystem services vulnerability. Land 9 (7), 222–245. https://doi.org/10.3390/land9070222.

Floridi, M., Pagni, S., Falorni, S., Luzzati, T., 2011. An exercise in composite indicators construction: assessing the sustainability of Italian regions. Ecol. Econ. 70 (8), 1440–1447. https://doi.org/10.1016/j.ecolecon.2011.03.003.

González-Leonardo, M., López-Gay, A., Recaño, J., Rowe, F., 2022. Changes of residence in times of COVID-19: a small respite from rural depopulation. Perspectives Demogràfiques 26, 1–4. https://doi.org/10.46710/ced.pd.eng.26.

Hernández-Maestro, R.M., González-Benito, O., 2014. Rural lodging establishments as drivers of rural development. J. Trav. Res. 53 (1), 83–95. https://doi.org/10.1177/0047287513481273.

Hospers, G.J., Reverda, N., 2015. The geography of population decline. In: Hospers, G.J., Reverda, N. (Eds.), Managing Population Decline in Europe's Urban and Rural Areas. Springer, Cham, pp. 29–37. https://doi.org/10.1007/978-3-319-12412-4_4.

IGE, 2020. IGE. Cifras poboacionais de referencia. https://www.ige.eu/igebdt/selector.jsp?COD=5230&paxina=001&c=0201001006.

IGE, 2020a. Banco de datos municipal. Consulta por temas. https://www.ige.eu/igebdt/esq.jsp?paxina=002003004&c=-1&idioma=es&ruta=navmunicipal.jsp%3FESP%3D.

Iglesias-Casal, A., López-Penabad, C., Rey-Ares, L., Saavedra, A., 2020. Despoblación en el ámbito rural en Galicia y Asturias. Análisis de la situación a nivel municipal. In: Odete, P., et al. (Eds.), XXX Jornadas Luso-Espanholas de Gestão Científica. Cooperaçãotransfronteiriça: desenvolvimento e coesão territorial, pp. 179–192. Bragança.

INE, 2021. Official population figures referring to revision of municipal register 1 january. https://www.ine.es/dynt3/inebase/index.htm?padre=517&capsel=517.

INE, 2021a. Census. Glossary. https://www.ine.es/censo_accesible/es/glosario.html.

Lebel, L., Anderies, J.M., Campbell, B., Folke, C., Hatfield-Dodds, S., Hughes, T.P., Wilson, J., 2006. Governance and the capacity to manage resilience in regional social-ecological systems. Ecol. Soc. 11 (1), 1–19. http://www.ecologyandsociety.org/vol11/iss1/art19/.

Lemke, C., Bastini, K., 2020. Embracing multiple perspectives of sustainable development in a composite measure: the Multilevel Sustainable Development Index. J. Clean. Prod. 246, 118884. https://doi.org/10.1016/j.jclepro.2019.118884.

López-González, F.J., Crecente-Maseda, R., Miranda-Barros, D., 2004. Caracterización rural de los municipios gallegos, de cara a una acertada aplicación de las iniciativas comunitarias de desarrollo rural. VIII Congreso Internacional de Ingeniería de Proyectos 1184–1192. https://www.aeipro.com/files/congresos/2004bilbao/ciip04_1184_1192.1336.pdf.

López-Iglesias, E., Peón, D., Rodríguez-Álvarez, J., 2018. Mobility innovations for sustainability and cohesion of rural areas: a transport model and public investment analysis for Valdeorras (Galicia, Spain). J. Clean. Prod. 172, 3520–3534. https://doi.org/10.1016/j.jclepro.2017.05.149.

Luzzati, T., 2009. Human needs, sustainable development, and public policy: learning from K.W. Kapp (1910–1976). In: Salvadori, N., Opocher, A. (Eds.), Long-Run Growth, Social Institutions and Living Standards. Edward Elgar Publishing, Cheltenham, pp. 305–321. https://doi.org/10.4337/9781781007761.00019.

Martínez-Vega, J., Echavarría, P., González, V., Martínez, N., 2009. Propuesta metodológica para el análisis de la sostenibilidad en la provincia de Cuenca. Boletín de la A.G.E. 49, 281–308.

Martínez-Vega, J., Rodríguez-Rodríguez, D., Fernández-Latorre, F.M., Ibarra, P., Echeverría, M., Echavarría, P., 2020. Proposal of a system for assessment of the sustainability of municipalities (sasmu) included in the Spanish network of national parks and their surroundings. Geosciences 10 (8), 298–324. https://doi.org/10.3390/geosciences10080298.

Ministry of Economic Affairs and Digital Transformation, 2021. https://avancedigital.mineco.gob.es/banda-ancha/cobertura/Paginas/informes-cobertura.aspx.

