Assessing the Spatial EBLUP in small area estimation: A simulation study and an application to confidence in police work

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Abstract

The use of spatially correlated random area effects is increasingly in use in small area estimation field. The spatial Empirical Best Linear Unbiased Predictor (SEBLUP), which borrows strength from correlated random area effects between neighbouring areas, have shown to reduce the estimates' variance and bias, both under simulated and real population studies. However, little attention has received the study of the effect of the number of areas under study, m, on SEBLUP performance. This paper assesses the effect of m and the spatial correlation parameter, ρ, on SEBLUP performance, in terms of bias and mean squared error. A simulation study and an application to confidence in police work in Europe are conducted. Our results show that SEBLUP estimator tends to perform better than traditional model-based estimators not only when the spatial correlation parameter ρ is closer to 1 and -1, but also when m is larger. Such results suggest that SEBLUP estimator is an appropriate method to be used when the level of spatial correlation of the variable of interest is high and/or when the number of areas under study is large. From a substantive perspective, the results of our application show that confidence in police work is higher in most Northern and Central European regions, while lower proportions of citizens who think the police do a good or very good job are estimated in Southern and Eastern regions. Also, the homicide rate, mean age and Human Development Index are shown to be good predictors of confidence in police work.

Keywords

Spatial correlation, SAR, contiguity matrix, spatial model, police legitimacy, policing

1 Introduction

The use of spatially correlated random area effects is increasingly in use in small area estimation field (e.g. Chandra et al. 2007; Marhuenda et al. 2013; Molina et al. 2009; Petrucci et al. 2005; Petrucci and Salvati 2006; Pratesi and Salvati 2008, 2009; Salvati 2004; Salvati et al. 2014). Small area estimation techniques, which seek to produce precise and reliable estimates for unplanned domains where small and zero sample sizes do not allow producing direct estimates of adequate precision (Rao and Molina 2015), have experienced new important developments during the past twenty years (see Pfeffermann 2013; Rao and Molina 2015). Among these, the extension of the Empirical Best Linear Unbiased Predictor (EBLUP), which is based on the Fay-Herriot (FH) model (Fay and Herriot 1979), considering correlated random area effects between neighbouring areas through the simultaneous autoregressive process (SAR), the spatial EBLUP (SEBLUP), have shown to reduce both variance and bias of the estimates (Petrucci and Salvati 2006; Pratesi and Salvati 2008, 2009; Salvati 2004; Salvati et al. 2014).

There have been several evaluations of SEBLUP estimator's performance in comparison with direct and traditional model-based estimators, both under simulated and real populations and under hypothetical and real contiguity matrices (see Asfar and Sadik 2016; Chandra et al. 2007; Petrucci and Salvati 2006; Pratesi and Salvati 2008, 2009; Salvati 2004). The sample size, n, and the spatial correlation parameter, ρ, have shown to be relevant to improve model-based estimates through the use spatially correlated random area effects, both in simulation studies and applications. However, less attention has received the study of the effect of the number of areas under study, m, on SEBLUP relative performance (e.g. Asfar and Sadik 2016; Salvati 2004). Salvati (2004) analysed the precision of SEBLUP estimates for m equal to 25 and 50, and $\rho = \{\pm 0.25, \pm 0.5, \pm 0.75\}$, and concluded that the improvement in the estimates' accuracy is higher when the spatial autoregressive coefficient increases, but also that "benefit is bigger as the number of small areas increase" (p. 11). Also, recent applications of SEBLUP estimator to survey recorded data suggest that m might have a large impact on SEBLUPs performance, arguing that SEBLUP estimator might gain precision when the number of areas is bigger, while SEBLUP estimates may be less precise than EBLUP estimates in cases of small number of areas under study (e.g. Buil-Gil et al. 2018).

Among the very few simulation studies that measure the impact of m on SEBLUPs performance, Asfar and Sadik's (2016) analysed SEBLUP relative mean squared errors under m equal to 16, 64 and 144. They found large relative improvement of SEBLUP estimates even when ρ is very small ($\rho = 0.05$) and small ($\rho = 0.25$), also in cases of very few areas under study ($m = 16$). In addition, such benefit was sometimes bigger when m was equal to 16 than in cases of m equal to 64 and 144. Such results do not correspond to other simulation studies results, which show that SEBLUPS relative performance improves as the number of areas increases (Salvati 2004), and SEBLUPs precision is not improved if $\rho \cong 0$, in cases of m equal to 25 and 50 (Salvati 2004), 61 (Petrucci and Salvati 2006), 23 (Chandra et al. 2007) and 42 (Pratesi and Salvati 2008, 2009). Therefore, further research is needed to understand how both the spatial correlation parameter and the number of small areas affect SEBLUP's relative precision. Specifically, simulation studies are required to assess whether SEBLUP estimators produce better estimates than traditional model-based estimators only in cases of a large number of areas under study, and whether such benefit increases when m increases.

The main aim of this paper is to assess the effect of the number of areas under study, m, on SEBLUP estimation performance, both in terms of bias and mean squared error. For that purpose, a simulation study and an application are conducted: the first under synthetic generated population and perfectly connected contiguity matrices based on hypothetical maps; and the second producing estimates of confidence in police work in Europe from the European Social Survey (ESS) data. In the first study, SEBLUP estimates' quality measures are compared to post-stratified and EBLUP estimates taking control for both the number of areas, m, and the spatial correlation parameter, ρ. In the application, estimates of confidence in police work are produced for three European subregions with different number of areas: Southern and Southwestern Europe ($m = 36$), Western Europe ($m = 58$) and Central, Northern and Eastern Europe ($m = 96$). Furthermore, the application presented contributes to the increasing criminological research on understanding citizens' perceptions of the police (e.g. Gau et al. 2012; Jackson et al. 2013; Jang et al 2010; Kääriäinen 2007; Piatkowska 2015; Staubli 2017; Tankebe 2012; Tyler 2004). From a methodological perspective, a better understanding of the effect of m and ρ on SEBLUP's performance is useful for policy makers and applied researchers who need to decide whether to use EBLUP or SEBLUP estimators to produce precise estimates of specific phenomena.

The paper is organised as follows. Section 2 describes the Fay-Herriot model with spatially correlated random effect (SEBLUP). Section 3 is devoted to present the simulation study as well as its results: SEBLUP estimates are compared to post-stratified and EBLUP estimates from $T = 1000$ simple random samples without replacement. Section 4 applies EBLUP and SEBLUP models to produce estimates of confidence in police work in Europe. Finally, section 5 draws conclusions and suggests future works.

