IMPERIAL

Spatio-temporal trends and socio-environmental determinants of suicides in England (2002 – 2022): an ecological population-based study

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Outline

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Background

- In the UK, an average of 11.0 per 100,00 yearly suicides. In the EU this is 10.2 per 100,000.
- One suicide costs the NHS £1.46 million.
- Historical regional variation in suicide is rarely explored sub-regionally.
- Understanding local socio-environmental determinants is vital for prevention.

Aim 1:
Develop high spatio-temporal model suitable to model suicides in England from 2002 to 2022.

Aim 2:
Understand the effect of local socio-environmental determinants on suicides in England.

Outline

Data

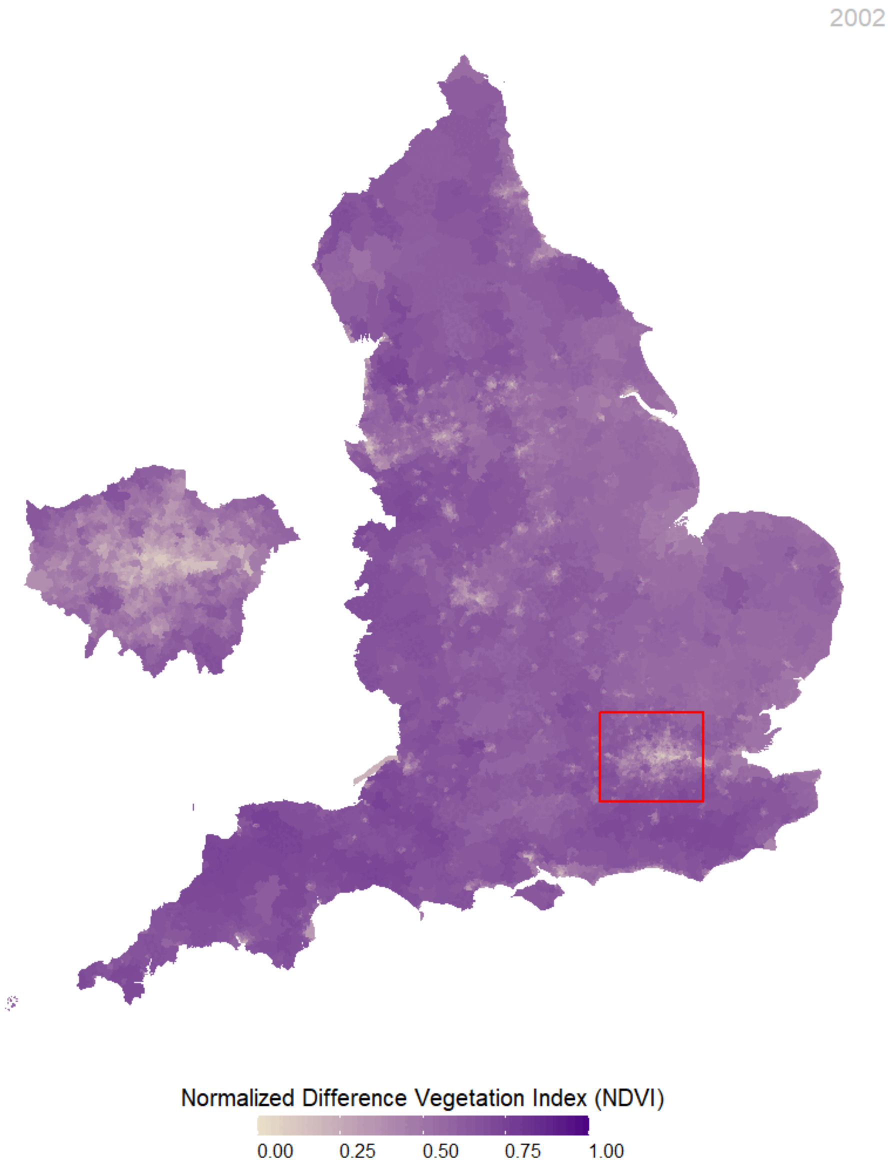
- Suicide outcome:
  - Intentional self harm (ICD-10 Codes: X60-X84).
  - Events of undetermined intent (ICD-10 Codes: Y10.0-Y33.8, Y40, Y87.0, and Y87.2).

