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# Living near coasts is associated with higher suicide rates among females but not males: A register-based linkage study in the Netherlands

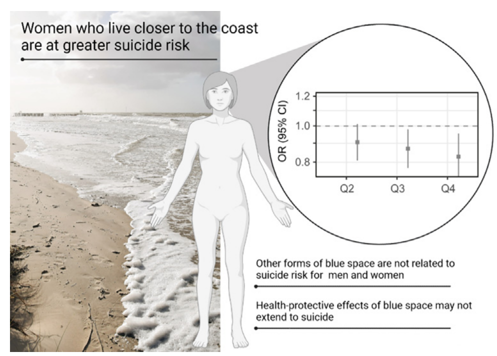
Marco Helbich [a,*], Matthew H.E.M. Browning [b], Mathew White [c,d], Paulien Hagedoorn [e]

[a] Department of Human Geography and Spatial Planning, Utrecht University, Princetonlaan 8a, 3584 CB Utrecht, the Netherlands
[b] Department of Parks, Recreation and Tourism Management, Clemson University, Clemson, SC, United States of America
[c] Cognitive Science Hub, University of Vienna, Vienna, Austria
[d] European Centre for Environment and Human Health, University of Exeter Medical School, Exeter, United Kingdom
[e] Department of Human Geography and Spatial Planning, Utrecht University, Utrecht, the Netherlands

## HIGHLIGHTS

- Largest study to-date on longitudinal blue space exposures and suicide risk
- Suggestive evidence that women who live closer to the coast are at greater risk of suicide.
- Living closer to inland blue spaces may add to the resilience against suicide in the total population.
- Health-protective effects of coastal areas may not extend to women being suicidal.

## GRAPHICAL ABSTRACT

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## ABSTRACT

Exposure to blue spaces may promote psychological wellbeing and reduce mental distress. Whether these effects extend to suicide is unknown. We used register data from 14 million Dutch adults aged 18–64-years between 2007 and 2016 in a nested case-control study to estimate associations between blue space exposures and suicide risk. Each suicide case was matched to ten randomly selected controls. Two blue space exposures were assigned over a ten-year residential address history: distance to the closest inland blue space and distance to the coast. We fitted (gender-stratified) conditional logistic regressions to the data. Possible effect modifications by income were also examined. In total, our analyses included 9757 cases and 95,641 controls. Effect estimates for distance to the closest inland blue space in the total population showed that people living farthest away from inland blue space were at-risk. Suicide risk was lower among women who lived farther away from the coast; no significant effect was observed for men. No evidence was observed that income modified these associations. Our findings provide suggestive evidence that living close to the coast is associated with greater suicide risk for women, while living closer to inland blue spaces may add to the resilience against suicide in the total population. Past research shows that coastal proximity protects against milder forms of mental illness, but these protective effects do not appear to hold for suicide. Blue space interventions for women with severe mental illness or propensities to engage in self-harm should be approached with caution.

* Corresponding author.
*E-mail address:* m.helbich@uu.nl (M. Helbich).

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## 1. Introduction

Death by suicide is a substantial contributor to premature mortality with an estimated 703,000 people dying from suicide every year (Naghavi, 2019; World Health Organization, 2021). The suicide rate per 100,000 inhabitants in the Netherlands increased markedly from 8.2 in 2007 to 11.1 in 2016 (Statistics Netherlands, 2017).

Many factors can lead a person to commit suicide (Turecki et al., 2019). Individual-level factors (e.g., socio-demographics) appear to explain a large proportion of suicide risk (Qin et al., 2003). Research suggests the living environment further relates to suicide ideation and behavior (Cairns et al., 2017), yet considerable uncertainty remains around the role of specific physio-chemical environmental exposures. A few studies have assessed air pollution as a suicide risk factor (Braithwaite et al., 2019), and even less studies have examined associations between suicide and green spaces (e.g., forests, parks) with varying results for the protective effects of natural environments on suicide (Helbich et al., 2018; Jiang et al., 2021; Mitchell and Popham, 2008).