2 Spatial EBLUP

Let us consider a target population portioned in m small areas. In the traditional Fay-Herriot model (Fay and Herriot 1979), we assume that a linking model linearly relates the quantity of inferential interest, which is usually an area mean or total δ_i, to p area level auxiliary variables $\boldsymbol{x}_i = (x_{i1}, \dots, x_{ip})'$ with a random effect v_i:

$$\delta_i = \boldsymbol{x}_i'\boldsymbol{\beta} + v_i, \qquad i = 1, \dots, m, \tag{1}$$

where $\boldsymbol{\beta}$ is the $p \times 1$ vector of regression parameters and $v_i \sim iid(0, \sigma_u^2)$. It is also assumed that a design-unbiased direct estimate y_i of δ_i is available for $i = 1, \dots, m$:

$$y_i = \delta_i + e_i, \qquad i = 1, \dots, m, \tag{2}$$

where $e_i \sim N(0, \psi_i)$ denotes the sampling errors, independent of v_i, and ψ_i refers to the sampling variance of the direct estimates (Rao and Molina 2015).

SEBLUP estimator borrows strength from neighbouring areas by adding spatially correlated random area effects (Petrucci and Salvati 2006; Pratesi and Salvati 2008; Rao and Molina 2015). Combining (1) with (2) we can write the full model

$$\boldsymbol{y} = \boldsymbol{X}\boldsymbol{\beta} + \boldsymbol{v} + \boldsymbol{e}, \tag{3}$$

where $\boldsymbol{y}$ is the vector of direct estimates $(y_1, \dots, y_m)'$ of m areas, $\boldsymbol{X}$ is the matrix $(\boldsymbol{x}_1, \dots, \boldsymbol{x}_m)'$ of covariates for m areas, $\boldsymbol{v}$ is a vector $(v_1, \dots, v_m)'$ of area effects and $\boldsymbol{e}$ is a vector $(e_1, \dots, e_m)'$ of sampling errors independent of $\boldsymbol{v}$. We assume $\boldsymbol{v}$ to follow a SAR process with unknown autoregression parameter $\rho \in (-1, 1)$ and a contiguity matrix $\boldsymbol{W}$ (Cressie 1993):

$$\boldsymbol{v} = \rho\boldsymbol{W}\boldsymbol{v} + \boldsymbol{u}. \tag{4}$$

We also assume $(\boldsymbol{I}_m - \rho\boldsymbol{W})$ to be non-singular, where $\boldsymbol{I}_m$ is a the $m \times m$ identity matrix, so we can express (4) as follows:

$$\boldsymbol{v} = (\boldsymbol{I}_m - \rho\boldsymbol{W})^{-1}\boldsymbol{u}, \tag{5}$$

where $\boldsymbol{u} = (u_1, \dots, u_m)'$ satisfies $\boldsymbol{u} \sim N(\boldsymbol{0}_m, \sigma_u^2\boldsymbol{I}_m)$. Thus,

$$\boldsymbol{y} = \boldsymbol{X\beta} + (\boldsymbol{I_m} - \boldsymbol{\rho W})^{-\mathbf{1}}\boldsymbol{u} + \boldsymbol{e}. \tag{6}$$

We now denote the vector of variance components as $\boldsymbol{\theta} = (\theta_1, \theta_2)' = (\sigma_u^2, \rho)'$. Then, the spatial Best Linear Unbiased Predictor (SBLUP) of $\delta_i = \boldsymbol{x_i'\beta} + v_i$ is given by

$$\tilde{\delta}_i^{SBLUP}(\boldsymbol{\theta}) = \boldsymbol{x_i'}\widetilde{\boldsymbol{\beta}}(\boldsymbol{\theta}) + \boldsymbol{b_i'}\boldsymbol{G}(\boldsymbol{\theta})\boldsymbol{\Sigma}^{-\mathbf{1}}(\boldsymbol{\theta})\{\boldsymbol{y} - \boldsymbol{X}\widetilde{\boldsymbol{\beta}}(\boldsymbol{\theta})\}, \tag{7}$$

where $\boldsymbol{b_i'}$ is a $1 \times m$ vector (0,…,1,0,…,0) with 1 in position i. $\boldsymbol{G}(\boldsymbol{\theta})$, the covariance matrix of $\boldsymbol{v}$, is given $\boldsymbol{G}(\boldsymbol{\theta}) = \sigma_u^2\{(\boldsymbol{I_m} - \boldsymbol{\rho W})'(\boldsymbol{I_m} - \boldsymbol{\rho W})\}^{-\mathbf{1}}$. $\boldsymbol{\Sigma}(\boldsymbol{\theta})$, which is the covariance matrix of $\boldsymbol{y}$, is defined as $\boldsymbol{\Sigma}(\boldsymbol{\theta}) = \boldsymbol{G}(\boldsymbol{\theta}) + \boldsymbol{\Psi}$, where $\boldsymbol{\Psi} = diag(\psi_1, \dots, \psi_m)$. And $\widetilde{\boldsymbol{\beta}}(\boldsymbol{\theta})$, the weighted least squares estimator of $\boldsymbol{\beta}$, is obtained as $\widetilde{\boldsymbol{\beta}}(\boldsymbol{\theta}) = \{\boldsymbol{X'\Sigma^{-1}}(\boldsymbol{\theta})\boldsymbol{X}\}^{-\mathbf{1}}\boldsymbol{X'\Sigma^{-1}}(\boldsymbol{\theta})\boldsymbol{y}$ (Petrucci and Salvati 2006).

SEBLUP is obtained by replacing a consistent estimator of $\boldsymbol{\theta}$ by $\widehat{\boldsymbol{\theta}} = (\hat{\sigma}_u^2, \hat{\rho})'$:

$$\hat{\delta}_i^{SEBLUP} = \hat{\delta}_i^{SEBLUP}(\widehat{\boldsymbol{\theta}}) = \boldsymbol{x_i'}\widetilde{\boldsymbol{\beta}}(\widehat{\boldsymbol{\theta}}) + \boldsymbol{b_i'}\boldsymbol{G}(\widehat{\boldsymbol{\theta}})\boldsymbol{\Sigma}^{-\mathbf{1}}(\widehat{\boldsymbol{\theta}})\{\boldsymbol{y} - \boldsymbol{X}\widetilde{\boldsymbol{\beta}}(\widehat{\boldsymbol{\theta}})\}. \tag{8}$$

If we assume the normality of the random effects, we can estimate σ_u^2 and ρ based on different procedures. In this research, we will consider the restricted maximum likelihood (REML) approximation, which takes into account for the loss in degrees of freedom derived from estimating $\boldsymbol{\beta}$, while other approximations, such as the maximum likelihood (ML), do not (see Pratesi and Salvati 2008).