- Population at risk:
  - Mid-year from ONS.

- Stratification:
  - Age: [15, 25), [25, 35), [35, 45), [45, 55), [55, 65), [65, 75), [75, 85), 85+.
  - Sex: Male, Female.
  - Middle layer Super Output Area (MSOA).

Covariates

- Deprivation:
  - ONS IMD in 2004, 2007, 2010, 2015, and 2019.
- Ethnic density:
  - ONS ethnic population totals in 2001, 2011, and 2021.
- Population density:
  - ONS mid-year population totals.
- Light pollution:
  - Yearly 1km x 1km satellite data.
- Railway network density:
  - OpenStreetMap.
- Road network density:
  - Ordnance Survey Open Map.
- Greenspace:
  - 16-day 250m x 250m satellite data.



Statistical Model: Age-Sex Standardisation

For MSOA i, year t, sex s, and age a let Y_{itas} and N_{itas} be the observed number of suicides and population at risk.

1. Define reference using whole study domain (England) and period (2002-2022):

$$R_{as} = \sum_{it} \frac{Y_{itas}}{N_{itas}}$$

2. Calculate expected suicides:

$$E_{itas} = N_{itas} \times R_{as}$$

3. Marginalise out age and sex:

$$Y_{it} = \sum_{as} Y_{itas}$$

$$E_{it} = \sum_{as} E_{itas} = \sum_{as} N_{itas} \times R_{as}$$

Statistical Model: Hurdle Model

For MSOA i, and year t let Y_{it} and E_{it} be the observed and (age-sex adjusted) expected number of suicides.

Let $Y_{it} = (z_{it}, o_{it})$ where:

$$z_{it} = \begin{cases} 1, \text{if } y_{it} \neq 0 \\ 0, \text{otherwise} \end{cases},$$

$$o_{it} = \begin{cases} \text{NA, if } y_{it} = 0 \\ y_{it}, \text{otherwise} \end{cases}$$

$$\begin{bmatrix} Y_{1,2002} \\ Y_{1,2003} \\ \vdots \\ Y_{6791,2002} \end{bmatrix} \rightarrow \begin{bmatrix} z_{1,2002} & \text{NA} \\ z_{1,2003} & \text{NA} \\ \vdots & \vdots \\ z_{6791,2022} & \text{NA} \\ -- & -- \\ \text{NA} & o_{1,2002} \\ \text{NA} & o_{1,2003} \\ \vdots & \vdots \\ \text{NA} & o_{6791,2022} \end{bmatrix} \rightarrow \begin{bmatrix} 1 & \text{NA} \\ 0 & \text{NA} \\ \vdots & \vdots \\ 1 & \text{NA} \\ -- & -- \\ \text{NA} & 7 \\ \text{NA} & \text{NA} \\ \vdots & \vdots \\ \text{NA} & 3 \end{bmatrix}$$

Therefore,

- z_{it} is a binary vector of suicide occurring or not.
- o_{it} is a non-zero integer of the number of suicides.

Statistical Model: Linear Predictor

Let $Y_{it} \sim \text{HurdlePoisson}(\pi_{it}, \lambda_{it} = \rho_{it} E_{it})$ where:

$z_{it} \sim \text{Binomial}(\pi_{it})$ and $o_{it} \sim \text{zt}-\text{Poisson}(\lambda_{it} = \rho_{it} E_{it} | o_{it} \geq 1)$

The linear predictor is written:

$$\text{logit}(\pi_{it}) = \beta_0^z + \boldsymbol{X\beta}^z + \delta_i + \gamma_t + \xi_{it}$$
$$\log(\rho_{it}) = \beta_0^o + \boldsymbol{X\beta}^o + \beta_\delta^o \delta_i + \beta_\gamma^o \gamma_t + \beta_\xi^o \xi_{it} + \log(E_{it})$$