Like green spaces, blue spaces might be environmental factors that influence suicide risk. Blue spaces encompass both natural aquatic environments (e.g., rivers and oceans) and manmade surface water features (e.g., canals) (McDougall et al., 2020). A small but inconsistent evidence base suggests that blue space exposures may be protective against all-cause mortality and mental illness (Smith et al., 2021; White et al., 2020). Since mental illness is often a precursor to committing suicide (Turecki et al., 2019), living near blue spaces might also protect against suicide. The assumed pathways between blue space exposure and reduced risk of suicide include reduced psychosocial stress (Ulrich et al., 1991) and negative emotions (Kaplan, 1995), among others. However, a clear understand about the mechanisms has yet to be established.

We are aware of only a single study that has examined associations between suicide and blue space exposures (Helbich et al., 2018). That study showed null associations for higher numbers of blue spaces in a municipality and coastal proximity, but their estimates originated from spatially aggregated data. Such findings are susceptible to ecological confounding due to a lack of adjustment in individual-level characteristics (Chang and Gunnell, 2018). The results were also cross-sectional and failed to incorporate long-term changes in environmental exposures that accumulate over a person's lifetime, as has been recommended in risk accumulation models for life course analyses (Kuh et al., 2003). Long-term exposure assessments are particularly important for phenomena like suicide, which exhibit a certain latency and develop into formative behaviors and propensities later in life (Gunnell and Lewis, 2005; Turecki et al., 2019). Therefore, the available evidence cannot answer whether the potential protective effects of blue space exposures on poor mental health extend to suicide. Further limiting our understanding of environmental factors of suicide risk is the widespread observation that exposures vary along socio-economic profiles (Mitchell and Popham, 2008; Qin et al., 2003). Notably, low socio-economic status groups cannot afford high-quality neighbourhoods and are disproportionally exposed to environmental pollutants and less green and blue spaces (Hajat et al., 2021).

We responded to these knowledge gaps by addressing the following objectives: 1) testing the hypothesis that women and men with more blue space exposure across a ten-year residential address history were less likely to commit suicide; and 2) evaluating whether these associations varied across socio-economic status. The Netherlands are an ideal location to pursue these objectives given its 450 km of coastline and numerous inland waterways and canals, and striking gender disparities in the number of suicides (Statistics Netherlands, 2017). Addressing these objectives has relevance for public health; blue space interventions are increasingly used to improve mental health, particularly among vulnerable populations, and could be expanded to reduce suicide risk (White et al., 2020). Thus, determining health-supportive factors in the environment is paramount because each suicide is preventable.

## 2. Materials and methods

### 2.1. Study population

Our data for the Dutch population were extracted from administrative registers (Bakker et al., 2014). Every resident has an assigned anonymous personal identification number, which allows for person-by-person register linkages. Eligibility criteria were: 1) legally residing in the country for more than ten years; 2) aged 18–64 years between January 1, 2007 and December 31, 2016; and 3) not living in institutional homes (e.g., prisons or care homes). This resulted in an eligible population of 14,171,753 people for our matched case-control study (Essebag et al., 2005).

We identified suicide cases and corresponding dates of suicide based on death certificates extracted from the cause-of-death register. Suicide included intentional self-harm coded as X60–X84 according to the 10$^{th}$ edition of the International Statistical Classification of Diseases and Related Health Problems (Supplementary Table S1). Each suicide case was matched through incidence-density sampling with ten randomly selected controls from the eligible study population of the same age and gender as the suicide case and who were alive at the time of the suicide case's death (Woodward, 2013).

Because registers have been computerized since 1997, we traced residential locations and move dates for ten years prior to the date of suicide or matching. The exact coordinates of each residential address were geocoded through the cadaster. Register data preprocessing was conducted in Stata, version 14.