3 Simulation study

In this section we describe the simulation study designed to assess the effect of the number of areas, m, and the spatial correlation parameter, ρ, over SEBLUP's performance (in terms of relative bias and relative error) in comparison to EBLUP and post-stratified estimators.

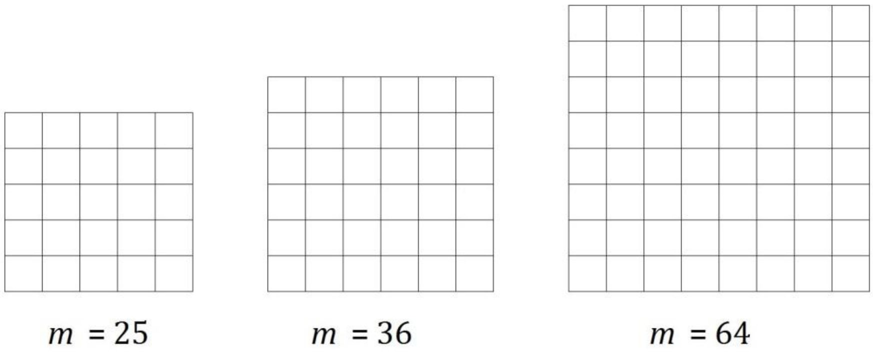
3.*1 Generating the population and simulation steps*

The population is generated based on previous simulation studies such as Petrucci and Salvati (2006) and Pratesi and Salvati (2008, 2009). Similar approaches have also been used in Asfar and Sadik (2016), Molina et al. (2009) and Salvati (2004). The experiment is designed according to the following linear mixed-effect model with random area effects of neighbouring areas correlated to the SAR dispersion matrix with fixed autoregressive coefficient:

$$y_{ij} = x_{ij}\beta + v_i + e_{ij}, \qquad i = 1 \dots m, \qquad j = 1 \dots N_i, \tag{9}$$

where x_{ij} is the value of the covariate *x* for unit *j* in area *i*, v_i denotes the area effect and e_{ij} is the individual error. The simulation parameters are given as follows: $\beta = 0.74$, $\sigma_u^2 = 90$, $\sigma^2 = 1.50$. $\mathbf{v} = [v_1, \dots, v_m]^T$ is generated from a $\text{MVN}(0, \sigma_u^2[(\mathbf{I} - \rho\mathbf{W})(\mathbf{I} - \rho\mathbf{W}^T)]^{-1})$, and $\mathbf{e} = [e_{11}, e_{12}, \dots, e_{ij}, \dots, e_{mN_m}]^T$ from a $N(0, \sigma^2)$. x_{ij} values are generated from a uniform distribution between 0 and 1000 and $N_i = [N_1, \dots, N_m]$ is generated from uniform distribution between 100 and 300. The size of the population is $N = \sum_{i=1}^{m} N_i$. Thus, we simulate 42 different populations based on different values of spatial autoregressive coefficient, $\rho = \{0, \pm 0.25, \pm 0.5, \pm 0.75\}$, and number of areas, $m = \{16, 25, 36, 64, 144, 225\}$. For this purpose, all maps used are hypothetical maps based on perfect squares divided into m number of areas, where the maximum number of neighbours is 8 and the minimum is 3 at the corners (see examples in Figure 1). Neighbouring areas are defined based on a 'Queen Contiguity' approximation, typically the most common structure used in simulation studies, which defines as neighbours all areas that share borders or at least one vertex. The $\boldsymbol{W}$ matrix is standardised by rows, so that every row adds up to 1.

Fig. 1 Three examples of hypothetical maps used in simulation study



The simulation consists in the following steps for each simulated population:

1. Selection of $t = 1, \ldots, T$ ($T = 1000$) simple random samples without replacement. Sample sizes are drawn with the only constraint of a minimum of two units selected in each area (Salvati 2004). The average sample size per area is $\bar{n} = 48.8$.
2. In each sample, post-stratified, EBLUP and SEBLUP estimates are computed and compared based on Pratesi and Salvati (2008). The post-stratified estimator is given by the following:

$$\hat{Y}_i(pst) = \sum_{j \in s_i} \frac{y_{ij}}{n_i}, \quad (10)$$

   where s_i is the set of n_i sample units falling in area i.
3. The results are evaluated by the absolute relative bias, absolute relative error, relative root mean squared error, and mean squared error averaged through the samples and small areas (see Petucci and Salvati 2006). These are denoted by $\overline{ARB}$, $\overline{ARE}$, $\overline{RRMSE}$, and $\overline{MSE}$, and given by the following formulas, respectively:

$$\overline{ARB} = \frac{1}{m} \sum_{i}^{m} \left| \frac{1}{T} \sum_{t=1}^{T} \left(\frac{\hat{Y}_{it}}{Y_i} - 1 \right) \right| \quad (11)$$

$$\overline{ARE} = \frac{1}{m} \sum_{i}^{m} \frac{1}{T} \sum_{t=1}^{T} \left(\left| \frac{Y_{it}}{Y_i} - 1 \right| \right) \quad (12)$$

$$\overline{RRMSE} = \frac{1}{m} \sum_{i}^{m} \frac{\left[\overline{MSE}(\hat{Y}_i)^{1/2} \right]}{Y_i} \quad (13)$$

   with

$$\overline{MSE} = \frac{1}{m} \sum_{i}^{m} \frac{1}{T} \sum_{t=1}^{T} (\hat{Y}_{it} - Y_i)^2, \quad (14)$$

   where $\hat{Y}_{it}$ denotes the estimate (post-stratified, EBLUP or SEBLUP) for small area *i* in sample *t* and Y_i the true value observed in the population for area *i*.

The simulation study has been coded and conducted in R software (see Molina and Marhuenda 2015) and results are detailed in Tables 1, 2, 3 and 4.

3.2 Results: Comparison of EBLUP and SEBLUP estimates

Table 1 shows the $\overline{\text{RRMSE}}$, $\overline{\text{ARB}}$ and $\overline{\text{ARE}}$ of post-stratified, EBLUP and SEBLUP estimates from each simulated population. Both EBLUP and SEBLUP estimators outperform post-stratified estimators in all cases, in terms of $\overline{\text{RRMSE}}$ and $\overline{\text{ARE}}$, regardless of the spatial correlation parameter and the number of areas under study. Post-stratified estimator performs better in terms of $\overline{\text{ARB}}$, as expected (Petrucci and Salvati 2006; Pratesi and Salvati 2008; Rao and Molina 2015).

