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Supplementary appendix

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Supplementary Materials

Natural Environments and Suicide Mortality in the Netherlands

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Contents

1. Regression model description

Statistical methods to determine the relationship between natural environmental exposures and suicide mortality are numerous, with Bayesian ecological regressions standing out,[1–3] particularly when studying risk and protective factors from a spatial standpoint.[4–11]

Bayesian generalized linear models with random effects were fitted. For the data model, we assumed a Poisson distribution to model suicide counts as an outcome (Eq. 1)[3]. The relative suicide risk (θ_i) was modeled through a set of risk and protective factors (x_{ip}) in the process model, whereas area-specific effects were further decomposed additively into a spatially structured (u_i) and an unstructured (v_i) component (Eq. 2). Such a model can smooth the relative (residual) suicide risk by sharing information across spatial units (i.e., municipalities).[2,12] The model is given by:

$$Y_i \sim \text{Poisson}(E_i \theta_i) \qquad (1)$$

$$\ln(\theta_i) = \beta_1 + \beta_2 x_i + \ldots + \beta_p x_{ip} + u_i + v_i \qquad (2)$$

Y_i refers to the number of suicides in municipality i ($i = 1, \ldots, 398$) and E_i is the age-adjusted indirectly standardized expected number of suicide cases. θ_i refers to the relative risk of having a suicide in area i. Besides adjusting for the covariates x_p, a structured random effect u_i was included to model spatial dependence among adjacent areas while an unstructured random effect v_i incorporated area-specific heterogeneity.[13] Omitting spatial dependence among adjacent areas, where present, would have severely biased the estimation of the regression parameters.[2]

Prior distributions for the unknown random parameters were assigned as follows. For the fixed effects, β_p diffuse priors based on normal distributions with mean zero and different precisions including 0.01, 0.001, and 0.0001 were investigated. The structured random effect u_i followed an intrinsic conditional autoregressive prior. Adjacency was operationalized as first-order queen contiguity where areas are considered neighbors when they share a common topological point or boundary.[5] Model robustness checks with an alternative neighbor specification, specifically the rook contiguity, was also carried out.[14,15] For the unstructured random effect v_i a normal prior with an exchangeable structure was chosen. Due to a lack of prior knowledge, non-informative priors based on a logged gamma distribution were specified for both u_i and v_i.[12] To ease the prior specification, the structured effect was additionally scaled.[16] As Bayesian models can be sensitive to prior specifications, sensitivity tests are obligatory.[17] We tested a range of alternative log-gamma($a;\ b$) priors with a shape a of 0.7, 1, and 1.3 as well as a precision b of 0.005, 0.0005, and 0.00005.

To obtain descriptive statistics of the marginal posterior distributions, Bayesian inference was carried out with the integrated nested Laplace approximation (INLA) approach.[18] INLA is a highly accurate and computationally fast alternative to Markov chain Monte Carlo methods while supporting numerous complex models.[19] The models were estimated with the R-INLA library (17.06.20) in R 3.4.2 (64 bit).[20] Relative risk estimates for β_p were obtained through the posterior means accompanied by the 95% credibility intervals (CI) for parameter uncertainty. To evaluate alternative prior specifications and to compare different models with a different degree of adjustment, the Watanabe–

Akaike information criterion (WAIC)[21] and the deviance information criterion (DIC)[22] were used. Both performance measures consider a penalty term adjusting for model complexity. Lower DIC and WAIC scores refer to a better model fit.

2. Descriptive statistics

Supplementary Table S1 reports descriptive statistics for the involved variables. Summary statistics and histograms were used to divide the environmental variables into three groups. Grouping the data is favorable by skewed distributions while permitting the analysis of dose–response relationships.