### 2.2. Blue space exposure assessment

We used the normalized difference water index (NDWI) from satellite imagery to map annual blue spaces (McFeeters, 1996). Other time-series data on land use and land cover of consistent quality were unavailable. NDWI values were calculated by subtracting the near-infrared band from the green band divided by the sum of the green and near-infrared bands (McFeeters, 1996). Depending on the earth surface's spectral reflectance, NDWI ranges from $-1$ to $+1$ with positive values representing water and negative ones representing non-liquid features (e.g., soil).

Data used to calculate the annual NDWI were multispectral Landsat satellite scenes with nationwide coverage between 1997 and 2016 retrieved from and processed in Google Earth Engine. We queried the available Tier 1 scenes (i.e., those of highest data quality and processing level) with a 30 $\times$ 30 m resolution from the Landsat 5, 7, and 8 satellites ($N$ = 1323). Images were processed by filtering the radiometrically corrected scenes with cloud interference of <40 %. Individual pixels with cloud scores >25 were masked before computing the pixel-wise median NDWI values in each year. Pixels with an NDWI value between >0 and $+1$ were classified as blue spaces. Visual accuracy assessments showed an accurate detection of water bodies.

We assumed that a case/control's primary exposure receptor point was their home address, which rendered a more complex multilevel design (i.e., people nested in spatial units) unnecessary. Due to the absence of a universal blue space metric (Smith et al., 2021), we calculated two exposure estimates:

1. *Distance to the closest inland blue space* was measured by the straight-line distance (in m) between the residential address coordinates and the closest inland blue space. The Euclidean distance was chosen because blue spaces can typically be reached off-road along trails not always mapped in official data.
2. *Distance to the coast* was measured as the shortest road network distance (in m) from the residential address coordinates to the coast. For coastal access, we sampled points every 100 m along the coast. Roads were extracted from the Dutch topographic map 1:10,000 for 2016.

To account for time-varying exposures and residential moves, both metrics were measured annually and weighted by the time spent at each residential location over the ten-year address history. First, we divided the ten-year residential address history into annual spells. Exposure time in each spell was assessed by the number of days (i.e., 365 or 366 days for full years). If a person lived at several addresses in a year, the year was divided into multiple spells based on the number of days lived at each address (e.g., 125 days at address *i* and 240 days at address *j*). To obtain the relative exposure time in each spell, we divided the number of days in the spell by the total number of days in the residential history (e.g., 3653 days for a full ten-year residential history). For example, the relative exposure time at address *i* in year *t* is 125/3653 = 0.034 days. Second, we added the exposure value corresponding to the address and year of each spell (e.g., a distance to the coast of 5600 m). Third, we time-weighted exposure estimates by multiplying blue space exposure by the relative time spent in each spell (e.g., 5600 m × 0.034 = 191 m). Finally, we obtained the overall exposure scores for each blue space metric by summing all time-weighted exposure across the 10-year residential history.

### 2.3. Covariates

Covariates were identified a priori based on the literature. In addition to age (in years) and sex (male, female), which were implicitly adjusted for in our matched case-control design, the following person-level covariates at matching date were included from the registers: ethnicity (Dutch, non-Dutch) to capture ethnic variation in suicide risk (Turecki et al., 2019), employment status (employed, unemployed, or nonworking) to account for labor market absences resulting in self-esteem declines (Nordt et al., 2015; Qin et al., 2003), a dummy variable differentiating movers from non-movers (i.e., those who did not change their address location) (Hagedoorn and Helbich, 2022), categorized standardized household income (low, mid, or high) as an indicator of socioeconomic status, marital status (married, never married, or not currently married), and household type (couple with children, couple without children, single parent with children, or other [mainly single]).