The spatial correlation parameter ρ and the number of areas m do not affect either the EBLUP or SEBLUP relative difference towards post-stratified estimates regardless the quality measure selected. The relative difference between post-stratified and SEBLUP estimates' $\overline{RRMSE}$, which expresses the absolute percentage change of the estimate quality measure, has been calculated as follows:

$$RD\% = \frac{\overline{RRMSE}\left[\hat{\delta}^{SEBLUP}\right] - \overline{RRMSE}\left[\hat{Y}(pst)\right]}{\overline{RRMSE}\left[\hat{Y}(pst)\right]} \times 100 \quad (15)$$

The reader may note that (15) gives the measure of efficiency of $\hat{\delta}^{SEBLUP}$ over $\hat{Y}(pst)$ estimates. The relative difference between post-stratified and SEBLUP estimates $\overline{RRMSE}$ varies between a maximum of -5.83% in the case of $m = 64$ and $\rho = 0.75$ and a minimum of -14.29% in the case of $m = 16$ and $\rho = 0$, having also small values such as -13.99% in the case of $m = 25$ and $\rho = 0.25$, -13.40% in the case of $m = 144$ and $\rho = 0$, and -13.00% in the case of $m = 144$ and $\rho = -0.5$. In other words, neither ρ nor m can be used to interpret the increased precision, in terms of $\overline{RRMSE}$ and $\overline{ARE}$, of EBLUP and SEBLUP estimates when compared to post-stratified estimates.

Table 1 Estimates' Relative Root Mean Squared Error, Absolute Relative Bias and Absolute Relative Error ($\times$ 100)

			m = 16	m = 25	m = 36	m = 64	m = 144	m = 225
ρ = -0.75	$\hat{Y}(pst)$	$\overline{RRMSE}\%$	12.91	12.50	14.54	12.61	13.08	13.18
		$\overline{ARB}\%$	0.38	0.32	0.42	0.36	0.33	0.31
		$\overline{ARE}\%$	8.95	8.55	10.09	8.78	9.07	9.15
	$\tilde{\theta}(\hat{\sigma}^2_{u_{REML}})$	$\overline{RRMSE}\%$	11.99	11.53	14.29	11.30	11.80	11.89
		$\overline{ARB}\%$	2.95	2.50	3.85	2.58	2.80	2.57
		$\overline{ARE}\%$	8.56	8.16	10.08	8.13	8.46	8.51
	$\tilde{\theta}(\hat{\sigma}^2_{u_{REML}}, \hat{\rho}_{REML})$	$\overline{RRMSE}\%$	12.23	11.57	14.25	11.21	11.42	11.51
		$\overline{ARB}\%$	2.99	2.53	3.87	2.57	2.78	2.55
		$\overline{ARE}\%$	8.69	8.19	10.05	8.09	8.25	8.34
ρ = -0. 5	$\hat{Y}(pst)$	$\overline{RRMSE}\%$	12.32	13.09	12.40	12.99	12.92	13.15
		$\overline{ARB}\%$	0.29	0.31	0.33	0.33	0.36	0.31
		$\overline{ARE}\%$	8.57	9.07	8.57	9.04	8.94	9.12
	$\tilde{\theta}(\hat{\sigma}^2_{u_{REML}})$	$\overline{RRMSE}\%$	11.31	12.21	11.21	11.72	11.24	11.86
		$\overline{ARB}\%$	2.59	2.40	2.31	2.66	2.65	2.90
		$\overline{ARE}\%$	8.11	8.65	7.99	8.42	8.10	8.51
	$\tilde{\theta}(\hat{\sigma}^2_{u_{REML}}, \hat{\rho}_{REML})$	$\overline{RRMSE}\%$	11.60	12.36	11.25	11.59	11.23	11.71
		$\overline{ARB}\%$	2.66	2.46	2.36	2.65	2.63	2.87
		$\overline{ARE}\%$	8.27	8.74	8.02	8.37	8.07	8.43
ρ = -0.25	$\hat{Y}(pst)$	$\overline{RRMSE}\%$	13.11	12.62	12.93	12.61	12.68	13.06
		$\overline{ARB}\%$	0.35	0.31	0.24	0.29	0.29	0.31
		$\overline{ARE}\%$	9.14	8.77	8.92	8.76	8.78	9.03
	$\tilde{\theta}(\hat{\sigma}^2_{u_{REML}})$	$\overline{RRMSE}\%$	12.35	11.40	11.71	11.49	11.18	11.34
		$\overline{ARB}\%$	2.80	2.35	2.57	2.51	2.56	2.79
		$\overline{ARE}\%$	8.79	8.16	8.35	8.23	8.04	8.18
	$\tilde{\theta}(\hat{\sigma}^2_{u_{REML}}, \hat{\rho}_{REML})$	$\overline{RRMSE}\%$	12.50	11.52	11.71	11.41	11.09	11.25
		$\overline{ARB}\%$	2.86	2.39	2.58	2.51	2.54	2.77
		$\overline{ARE}\%$	8.88	8.22	8.34	8.20	8.02	8.15