Supplementary Table S1: Descriptive statistics of the variables

	Minimum	25th percentile	Median	75th percentile	Maximum	Category (%)
Suicide cases 2005–14*	6.00	14.00	25.00	40.80	898.00	
Average population 2005-14	1,508	16,578	25,770	42,848	776,860	
Environmental variables:						
Green space: low						6
Mid						69
High						25
Blue space: low						24
Mid						55
High						21
Coastal proximity: low						25
Mid						50
High						25
Covariates:						
Urbanicity: urban						27
Rural						73
Male (%)	46.78	49.19	49.78	50.23	52.25	
Divorce (%)	1.80	4.93	6.00	7.30	11.60	
Unemployed (%)	3.40	4.30	4.80	5.60	10.10	
Housing prices (in €1,000)	116.00	182.00	216.00	252.80	565.00	
Supply of GPs (km)	0.40	0.80	1.00	1.30	2.90	
Orthodox Protestant (%)	0.00	0.10	0.20	1.36	33.40	

* Note that municipalities with ≤5 suicide cases were censored

3. Model diagnostics and sensitivity tests of the Bayesian regression

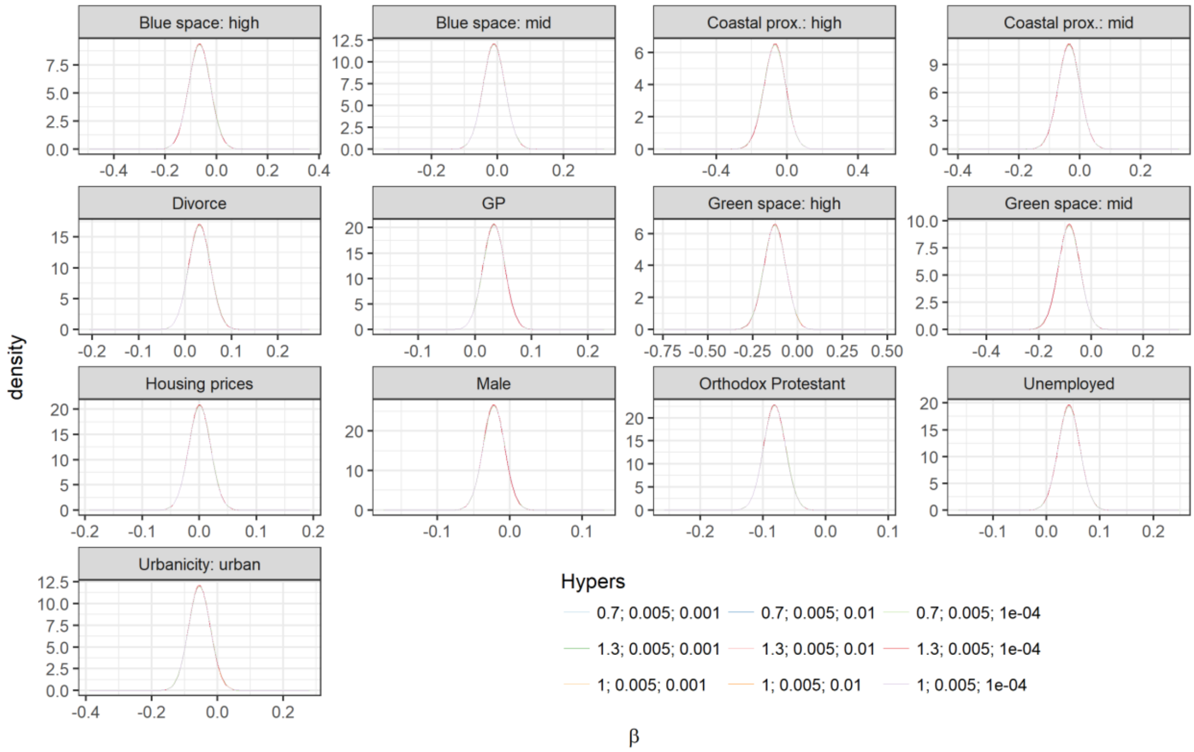
Non-spatial regressions were initially fitted. Residual independence was not confirmed across the models by Moran's *I* statistics (I: 0.146; p<0.001), supporting the application of spatially explicit models. In order to evaluate the sensitivity of different prior specifications, the fully adjusted model 2 was re-estimated with the aforementioned priors. In total, 27 models were fitted for this sensitivity study. For the spatially structured (u_i) and unstructured (v_i) components, different priors with different shape a and precision b were tested. For the fixed effects, β_p different precisions k were tested. The model fits are shown in Supplementary Table S2. As indicated by the WAIC and DIC scores, the models showed minor variations in the goodness-of-fit with different prior specifications. The best fitting model (i.e., lowest WAIC score) was used in the paper.