- Independent across both
- Shared across both likelihoods
- zt-Poisson likelihood only
- Binomial likelihood only

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$$\beta_0 = \text{intercept}$$

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$$\beta_0 = \text{intercept}$$
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\beta_0 &= \text{intercept} \\
\boldsymbol{X\beta} &= \text{Socio}-\text{environmental terms} \\
\delta_i &= \text{Spatial random effects}
\end{aligned}$$

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\beta_0 &= \text{intercept} \\
\boldsymbol{X\beta} &= \text{Socio}-\text{environmental terms} \\
\delta_i &= \text{Spatial random effects} \\
\gamma_t &= \text{Temporal random effects} \\
\xi_{it} &= \text{Spatio}-\text{temporal random effects} \\
\beta_*^o &= \text{Scale parameters}
\end{aligned}$$

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\delta_i &= \text{Spatial random effects} \\
\gamma_t &= \text{Temporal random effects} \\
\xi_{it} &= \text{Spatio}-\text{temporal random effects} \\
\beta_*^o &= \text{Scale parameters} \\
\log(E_{it}) &= \log-\text{offset}
\end{aligned}
$$

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- Shared across both likelihoods
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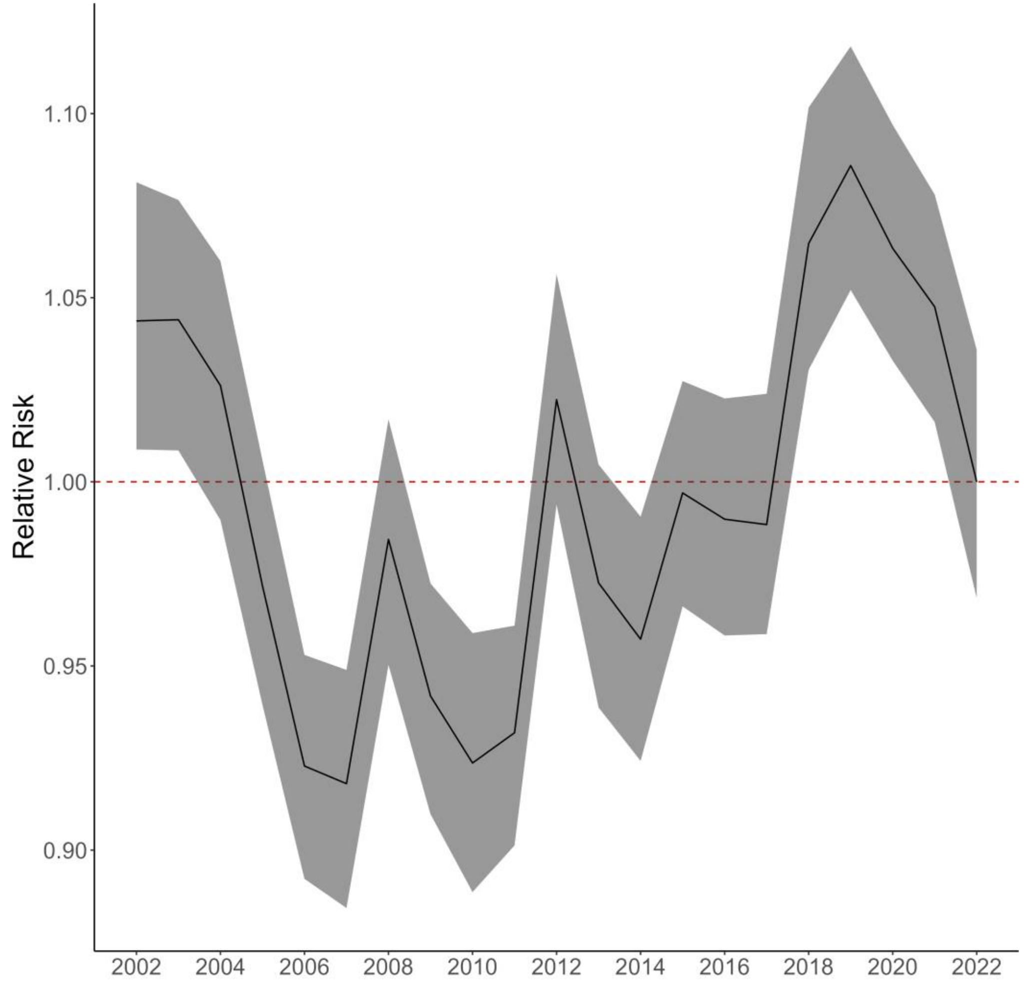
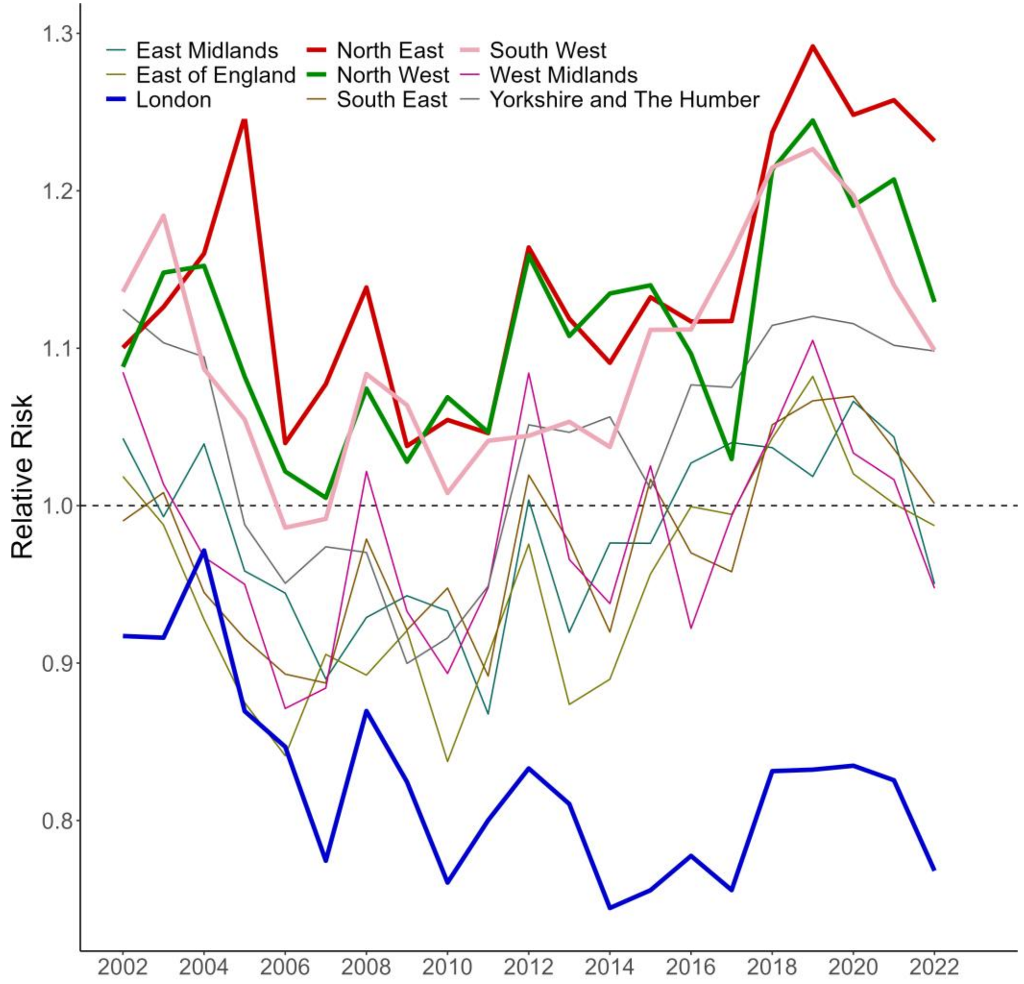
Outline