ρ = 0	$\hat{Y}(pst)$	$\overline{RRMSE}\%$	11.97	12.47	12.77	12.65	12.69	12.99
		$\overline{ARB}\%$	0.36	0.28	0.33	0.36	0.33	0.35
		$\overline{ARE}\%$	8.34	8.65	8.86	8.75	8.79	8.97
	$\tilde{\theta}(\hat{\sigma}^2_{u_{REML}})$	$\overline{RRMSE}\%$	10.26	10.96	11.52	11.19	10.99	11.47
		$\overline{ARB}\%$	2.38	2.60	2.95	2.61	2.76	2.63
		$\overline{ARE}\%$	7.46	7.93	8.29	8.03	7.95	8.23
	$\tilde{\theta}(\hat{\sigma}^2_{u_{REML}}, \hat{\rho}_{REML})$	$\overline{RRMSE}\%$	10.62	11.08	11.60	11.23	11.03	11.46
		$\overline{ARB}\%$	2.59	2.67	3.00	2.63	2.77	2.62
		$\overline{ARE}\%$	7.70	7.98	8.35	8.06	7.97	8.22
ρ = 0.25	$\hat{Y}(pst)$	$\overline{RRMSE}\%$	11.18	11.58	13.84	11.78	12.77	12.92
		$\overline{ARB}\%$	0.27	0.31	0.44	0.25	0.31	0.33
		$\overline{ARE}\%$	7.77	8.04	9.60	8.16	8.84	8.95
	$\tilde{\theta}(\hat{\sigma}^2_{u_{REML}})$	$\overline{RRMSE}\%$	9.99	9.96	12.39	10.29	11.48	11.32
		$\overline{ARB}\%$	2.26	2.04	3.29	2.44	2.68	2.67
		$\overline{ARE}\%$	7.20	7.20	8.91	7.41	8.22	8.16
	$\tilde{\theta}(\hat{\sigma}^2_{u_{REML}}, \hat{\rho}_{REML})$	$\overline{RRMSE}\%$	10.15	10.12	12.59	10.30	11.45	11.29
		$\overline{ARB}\%$	2.29	2.12	3.35	2.45	2.68	2.66
		$\overline{ARE}\%$	7.29	7.30	9.01	7.41	8.21	8.15
ρ = 0.5	$\hat{Y}(pst)$	$\overline{RRMSE}\%$	11.25	15.13	12.92	15.23	12.26	12.97
		$\overline{ARB}\%$	0.23	0.39	0.29	0.37	0.31	0.32
		$\overline{ARE}\%$	7.76	10.54	8.99	10.53	8.48	8.98
	$\tilde{\theta}(\hat{\sigma}^2_{u_{REML}})$	$\overline{RRMSE}\%$	9.85	13.24	11.81	14.12	10.73	11.50
		$\overline{ARB}\%$	2.23	2.97	2.64	3.03	2.45	2.66
		$\overline{ARE}\%$	7.04	9.58	8.48	9.99	7.72	8.27
	$\tilde{\theta}(\hat{\sigma}^2_{u_{REML}}, \hat{\rho}_{REML})$	$\overline{RRMSE}\%$	10.01	13.36	11.66	13.99	10.63	11.26
		$\overline{ARB}\%$	2.28	3.02	2.68	3.04	2.44	2.65
		$\overline{ARE}\%$	7.13	9.65	8.41	9.95	7.67	8.13
ρ = 0.75	$\hat{Y}(pst)$	$\overline{RRMSE}\%$	12.81	11.02	13.06	11.15	15.71	15.06
		$\overline{ARB}\%$	0.21	0.27	0.29	0.29	0.34	0.39
		$\overline{ARE}\%$	8.88	7.65	9.08	7.69	10.88	10.42
	$\tilde{\theta}(\hat{\sigma}^2_{u_{REML}})$	$\overline{RRMSE}\%$	11.81	10.36	11.62	10.50	14.61	13.94
		$\overline{ARB}\%$	2.64	2.11	2.84	1.97	2.95	2.84
		$\overline{ARE}\%$	8.41	7.33	8.37	7.39	10.35	9.90
	$\tilde{\theta}(\hat{\sigma}^2_{u_{REML}}, \hat{\rho}_{REML})$	$\overline{RRMSE}\%$	11.96	10.07	11.33	9.98	13.69	13.02
		$\overline{ARB}\%$	2.66	2.13	2.86	1.98	2.95	2.82
		$\overline{ARE}\%$	8.51	7.19	8.22	7.04	9.86	9.41

However, both ρ and m have a large impact in the improvement of SEBLUP estimates, which perform substantially better than EBLUPs for those cases of high and medium spatial correlation parameter (especially $\rho = \{\pm 0.50, \pm 0.75\}$) and large number of areas under study (notably $m = \{144, 255\}$) (see Tables 2, 3 and 4). Table 2 shows the relative difference between EBLUP and SEBLUP estimates' $\overline{RRMSE}$, as shown in Eq. (15), formatting the cells based on a black-to-white colour scale, where darker scales represent positive values, meaning a better performance of EBLUP estimates, and white tones refer to negative numbers, which show that SEBLUP estimates improve their quality measure when compared to EBLUP estimates.

First, it is clear from Table 2 that SEBLUP estimates perform better than EBLUP estimates, in terms of $\overline{RRMSE}$, when the spatial correlation parameter is high and very high (Asfar and Sadik 2016; Chandra et al. 2007; Petrucci and Salvati 2006; Pratesi and Salvati 2008, 2009; Salvati 2004); but EBLUP estimates tend to be more precise than the SEBLUP when ρ is close to 0. Second, the relative difference between EBLUP and SEBLUP estimates' $\overline{RRMSE}$ also shows that the benefit obtained by borrowing strength from neighbouring areas is bigger as the number of areas under study increases. For example, for $m = 25$ the relative difference of the $\overline{RRMSE}$ only shows that SEBLUP estimates are more precise than EBLUPs when the spatial correlation parameter is very large ($\rho = 0.75$); but such value indicates that SEBLUP estimates outperform EBLUP estimates in all cases for $m = 255$, even when $\rho = 0$. In other words, both ρ and m need to be taken into account to explain SEBLUP estimates increased precision in terms of $\overline{RRMSE}s$, and SEBLUP estimates perform clearly better as the number of areas under study increases (Salvati 2004).

Table 2 Relative difference between EBLUP and spatial EBLUP's RRMSE ($\times$ 100)

	m = 16	m = 25	m = 36	m = 64	m = 144	m = 255
ρ = -0.75	2.00	0.35	-0.28	-0.80	-3.22	-3.20
ρ = -0.5	2.56	1.23	0.36	-1.11	-0.09	-1.26
ρ = -0.25	1.21	1.05	0.00	-0.70	-0.81	-0.79
ρ = 0	3.51	1.09	0.69	0.36	0.36	-0.09
ρ = 0.25	1.60	1.61	1.61	0.10	-0.26	-0.27
ρ = 0.5	1.62	0.91	-1.27	-0.92	-0.93	-2.09
ρ = 0.75	1.27	-2.80	-2.50	-4.95	-6.30	-6.60

Table 3 shows the relative difference between EBLUP and SEBLUP estimates' $\overline{ARB}$ and Table 4 shows the relative difference between their $\overline{ARE}$. Looking at Table 3, it is even more clear that SEBLUP estimates perform better than EBLUPs, in terms of $\overline{ARB}$, when the number of areas under study is high (especially $m = \{144, 255\}$), but not in cases of $m = \{16, 25, 36\}$. For $m = 64$, SEBLUP estimates $\overline{ARB}$ is only improved when $\rho = -0.5$ and $\rho = -0.75$. Again, while the $\overline{ARB}$ of SEBLUP estimates were not improved in any case for $m = \{16, 25, 36\}$, such quality measure shows that SEBLUP estimates outperform EBLUPs, in terms of $\overline{ARB}$, in all simulations performed for $m = 255$.

