Appendix

Table A1: Mapping of detailed CLC classes to land use aggregates

CLC code	Description	Aggregate	
111	Continuous urban fabric	Settlement	Urban
112	Discontinuous urban fabric	Settlement	Urban
121	Industrial or commercial units	Artificial	Urban
122	Road and rail networks and associated land	Artificial	Urban
123	Port areas	Artificial	Urban
124	Airports	Artificial	Urban
131	Mineral extraction sites	Artificial	Urban
132	Dump sites	Artificial	Urban
133	Construction sites	Artificial	Urban
141	Green urban areas	Artificial	Urban
142	Sport and leisure facilities	Artificial	Urban
211	Non-irrigated arable land	Cropland	Agricultural
212	Permanently irrigated land	Cropland	Agricultural
213	Rice fields	Cropland	Agricultural
221	Vineyards	Cropland	Agricultural
222	Fruit trees and berry plantations	Cropland	Agricultural
223	Olive groves	Cropland	Agricultural
231	Pastures	Grassland	Agricultural
241	Annual crops associated with permanent crops	Cropland	Agricultural
242	Complex cultivation patterns	Cropland	Agricultural
243	Land principally occupied by agriculture & natural vegetation	Forest	
244	Agro-forestry areas	Forest	
311	Broad-leaved forest	Forest	
312	Coniferous forest	Forest	
313	Mixed forest	Forest	
321	Natural grasslands	Other	
322	Moors and heathland	Other	
323	Sclerophyllous vegetation	Other	
324	Transitional woodland-shrub	Other	
331	Beaches dunes sands	Other	
332	Bare rocks	Other	
333	Sparsely vegetated areas	Other	
334	Burnt areas	Other	
335	Glaciers and perpetual snow	Excluded	
415	Inland marshes	Excluded	
412	Peat bogs	Excluded	
421	Salt marshes	Excluded	
422	Salines	Excluded	
423	Intertidal flats	Excluded	
511	Water courses	Excluded	
512	Water bodies	Excluded	
521	Coastal lagoons	Excluded	
522	Estuaries	Excluded	
523	Sea and ocean	Excluded	
999	No data	Excluded	

Marginal effects

Similar to the marginal effects of the spatial Durbin logit model (see Krisztin and Piribauer, 2020), in the presented multinomial logit model the interpretation of marginal effects of the k-th explanatory variable (with $k = 1, ..., K$) differs from those in linear models. This is due to the fact that the multinomial logit model is non-linear in nature, but also the the presence of spatial autocorrelation gives rise to an $N \times N$ matrix of partial derivatives, which makes interpretation of marginal effects richer, but also more complicated (see also LeSage and Pace 2009).

As is standard in the logit literature, and analogous with the proposed marginal effects of the spatial logit model (Krisztin and Piribauer, 2020), we provide marginal effects relative to the mean of the k-th explanatory variable, which we denote as $\overline{x_k} = \sum_{i=1}^{N} x_{ik}/N$. [1] Thus the interpretation of the marginal effects is the change in probability of observing $y = j$ associated with a change in the average sample observation of the k-th explanatory variable. To write the partial derivatives of the model, with respect to the k-th coefficient let us define:

$$
\begin{aligned}
\boldsymbol{\mu}_{kj} &= \boldsymbol{A}_j^{-1} \boldsymbol{I}_N \overline{x_k} \beta_{kj} + \boldsymbol{A}_j^{-1} \overline{x_{Wk}} \theta_{kj}, \\
\boldsymbol{\zeta}_{kj} &= \boldsymbol{A}_j^{-1} \boldsymbol{I}_N \beta_{kj} + \boldsymbol{A}_j^{-1} \boldsymbol{W} \theta_{kj}, \text{ and} \\
\boldsymbol{p}_{kj} &= \frac{\exp \boldsymbol{\mu}_{kj}}{\sum_{j'}^{J} \exp \left(\boldsymbol{\mu}_{kj'} \right)}.
\end{aligned}
$$

β_{kj} and θ_{kj} denote the k-th element of $\boldsymbol{\beta}_j$ and $\boldsymbol{\theta}_j$, respectively. $\overline{x_{Wk}}$ denotes the average value of the k-th spatially lagged explanatory variable. The partial derivatives can then be expressed as:

$$
\begin{aligned}
\frac{\partial p(y = j | \overline{x}_k)}{\partial \overline{x}_k'} &= \boldsymbol{p}_{kj} \odot \left[\boldsymbol{\zeta}_{kj} - \sum_{j'}^{J} \boldsymbol{p}_{kj'} \odot \boldsymbol{\zeta}_{kj'} \right], \\
&= \boldsymbol{\Lambda}_{kj},
\end{aligned}
\tag{1}
$$

where $\odot$ is the Hadamard product. Note that marginal effects of the k-th coefficient on class j, denoted as $\boldsymbol{\Lambda}_{kj}$, are an $N \times N$ matrix due to the presence of the $N \times N$ spatial multiplier $\boldsymbol{A}_j^{-1}$.

Interpreting $N \times N$ marginal effects proves cumbersome, therefore we define summary impact effects (LeSage and Pace, 2009). These can be readily calculated from $\mathbf{\Lambda}_{kj}$:

$$direct_{kj} = \frac{1}{N} \boldsymbol{\iota}'_N diag(\mathbf{\Lambda}_{kj}) \tag{2}$$

$$total_{kj} = \frac{1}{N} \boldsymbol{\iota}'_N \mathbf{\Lambda}_{kj} \boldsymbol{\iota}_N \tag{3}$$

$$indirect_{kj} = total_{kj} - direct_{kj}, \tag{4}$$

where $\boldsymbol{\iota}_N$ denotes an $N \times 1$ vector of ones.

Notes

[1]While herein we focus on marginal effects relative to the means of the explanatory variables, the marginal effects can be also calculated at the actual levels of the explanatory variables. As remarked by Lacombe and LeSage (2018), due to the non-linearity of the multinomial logit model, the marginal effects at the actual levels might be sufficiently different from the marginal effects at the means. Note, that the summary impact effects presented in this appendix can be adopted to accommodate marginal effects at the levels of the explanatory variables with ease, by exchanging the mean $\overline{x_k}$ in Eq. (1) with the level of the explanatory variable under scrutiny.

References

Krisztin T and Piribauer P (2020) A Bayesian spatial autoregressive logit model with an empirical application to European regional FDI flows. *Empirical Economics*

Lacombe DJ and LeSage JP (2018) Use and interpretation of spatial autoregressive probit models. *The Annals of Regional Science* 60(1), 1–24

LeSage JP and Pace RK (2009) *Introduction to Spatial Econometrics*. CRC Press, Boca Raton London New York