National and Regional Trends

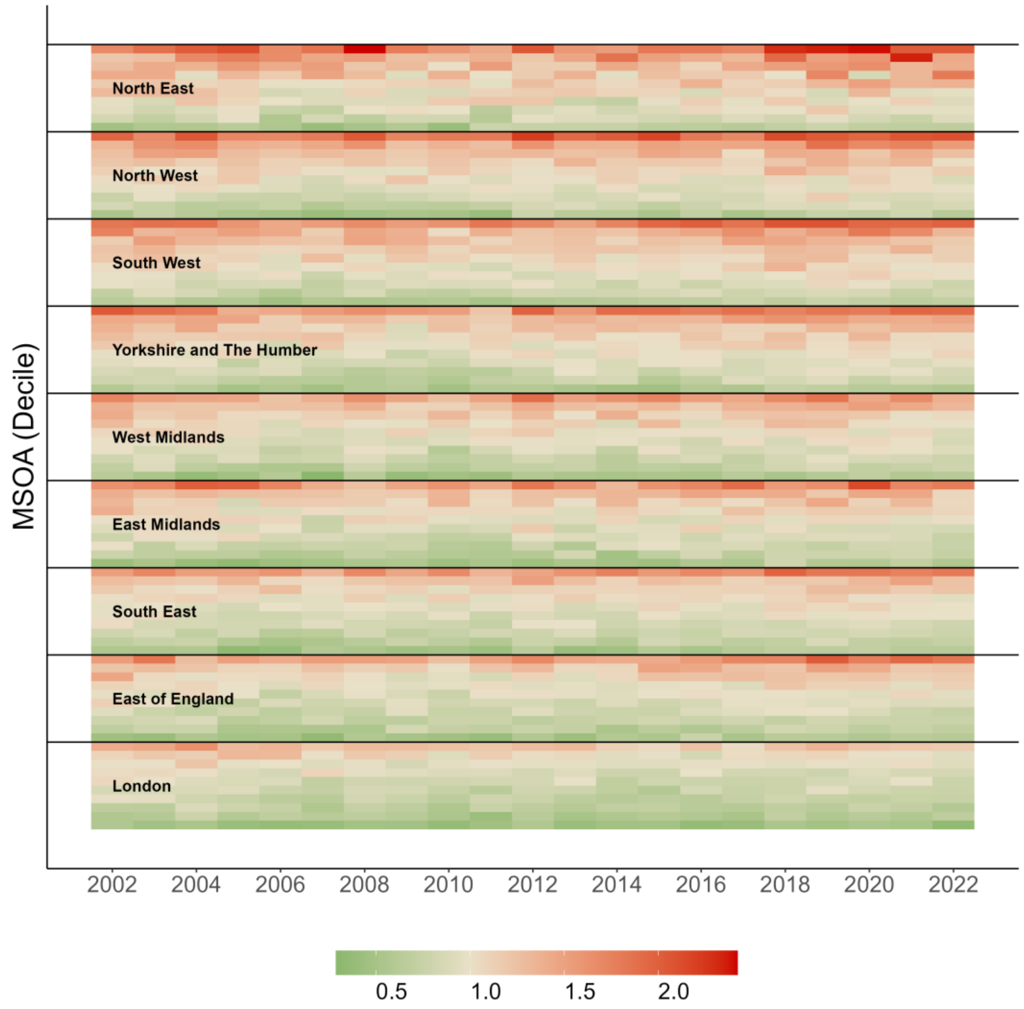


National Suicide Risk

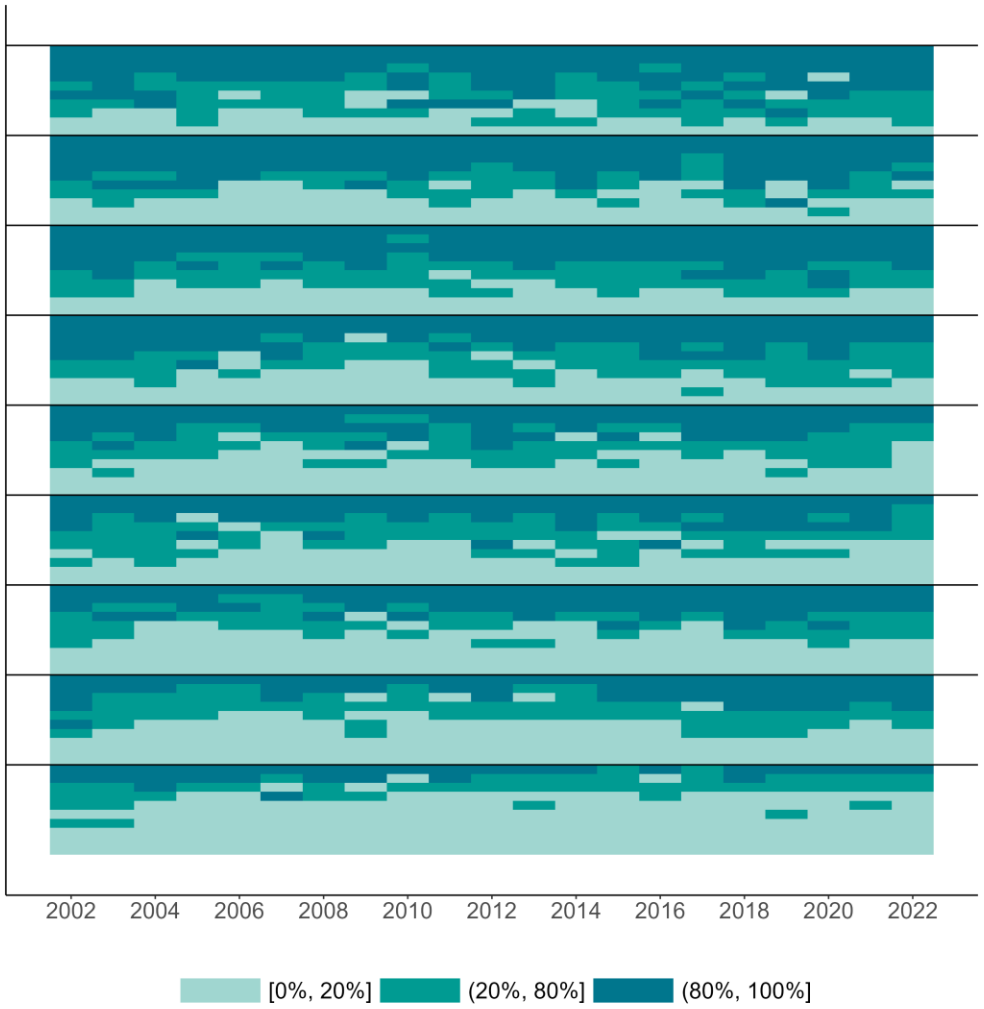


Regional Suicide Risk

Spatio-Temporal Trends

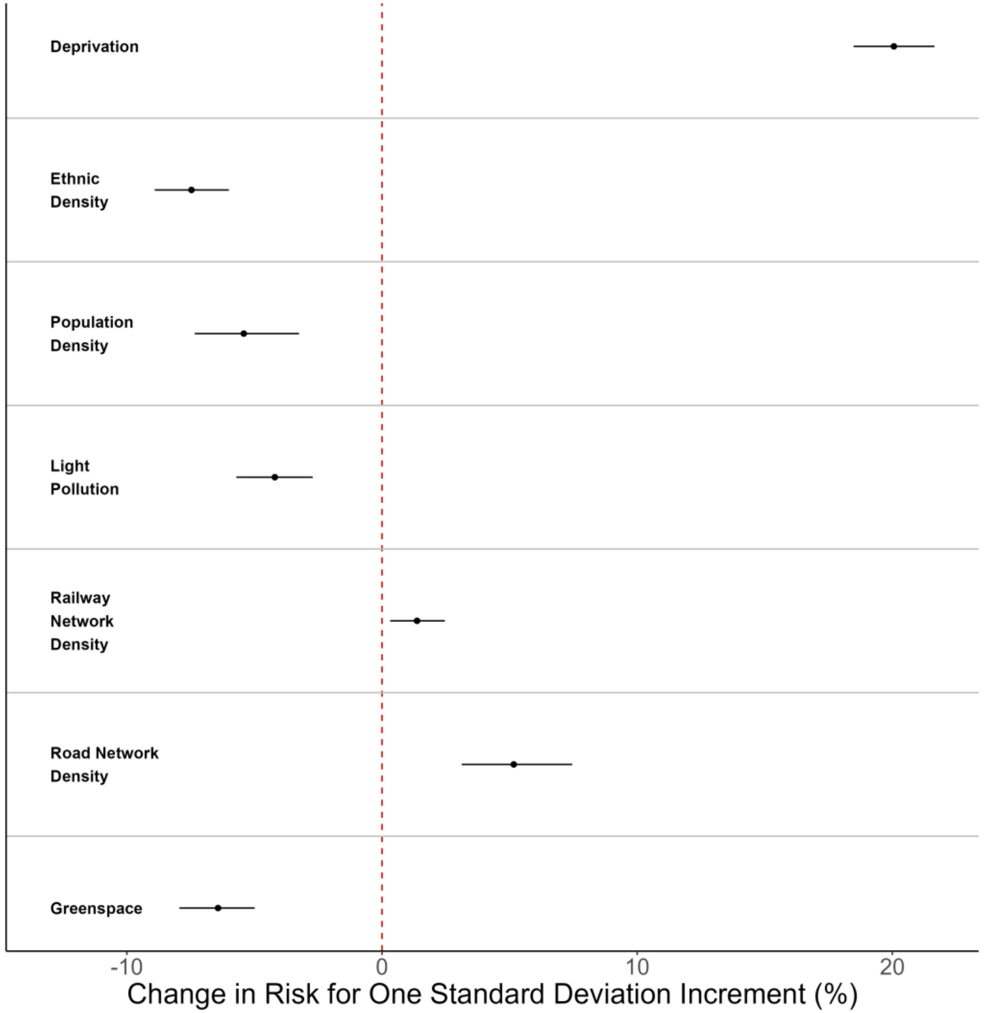


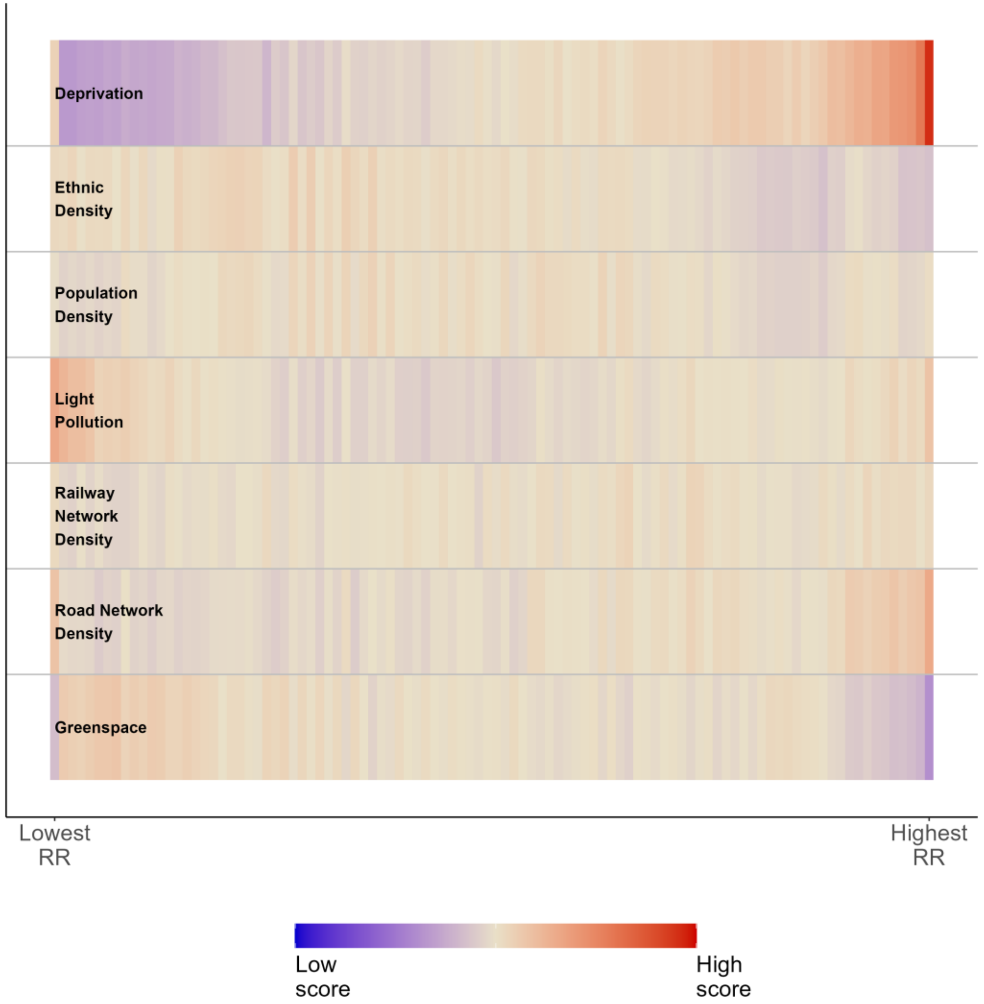
MSOA Suicide Risk



P(MSOA Suicide Risk > 1)

Socio-Environmental Factors and Profiles





Outline

Conclusions

Spatio-temporal

- **Overall National Change:** None from 2002 to 2022. ?
- **Subnational variation:** London has 38.8% lower suicide risk than North East.

Socio-environmental determinants