Table 3 Relative difference between EBLUP and spatial EBLUP's ARB ($\times$ 100)

	m = 16	m = 25	m = 36	m = 64	m = 144	m = 255
ρ = -0.75	1.36	1.20	0.52	-0.39	-0.71	-0.78
ρ = -0.5	2.70	2.50	2.16	-0.38	-0.75	-1.03
ρ = -0.25	2.14	1.70	0.39	0.00	-0.78	-0.72
ρ = 0	8.82	2.69	1.69	0.77	0.36	-0.38
ρ = 0.25	1.33	3.92	1.82	0.41	0.00	-0.37
ρ = 0.5	2.24	1.68	1.52	0.33	-0.41	-0.38
ρ = 0.75	0.76	0.95	0.70	0.51	0.00	-0.70

Table 4 also shows that both ρ and m have a large impact to improve SEBLUP estimates' precision, now in terms of $\overline{ARE}$. For example, for $m = 25$ the relative difference between EBLUP and SEBLUP's $\overline{ARE}$ shows that EBLUP estimates outperform SEBLUPs in all cases except for $\rho = 0.75$; while for $m = 144$ such value shows better precision of SEBLUP estimates except when $\rho = 0$ and for $m = 255$ the relative difference shows that SEBLUP estimator produces better estimates than EBLUP in every single case.

Table 4 Relative difference between EBLUP and spatial EBLUP's ARE ($\times$ 100)

	m = 16	m = 25	m = 36	m = 64	m = 144	m = 255
ρ = -0.75	1.52	0.37	-0.30	-0.49	-2.48	-2.00
ρ = -0. 5	1.97	1.04	0.38	-0.59	-0.37	-0.94
ρ = -0.25	1.02	0.74	-0.12	-0.36	-0.25	-0.37
ρ = 0	3.22	0.63	0.72	0.37	0.25	-0.12
ρ = 0.25	1.25	1.39	1.12	0.00	-0.12	-0.12
ρ = 0.5	1.28	0.73	-0.83	-0.40	-0.65	-1.69
ρ = 0.75	1.19	-1.91	-1.79	-4.74	-4.73	-4.95

4 Application: Confidence in police work in Europe

With the aim of assessing SEBLUP estimator performance under different number of small areas m in a real case scenario, direct, EBLUP and SEBLUP estimators are applied to produce estimates of confidence in police work at Nomenclature of Territorial Units for Statistics 2 (NUTS-2) level (with the exception of Germany and UK, at NUTS-1 level due to lack of data at lower geographical levels) in Europe using data from the European Social Survey. Such an application provides further evidence about SEBLUP estimator performance. However, this application also deepens the macro-level explanatory mechanisms of confidence in police work, by which we mean the proportion of citizens who think the police do a good job (e.g. European Social Survey 2011; Staubli 2017), and draws the map of its distribution in Europe. With these aims, data from the European Social Survey 5 (2010/2011) have been used to produce estimates of confidence in police work for three European sub-regions: Southern and Southwestern Europe ($m = 36$), Western Europe ($m = 58$) and Central, Northern and Eastern Europe ($m = 96$). Southern and Southwestern Europe is composed by Greece (n=2715), Portugal (n=2150) and Spain (n=1885). Western Europe includes Belgium (n=1704), France (n=1728), Ireland (n=2576), Netherlands (n=1829), and UK (n=2422). And Central, Northern and Eastern Europe contains citizens sampled in Bulgaria (n=2434), Croatia (n=1649), Czech Republic (n=2386), Denmark (n=1576), Estonia (n=1793), Finland (n=1878), Germany (n=3031), Hungary (n=1561), Lithuania (n=1677), Norway (n=1548), Poland (n=1751), Slovakia (n=1856), Slovenia (n=1403), Sweden (n=1497), and Switzerland (n=1506). The average sample size in Southwestern Europe is $\bar{n} = 184.9$, while it is $\bar{n} = 175.5$ in Western Europe and $\bar{n} = 292.6$ in Central, Northern and Eastern Europe. The division of Europe in three sub-regions (Southwestern Europe, Western Europe, and Central, Northern and Eastern Europe) is based on the USA Central Intelligence Agency's World Factbook classification. Direct estimates are produced from the Horvitz-Thompson estimator (Horvitz and Thompson 1952):

$$\hat{Y}_d(dir) = N_d^{-1} \sum_{i \in s_d} w_{di} y_{di}, \tag{16}$$

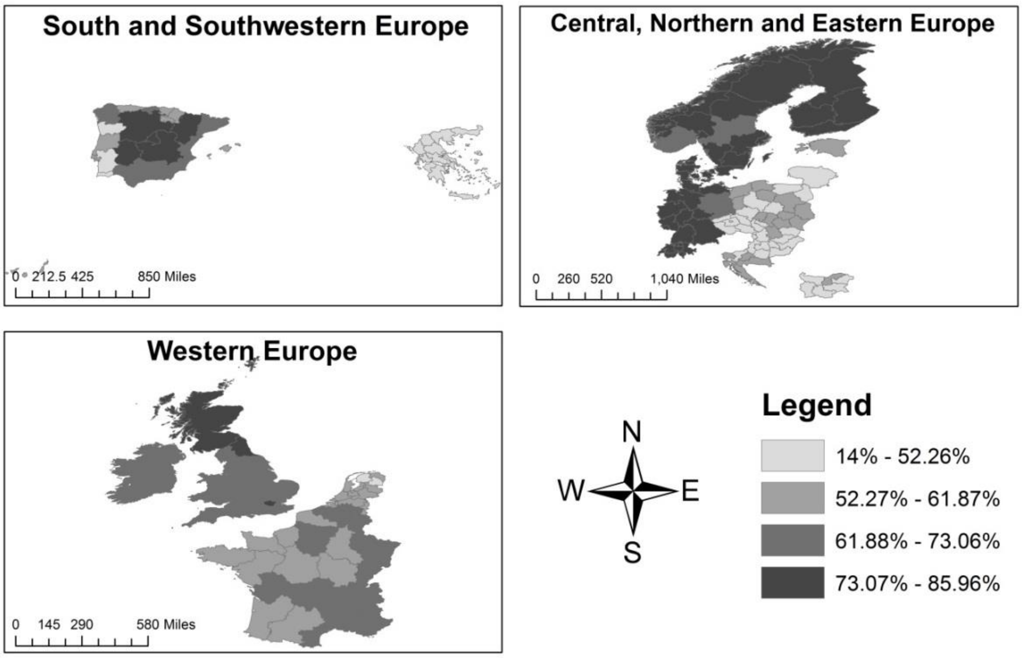
where w_{di} corresponds to the survey weight of unit i from area d obtained from combining the ESS design weights and the population size weights, as suggested in European Social Survey (2014), and y_{di} is the score of unit i from area d. A first-order 'Queen Contiguity' approximation has been used to define neighbouring areas and compute the proximity matrix $\boldsymbol{W}$.