We also included five environmental covariates measured in 300 m buffers (i.e., intended to capture the immediate residential surroundings) centered on a case/control's address over the residential trajectory. Similar to blue space exposure estimates, the environmental covariates were time-weighted based on the proportion of time spent at each residential location in the ten-year period. We included mean concentration of ultra-fine particles ($PM_{2.5}$, in μg $m^{-3}$) for the year 2009, since pollutants can induce oxidative stress and neuroinflammation (Braithwaite et al., 2019); annual normalized difference vegetation index values to capture green spaces, since such exposures may reduce emotional pain and suicidal thoughts (Helbich et al., 2020); annual population density to capture urban-rural suicide inequalities (Mitchell and Popham, 2008); area-level unemployment rates as a proxy for neighbourhood deprivation (Hagedoorn et al., 2020); and social fragmentation to account for poorly integrated communities being at higher risk of suicide (Hagedoorn et al., 2020). In-depth variable descriptions are given in the Supplementary Text.

### 2.4. Statistical analyses

#### 2.4.1. Main analyses

Descriptive statistics summarized the data. Exposure correlations were assessed with Spearman's coefficients ($r$). We tested for associations between blue space exposures and suicide risk with conditional logistic regression models within the total population and within subpopulations stratified by gender. Correlations introduced by the case-control matching necessitated conditional logistic regressions. The three exposure estimates were split into quartiles to allow for the possibility of different dose-response relationships. Generalized variance inflation factors (GVIF) measured multicollinearity with values <3 were deemed acceptable. Regression coefficients were expressed as odds ratios (ORs) and 95 % confidence intervals (CIs).

We specified three models with incremental levels of potential covariate adjustment. Model 1 included the two blue space exposure estimates and was minimally adjusted by design for age. Model 2 added the person-level covariates (i.e., ethnicity, employment status, movers, household income, marital status, and household type). Model 3, which was our main model, added the environmental covariates over the residential trajectory (i.e., $PM_{2.5}$, green spaces, population density, deprivation, and social fragmentation). Analyses were performed in the R software, version 4.0.

#### 2.4.2. Secondary analyses

To distinguish subpopulations who might be more vulnerable than others (Mitchell and Popham, 2008), we tested potential effect modification by introducing interaction terms between categorized household income and the blue space exposure estimates that were significant in Model 3. We chose individual-level socioeconomic status since it tends to be stronger associated with health than area-level measures (Hajat et al., 2021; Qin et al., 2003). The interaction term was tested for significance through a likelihood ratio test. If significant, the data were split for strata-specific estimates between those with low and high income.

#### 2.4.3. Sensitivity analyses

We performed several uncertainty tests with the fully adjusted main models. First, we tested another distance category (i.e., <6 km, 6–15 km, >15–25 km, and >25 km; a narrower first category led to too few suicide cases) (Garrett et al., 2019) to determine whether our estimates were stable. Second, to evaluate whether estimates were dependent on 300 m buffers, we repeated the modeling with 1000 m buffers. This distance represents typical neighbourhood activity spaces (Crouse et al., 2018). Third, for exposure estimates that were significant in the main model, we tested the possibility of complex non-linear associations by replacing the quartiles of the exposure estimates with thin plate splines (Wood, 2003). Fourth, due to possible residual confounding between suicide and mental illness (i.e., healthier people might choose and be able to live nearer blue spaces), we additionally adjusted for antidepressant prescriptions in the year prior to the matching date (Li et al., 2011). Dummy-coded medication data ('N06A' in the Anatomical Therapeutic Chemical Classification System) represented prescriptions that were paid for by healthcare insurance companies as part of the obligatory basic insurance coverage in the Netherlands. Fifth, we tested for associations with only the latest address as the exposure window.

## 3. Results

### 3.1. Description of the study population

In total, 9757 suicide cases and 95,641 controls were included in the analyses (Supplementary Fig. S1). Table 1 provides descriptive information on the study population. $Chi^2$ tests showed that suicide cases had lower rates of marriage, children in the home, employment, and mid/high income earnings than control cases. In contrast, a greater share of suicide cases had moved residential addresses than had control cases.