Supplementary Table S2: Goodness-of-fit measures associated with the fully adjusted model 2 and different prior specifications for the structured, unstructured, and fixed effects

a	*b*	*k*	WAIC	DIC
0.700	0.005	0.000	2,501.532	2,499.633
0.700	0.005	0.001	2,501.534	2,499.633
0.700	0.005	0.010	2,501.536	2,499.633
1.000	0.005	0.010	2,502.711	2,499.868
1.000	0.005	0.001	2,502.712	2,499.872
1.000	0.005	0.000	2,502.720	2,499.871
1.300	0.005	0.000	2,503.909	2,500.138
1.300	0.005	0.010	2,503.914	2,500.138
1.300	0.005	0.001	2,503.918	2,500.139
0.700	0.000	0.010	2,507.779	2,501.400
0.700	0.000	0.000	2,507.789	2,501.402
0.700	0.000	0.001	2,507.801	2,501.407
1.000	0.000	0.000	2,510.241	2,502.363
1.000	0.000	0.010	2,510.252	2,502.369
1.000	0.000	0.001	2,510.263	2,502.366
0.700	0.000	0.000	2,510.696	2,502.267
0.700	0.000	0.010	2,510.702	2,502.270
0.700	0.000	0.001	2,510.708	2,502.272
1.300	0.000	0.010	2,510.869	2,502.341
1.300	0.000	0.000	2,510.870	2,502.342

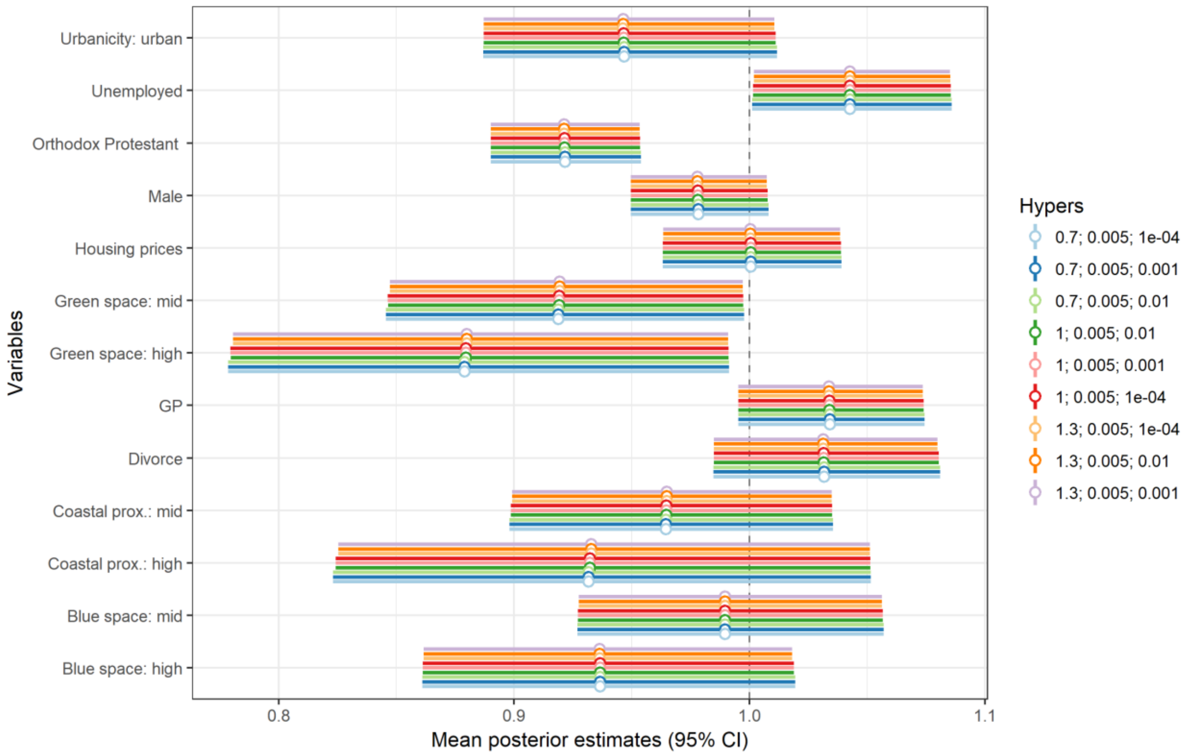
1.300	0.000	0.001	2,510.871	2,502.342
1.000	0.000	0.001	2,512.334	2,502.990
1.000	0.000	0.000	2,512.341	2,502.993
1.000	0.000	0.010	2,512.347	2,502.996
1.300	0.000	0.010	2,513.635	2,503.439
1.300	0.000	0.001	2,513.637	2,503.440
1.300	0.000	0.000	2,513.639	2,503.440