- **Risk Factors:** Deprivation, Railway network density and road network density.
- **Protective factors:** Ethnic density, population density, light pollution, and greenspace.
- **Interpretation:** can change when considering full area profile.

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Thank you

connorgascoigne / englishSuicides Public

Code | Issues | Pull requests | Actions | Projects | Security | Insights

main | 1 Branch | 0 Tags | Go to file | Code

Gascoigne update file name from 'xxx_' to 'zzz_' | f4b3674 · last month | 17 Commits

code	updated sd for temporal and spatial dimensions	2 months ago
results	update gif formatting	last month
.gitignore	Initial commit for English Suicide study	2 months ago
README.md	update to include population simulation code	2 months ago

README

Spatio-temporal trends and socio-environmental determinants of suicides in England from 2002 - 2022: an ecological population-based study

This is the GitHub repository for the paper.

Running the Code

In general, all code-related files are designed to be as automated as possible. However, a few manual steps are required to get everything working after cloning the repository.

1. Installing Required Packages

Each `.R` file includes a section titled `## 0.1. packages`. This section will attempt to load or install the necessary `R`

ELSEVIER

The Lancet Regional Health - Europe

Volume 56, September 2025, 101386

Articles

Spatio-temporal trends and socio-environmental determinants of suicides in England (2002–2022): an ecological population-based study

Connor Gascoigne [a], Annie Jeffery [b], Ioannis Rotous [c], Xuewen Yu [d], Sara Geneletti [d], Bethan Davies [a e], Gianluca Baio [c], James B. Kirkbride [b], Alexandra Pitman [b f], Marta Blangiardo [a]

ROYAL STATISTICAL SOCIETY

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