Miranda-García, M., Gallardo-Cobos, R., Sánchez-Zamora, P., 2019. La Metodología Leader y la despoblación rural: el caso de la comarca de Sierra Grande-Tierra de Barros (Badajoz). Econ. Agrar. Recur. Nat. 19 (2), 9–28. https://doi.org/10.7201/earn.2019.02.01.

Mitrică, B., Mocanu, I., Dumitraşcu, M., Grigorescu, I., 2017. Socio-economic disparities in the development of the Romania's border areas. Soc. Indicat. Res. 134 (3), 899–916. https://doi.org/10.1007/s1120 5-016-1462-7.

Nardo, M., Saisana, M., Saltelli, A., Tarantola, S., Hoffman, A., Giovannini, E., 2005. Handbook on constructing composite indicators: methodology and user guide. OECD Stat. Work. Pap. https://doi.org/10.1787/533411815016, 2005/03, OECD Publishing.

Nieto-Masot, A., Cárdenas-Alonso, G., Engelmo-Moriche, A., 2020. Design of a Development index for Spanish Municipalities. Sustainability 12, 8910.

Ónega-López, F.J., Puppim de Oliveira, J.A., Crecente-Maseda, R., 2010. Planning innovations in land management and governance in fragmented rural areas: two examples from Galicia (Spain). Eur. Plann. Stud. 18 (5), 755–773. https://doi.org/10.1080/09654311003594067.

Pinilla, V., Sáez, L.A., 2021. What do public policies teach us about rural depopulation: the case study of Spain. Eur. Countrys. 13 (2), 330–351. https://doi.org/10.2478/euco-2021-0021.

Rodríguez-Rodríguez, D., Larrubia, R., Sinoga, J.D., 2021. Are protected areas good for the human species? Effects of protected areas on rural depopulation in Spain. Sci. Total Environ. 763, 144399 https://doi.org/10.1016/j.scitotenv.2020.144399.

Salvati, L., Carlucci, M., 2014. A composite index of sustainable development at the local scale: Italy as a case study. Ecol. Indicat. 43, 162–171. https://doi.org/10.1016/j.ecolind.2014.02.021.

Sánchez-Zamora, P., Gallardo-Cobos, R., Ceña-Delgado, F., 2014. Rural areas face the economic crisis: analyzing the determinants of successful territorial dynamics. J. Rural Stud. 35, 11–25. https://doi.org/10.1016/j.jrurstud.2014.03.007.

Schouten, M.A.H., van der Heide, C.M., Heijman, W.J.M., Opdam, P.F.M., 2012. A resilience-based policy evaluation framework: application to European rural development policies. Ecol. Econ. 81, 165–175. https://doi.org/10.1016/j.ecolecon.2012.07.004.

Shepherd, A., 1998. Sustainable Rural Development. Palgrave Macmillan, London. https://doi.org/10.1007/978-1-349-26211-3.

Simar, L., Wilson, P.W., 1998. Sensitivity analysis of efficiency scores: how to bootstrap in nonparametric frontier models. Manag. Sci. 44 (1), 49–61. http://www.jstor.org/stable/2634426.

Simar, L., Wilson, P.W., 2002. Nonparametric tests of returns to scale. Eur. J. Oper. Res. 139 (1), 115–132. https://doi.org/10.1016/S0377-2217(01)00167-9.

Simar, L., Wilson, P.W., 2007. Estimation and inference in two-stage, semi-parametric models of production processes. J. Econom. 136 (1), 31–64. https://doi.org/10.1016/j.jeconom.2005.07.009.

Singh, R.K., Murty, H.R., Gupta, S.K., Dikshit, A.K., 2012. An overview of sustainability assessment methodologies. Ecol. Indicat. 15 (1), 281–299. https://doi.org/10.1016/j.ecolind.2011.01.007.

Tone, K., 2002. A slacks-based measure of super-efficiency in data envelopment analysis. Eur. J. Oper. Res. 143 (1), 32–41. https://doi.org/10.1016/S0377-2217(01)00324-1.

UNDP, 2016. Human Development Report 2016. United Nations Development Programme, 05.10.20. http://hdr.undp.org/sites/default/files/2016_human_development_report.pdf.

Valiente, L., 2019. ¿Podría estar contribuyendo el cooperativismo a fijar la población en el territorio de Andalucía? Revista de Economía Pública. Social y Cooperativa 97, 49–74. https://doi.org/10.7203/CIRIEC-E.97.13046.

World Bank, 1997. Expanding the Measure of Wealth. Indicators of Environmentally Sustainable Development. World Bank, Washington, DC.

Wu, J., Chu, J., Zhu, Q., Li, Y., Liang, L., 2016. Determining common weights in data envelopment analysis based on the satisfaction degree. J. Oper. Res. Soc. 67, 1446–1458. https://doi.org/10.1057/jors.2016.35.