Supplementary Figure S3 shows the posterior densities of each fixed effect for the 9 best performing models in Table S2 with different alternative priors. The alternative priors showed very close agreement.

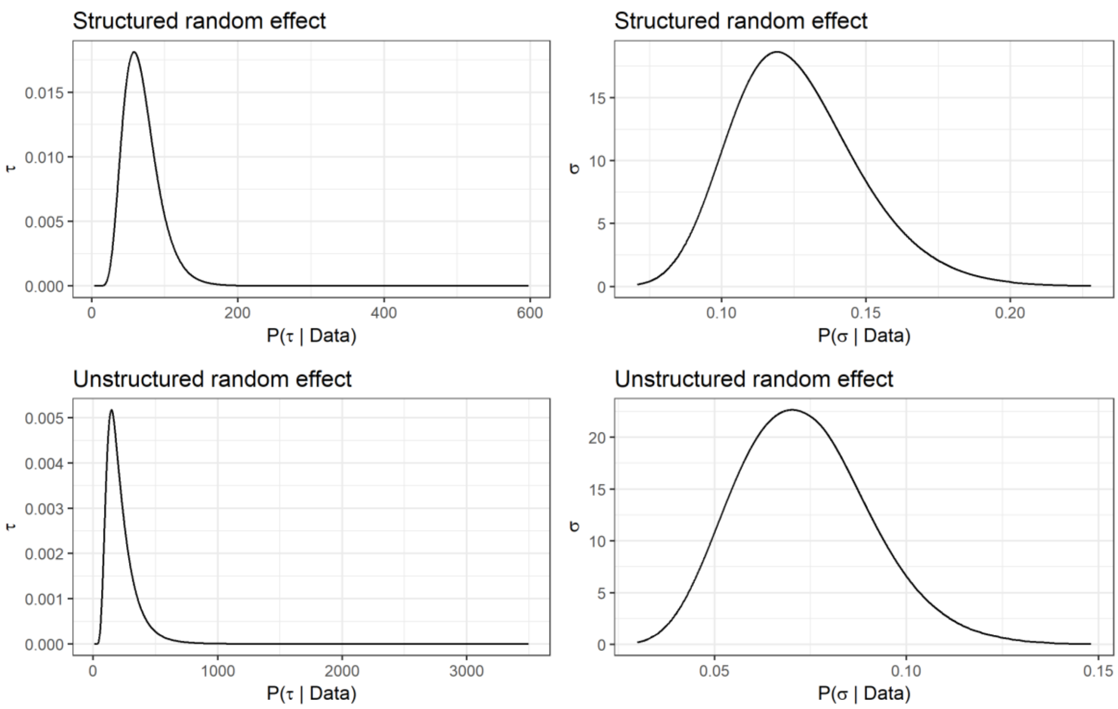


Supplementary Figure S3: Posterior densities of the 9 best performing models (the first value refers to hyperparameter *a*, the second to *b*, and the third to *k*)

Supplementary Figure S4 shows the posterior means along with the 95% CIs for the first 9 models. No significant differences were obtained. Supplementary Figure S5 plots the posterior marginal distribution of tau and sigma for the best fitting model, which is also used in the paper.



