**Appendix 1: Bias of the SVC estimates**

Here we compare the biases of the SVC estimates from the six SVC models assesed in the Monte Carlo simulation experiment of section 4. The biases are formulated as follows:

|  |  |
| --- | --- |
|  | (A1) |

Figures A1 to A5 compare the estimated biases for chosen SVC model pairs, mimicing the plots done in section 4 for RMSE. Results show that the biases of SVC estimates are sufficiently small whichever models are used. Still, biases typically increase when the predictors have large-scale spatial variations. The results are consistent with the finding of Paciorek (2009) that, in case of a spatial regression model, large-scale predictors tend to confound with the residual spatial process, and introduce a bias. For the bias in our case, the bias increase would be due to the confounding between the large-scale predictors and the SVC processes.

**Appendix 2: Smoothly-varying coefficient processes**

The SMA process, which was used to generate the **β***k*s, in sections 3 and 4 describes a stationary process. However, the coefficients may have a deterministic linear or non-linear trend. Because the Moran’s eigenvectors describe only a stationary process (Murakami and Griffith, 2015), ESF and RE-ESF may struggle to accurately estimate such smoothly-varying coefficient processes. To examine this, we performed a third simulation experiment, following that studied in Fotheringham et al. (2017). They assumed locations on a 25 by 25 regular grid, and generated synthetic data on the locations following Eq. (A2):

|  |  |
| --- | --- |
| ,  . | (A2) |

where *six* and *siy* represent *x*- and *y*-coordinates. *β0*(*si*) is a constant, and *β*1(*si*) and *β*2(*si*) have a linear trend and a circular trend, respectively. The predictors are generated from the standard normal distributions, and the response is found accordingly. Data are generated 200 times.

The resulting RMSEs (as defined in section 4.2) are summarized in Table A1. Clearly, ESF is the poorest performing model, which is consistent with the negative findings on ESF in Oshan and Fotheringham (2017). Regarding RE-ESF, its estimates for *β*1(*si*) are less accurate relative to the GWR models whereas its estimates *β*2(*si*) are the most accurate. The result shows that the RE-ESF estimates can be inaccurate if the true spatially varying process has a large-scale non-stationary trend, as with *β*1(*si*), that the Moran’s eigenvectors cannot capture. It is also conceivable that FB-GWR, FB-GWRa, and RE-ESF all successfully identified *β*0(*si*) as constant coefficients. Another interesting finding is that FB-GWR clearly outperforms FB-GWRa, which is contrary to the findings of the main study. This suggests that different SVC models suit different SVC processes.

Figure A1: Bias: RE-ESF (*x*-axis) vs GWR (*y*-axis). “Large-scale” means the large-scale (*r*). The lighter end of the “Significant” line means a small variance of the spatially dependent component (*sx*), while the darker end means a large variance.

Figure A2: Bias: RE-ESF (*x*-axis) vs ESF (*y*-axis). “Large-scale” means the large-scale (*r*). The lighter end of the “Significant” line means a small variance of the spatially dependent component (*sx*), while the darker end means a large variance.

Figure A3: Bias: RE-ESF (*x*-axis) vs FB-GWR (*y*-axis). “Large-scale” means the large-scale (*r*). The lighter end of the “Significant” line means a small variance of the spatially dependent component (*sx*), while the darker end means a large variance.

Figure A4: Bias: RE-ESF (*x*-axis) vs GWRa (*y*-axis). “Large-scale” means the large-scale (*r*). The lighter end of the “Significant” line means a small variance of the spatially dependent component (*sx*), while the darker end means a large variance.

Figure A5: Bias: RE-ESF (*x*-axis) vs FB-GWRa (*y*-axis). “Large-scale” means the large-scale (*r*). The lighter end of the “Significant” line means a small variance of the spatially dependent component (*sx*), while the darker end means a large variance.