The police effectiveness in maintaining order and preventing crime depends on its relationship with the public (Jackson et al. 2013; Tyler 2004). Citizens' willingness to cooperate and support police officers is essential for an effective policing service; and such public cooperation is shaped by citizens' views and perceptions about police work (Tyler 2004). Increasing criminological research focuses on understanding police legitimacy and confidence in police work (e.g. Gau et al. 2012; Jackson et al. 2013; Jang et al 2010; Kääriäinen 2007; Piatkowska 2015; Staubli 2017; Tankebe 2012; Tyler 2004); which are driven by a series of physiological and social variables that operate at micro, meso and macro levels. There are some individual characteristics that have been related with decreased confidence in the police and less willingness to cooperate with the police, such as belonging to an ethnic minority, low education, low income, being male and young, and personal perceptions of procedural justice and contact with the police (e.g. Jackson et al. 2013; Jang et al. 2010; Staubli 2017; Tankebe 2012; Tyler 2004). However, research has also found macro-level predictors that shape public perceptions about the police at a higher level (Cao and Zhao 2005; Gau et al. 2012; Jang et al 2010; Kääriäinen 2007; Piatkowska 2015). Confidence in police is higher in certain neighbourhoods than others, but it also shows differences between regions within countries and between countries (e.g. Cao and Zhao 2005; Gau et al. 2012; Jang et al 2010; Kääriäinen 2007; Piatkowska 2015). Some of the variables that have been used to explain macro-level distribution in confidence in police work are the homicide rate, government corruption, income levels, the size of the city/village, the concentration of immigrants, the order and safety expenditure as a proportion of GDP and welfare expenditure (e.g. Cao and Zhao 2005; Gau et al. 2012; Jang et al 2010; Kääriäinen 2007; Piatkowska 2015).

The variable used to measure confidence in police work has been obtained from the question “Taking into account all the things the police are expected to do, would you say they are doing a good job or a bad job?”, as suggested by European Social Survey (2011) and Staubli (2017). In order to produce more easily interpretable results, responses were dichotomised to a 0-1 measure, where 0 refers to “Neither good nor bad job”, “Bad job” and “Very bad job”, while “Good job” and “Very good job” were recoded as 1. We then produce estimates of the proportion of people who think the police are doing a good or very good job. Based on the literature review we fitted EBLUP and SEBLUP models using the following area-level covariates: Homicide rate 2011, Mean age 2011 and Human Development Index 2009. The Human Development Index (HDI) is a United Nations Development Programme’s summary measure composed from three dimensions: life expectancy at birth, education and gross national income per capita (Anand and Sen 1994).

Figure 2 shows the geographical distribution of SEBLUP estimates of confidence in police work at regional level in Europe, where lighter scales of grey show a lower proportion of citizens who think that police do a good or a very good job, and darker scales of grey shows higher confidence in police work. The colour division is based on quartiles. The highest estimates of confidence in police work have been found in the Finish regions of Etelä-Suomi (85.96%), Länsi-Suomi (83.87%) and Itä-Suomi (83.54%); but there are also high estimated proportions of citizens who think that police do a good or a very good job are in Zentralschweiz (CH) (82.23%) and Midtjylland (DK) (81.60%). The lowest proportions have been estimated in Sterea Ellada (GR) (14.52%), Algarve (PT) (18.97%) and four other Greek regions: Ionia Nisia (31.07%), Dytiki Makedonia (31.52%), Kriti (32.22%) and Attiki (33.36%). From a broader perspective, these results add some evidence to Kääriäinen’s (2007) research findings, which showed the highest levels of trust in police in Northern Europe (especially Finland, Denmark, Norway and Sweden). The lowest estimates of confidence in police work have been produced in South and Eastern Europe.

Fig. 2 Proportion of citizens who think the police do a good or very good job (SEBLUP estimates)



In order to assess the estimates produced in each sub-region, Table 5 shows direct, EBLUP and SEBLUP estimates' average $RRMSE$, as well as the average Relative Difference ($\overline{RD}\%$) between EBLUP and SEBLUP's estimates $\overline{RRMSE}$. The direct estimates' $RRMSE$ is the Coefficient of Variation (Rao and Molina 2015), while the EBLUP estimates' $RRMSE$ is obtained from Prasad-Rao analytical approximation (Prasad and Rao 1990) and SEBLUPs' $RRMSEs$ have been produced using an analytical approximation as in Molina et al. (2009).

Table 5 Estimates' quality measures

	$m = 36$	$m = 58$	$m = 96$
$\overline{RRMSE}\%\ [\hat{Y}(dir)]$	17.11	13.69	10.19
$\overline{RRMSE}\%[\tilde{\theta}(\hat{\sigma}^2_{u_{REML}})]$	13.82	7.48	7.98
$\overline{RRMSE}\%\ [\tilde{\theta}(\hat{\sigma}^2_{u_{REML}}, \hat{\rho}_{REML})]$	12.71	5.85	6.42
$\overline{RD}\%[\tilde{\theta}(\hat{\sigma}^2_{u_{REML}}), \tilde{\theta}(\hat{\sigma}^2_{u_{REML}}, \hat{\rho}_{REML})]$	-7.08	-8.13	-18.22
$\bar{\rho}$	0.74	0.89	0.89