Supplementary Figure S4: Posterior means and 95% CIs for the first 9 best performing models (the first value refers to hyperparameter *a*, the second to *b*, and the third to *k*)



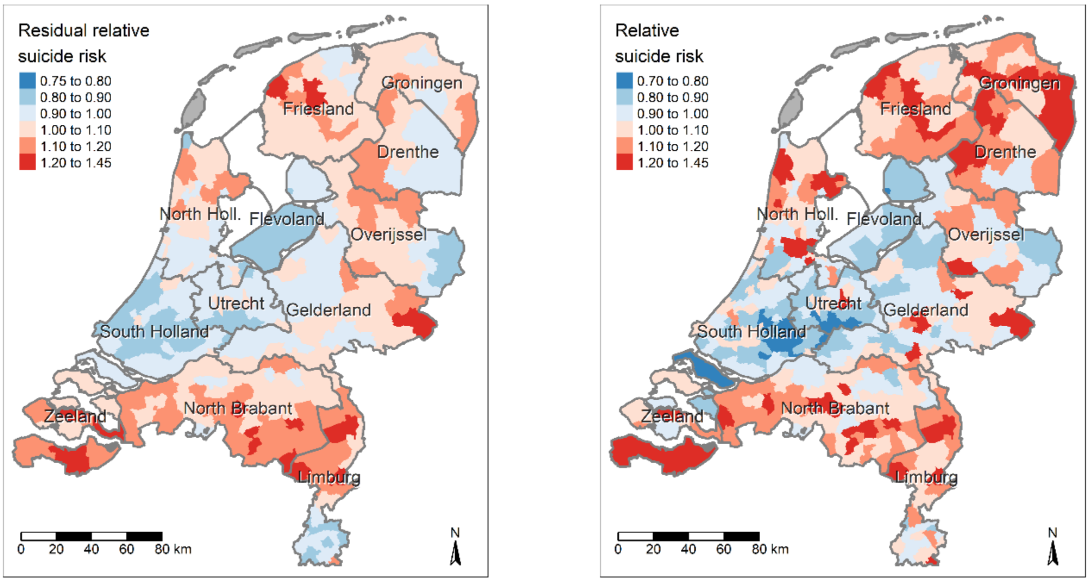
Supplementary Figure S5: Posterior marginal distribution of tau and sigma for the best fitting model

We also tested model sensitivity concerning two neighborhood specifications (i.e., rook vs. queen adjacency). As indicated by the descriptive statistics of the neighborhood matrices (Table S6), both specifications are similar. Therefore, it was not surprising that switching between the queen and the rook case did not translate into substantial differences in the posterior distributions. We followed the majority of studies and utilized queen contiguity as adjacency definition.[5,6,12]

Supplementary Table S6: Summary statistics of two neighborhood matrices

	Rooks's case	Queen's case
Number of non-zero links	2,090	2,082
Percentage of non-zero weights	1.319	1.314
Average number of links	5.251	5.231

The residual relative suicide risk of the fully adjusted model is shown in Figure S7 (left panel) next to the relative risk of the unadjusted model (right panel). Both maps show the sum of the structured and the unstructured effect.



Supplementary Figure S7: Residual relative risk of the fully adjusted model (left panel) and the unadjusted model (right panel) per municipality

Supplementary Table S8: Model 2 with a green space–urbanicity interaction

	Relative risk	2.5% CI	97.5% CI
Intercept	1.163	1.016	1.331
Green space (ref.=low): mid	0.864	0.770	0.969
Green space: high	0.836	0.723	0.965
Green space: mid × urban	1.122	0.968	1.300
Green space: high × urban	1.057	0.851	1.310
Urbanicity (ref.=rural): urban	0.870	0.763	0.992
Blue space (ref.=low): mid	0.988	0.925	1.056
Blue space: high	0.937	0.861	1.020
Coastal proximity (ref.=low): mid	0.967	0.900	1.038
Coastal proximity: high	0.930	0.821	1.050
Male	0.981	0.952	1.011
Divorce	1.038	0.990	1.088
Unemployed	1.045	1.004	1.089
Housing prices	1.003	0.966	1.042
Supply of GPs	1.036	0.997	1.077
Orthodox Protestant	0.926	0.894	0.959

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