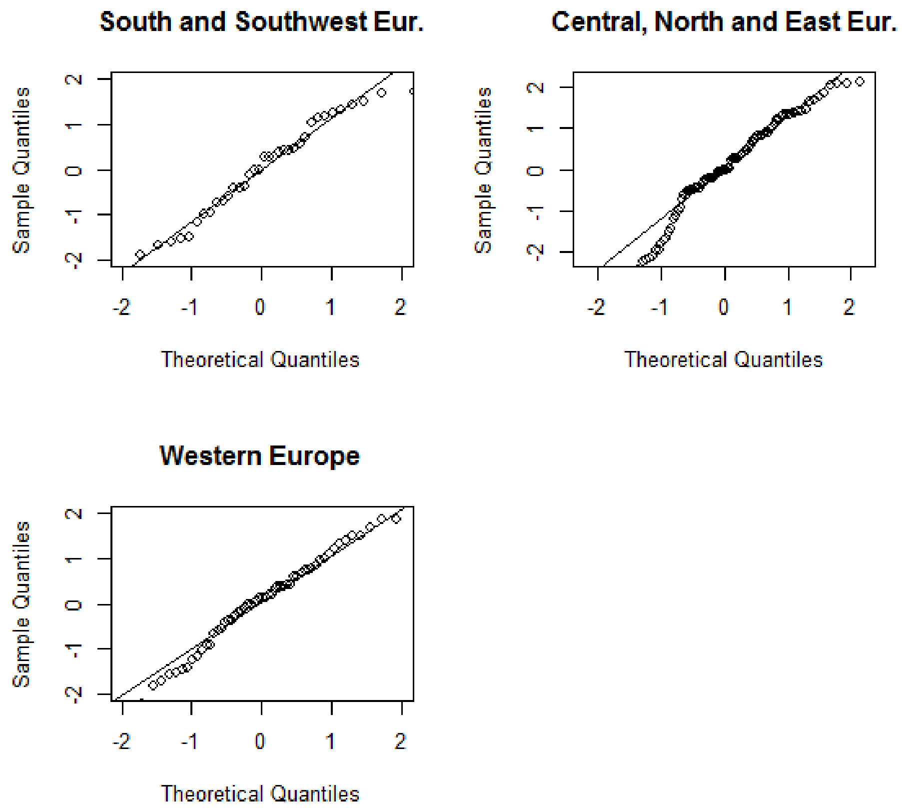
First, results from Table 5 show that direct estimates are the least precise (larger $\overline{RRMSE}$) in all cases, as expected (Petrucci and Salvati 2006; Pratesi and Salvati 2008, 2009; Rao and Molina 2015). Second, SEBLUP estimates are more reliable than EBLUPs, in terms of $\overline{RRMSE}$, in all three scenarios. However, as hypothesised, the average Relative Difference between EBLUP and SEBLUP's estimates $\overline{RRMSE}$, which shows the increased precision of SEBLUP estimates compared to EBLUPs, decreases as the number of areas under study increases. For $m = 36$ the $\overline{RD}\%$ equals -7.08, while it is -8.13 for $m = 58$, and $\overline{RD}\% = -18.22$ for $m = 96$. Again, the benefit obtained from introducing spatial information in the small area estimation process increases as the number of areas under study becomes larger. It is important to mention that the spatial correlation parameter is very high in all three cases: $\rho = 0.75$ for $m = 36$, and $\rho = 0.89$ for $m = 58$ and $m = 96$, showing that the spatial concentration of confidence in police work is very high in Europe. Then, even though the high ρ partly explains the increased precision of SEBLUP estimates when compared to EBLUPs in each case, the spatial autocorrelation parameter cannot be used to explain why such increased precision is higher in the case of $m = 96$ than $m = 36$ and $m = 58$.

We provide an assessment of our spatial model by analysing the normality of SEBLUP standard residuals. See normal *q-q* plots in Figure 3. As suggested by Petrucci and Salvati (2006), residuals are produced as follows:

$$r = (\tilde{\theta}^S(\hat{\sigma}^2_{u_{REML}}, \hat{\rho}_{REML}) - \mathbf{X}\boldsymbol{\beta})/(diag(\mathbf{V}))^{1/2} \text{ as } iid\ N(0,1). \quad (17)$$

Although a few outliers are shown in all three regions, especially in both tails of the *q-q* plot produced to assess the model of Central, North and Eastern Europe ($m = 96$), most residuals show no important deviations. The Shapiro-Wilk test for normality also suggests no rejection of the null hypothesis of normal distribution in all three cases: $W = 0.963$ and $p - value = 0.273$ in the case of South and Southwestern Europe, $W = 0.963$ and $p - value = 0.202$ in the model fitted for Central, North and Eastern Europe, and $W = 0.977$ and $p - value = 0.326$ for Western Europe.

Fig. 3 Normal q-q plots of standardised residuals of SEBLUP estimates



In addition, goodness of fit indices are analysed to assess the spatial models used in this application. For the model fitted in Southern and Southwestern Europe ($m = 36$), the log-likelihood is equal to 21.01, while $AIC = -30.01$ and $BIC = -20.51$. In Western Europe ($m = 58$), the log-likelihood estimate is 53.12, $AIC = -94.24$ and $BIC = -81.88$. And, for the model fitted in Central, Northern and Eastern Europe ($m = 96$), log-likelihood = 105.16, $AIC = -198.32$ and $BIC = -192.93$. Future work will explore improving the models using other covariates.

5 Conclusions

Small area estimation techniques are increasingly making use of spatially correlated random area effects in order to provide more reliable and precise estimates (Buil-Gil et al. 2018; Chandra et al. 2007; Marhuenda et al. 2013; Molina et al. 2009; Petrucci et al. 2005; Petrucci and Salvati 2006; Pratesi and Salvati 2008, 2009; Salvati 2004; Salvati et al. 2014; Rao and Molina 2015). Among these approaches, SEBLUP estimator has repeatedly shown to reduce both variance and bias of the estimates. However, research focused on assessing SEBLUP estimator's relative performance under different theoretical and applied scenarios is scarce (e.g. Asfar and Sadik 2016; Chandra et al. 2007; Petrucci and Salvati 2006; Pratesi and Salvati 2008, 2009; Salvati 2004). And particularly rare is research analysing the impact of the number of areas under study, m, on SEBLUP's relative performance (e.g. Asfar and Sadik 2016; Salvati 2004).

In order to assess whether SEBLUP estimator produces more reliable estimates than traditional model-based estimators under different m and ρ parameters, we have performed a simulation study using synthetic generated populations and hypothetical maps, and an application study with survey data from ESS and real European maps. Our results show that SEBLUP estimator tends to outperform traditional model-based estimators (in this case EBLUP) not only when the spatial correlation parameter ρ is closer to 1 and -1, but also when m, the number of areas, is larger. SEBLUP estimator performs better as the number of areas under study increases, while EBLUP estimator outperforms SEBLUP both when $\rho \cong 0$ and m is small. Such results have been shown both in the simulation study and application.

Our research results are useful for applied researchers and policy makers willing to make use of small area estimation techniques to produce estimates of specific phenomena. Such results suggest that SEBLUP estimator is an appropriate method to be used when the level of spatial correlation of the variable of interest is high or very high and/or when the number of areas under study is large. Otherwise, when the spatial correlation parameter is close to 0 and m is small or very small, other small area estimation techniques, such as traditional EBLUP or estimators that borrow strength from temporal series based on Rao-Yu model (Rao and Yu 1994), may provide better results.

From a criminological perspective, the results of our application show that confidence in police work is higher in most Northern and Central European regions, while lower proportions of citizens who think the police do a good or very good job are estimated in Southern and Eastern/post-communist regions. Also, homicide rate, mean age and Human Development Index are shown to be good predictors of confidence in police work (Cao and Zhao 2005; Gau et al. 2012; Jang et al 2010; Kääriäinen 2007; Piatkowska 2015), and other predictors will need to be addressed in future substantive research, such as the population density and public corruption.

Future work will need to verify the performance on the SEBLUP estimator under complex contiguity matrices, such as second-order 'Queen Contiguity' and distance weighted matrices. Also, research applying SEBLUP and other small area estimators to criminological phenomena such as attitudes towards crime and proportion of citizens who report victimisation might contribute to the increasing criminological interest in micro-environmental approaches.

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