Exposure-related descriptive statistics are given in Supplementary Table S2. We found few differences in blue space exposure estimates between cases and controls. A significant case-control difference was observed for distance to the coast among women but not for men or for the total study population. We observed no significant case-control differences in distance to the closest inland blue space across the ten-year residential address history or at the latest address. There were case-control differences for the other environmental exposures, however. Independent of buffer size and the exposure window, there were significant differences ($p < 0.001$) for women, men, and the total study population regarding urbanicity, social fragmentation, deprivation, green spaces, and $PM_{2.5}$. Supplementary Tables S3 and S4 further summarize the characteristics of the study population based on the quartiles of both blue space measures.

**Table 1**
Socio-demographic profiles of the study population stratified by gender as well as by suicide cases vs. controls.

| | Total study population | | | Men | | | Women | | |
|---|---|---|---|---|---|---|---|---|---|
| | Suicide cases ($N$ = 9757) | Controls ($N$ = 95,641) | $p$-val. | Suicide cases ($N$ = 6748) | Controls ($N$ = 66,133) | $p$-val. | Suicide cases ($N$ = 3009) | Controls ($N$ = 29,508) | $p$-val. |
| Age (mean [SD]) | 46.217 (11.982) | 46.201 (11.989) | 0.907 | 45.890 (12.123) | 45.873 (12.129) | 0.927 | 46.951 (11.629) | 46.934 (11.638) | 0.938 |
| Nationality: Dutch | 8372 (85.8 %) | 80,900 (84.6 %) | 0.001 | 5828 (86.4 %) | 56,258 (85.1 %) | 0.004 | 2544 (84.5 %) | 24,642 (83.5 %) | 0.143 |
| Non-Dutch | 1385 (14.2 %) | 14,741 (15.4 %) | | 920 (13.6 %) | 9875 (14.9 %) | | 465 (15.5 %) | 4866 (16.5 %) | |
| Marital status: Married | 3464 (35.5 %) | 56,882 (59.5 %) | <0.001 | 2379 (35.3 %) | 38,749 (58.6 %) | <0.001 | 1085 (36.1 %) | 18,133 (61.5 %) | <0.001 |
| Never married | 4086 (41.9 %) | 27,867 (29.1 %) | | 3036 (45.0 %) | 20,832 (31.5 %) | | 1050 (34.9 %) | 7035 (23.8 %) | |
| Non-married | 2207 (22.6 %) | 10,892 (11.4 %) | | 1333 (19.8 %) | 6552 (9.9 %) | | 874 (29.0 %) | 4340 (14.7 %) | |
| Household: Couple with child(ren) | 2793 (28.6 %) | 47,286 (49.4 %) | <0.001 | 2096 (31.1 %) | 33,910 (51.3 %) | <0.001 | 697 (23.2 %) | 13,376 (45.3 %) | <0.001 |
| Couple without children | 1971 (20.2 %) | 27,929 (29.2 %) | | 1229 (18.2 %) | 18,402 (27.8 %) | | 742 (24.7 %) | 9527 (32.3 %) | |
| Single parent | 749 (7.7 %) | 5229 (5.5 %) | | 434 (6.4 %) | 2794 (4.2 %) | | 315 (10.5 %) | 2435 (8.3 %) | |
| Other | 4244 (43.5 %) | 15,197 (15.9 %) | | 2989 (44.3 %) | 11,027 (16.7 %) | | 1255 (41.7 %) | 4170 (14.1 %) | |
| Employment status: Employed | 4198 (43.0 %) | 71,649 (74.9 %) | <0.001 | 3229 (47.9 %) | 52,216 (79.0 %) | <0.001 | 969 (32.2 %) | 19,433 (65.9 %) | <0.001 |
| Unemployed | 349 (3.6 %) | 2375 (2.5 %) | | 279 (4.1 %) | 1698 (2.6 %) | | 70 (2.3 %) | 677 (2.3 %) | |
| Non-working | 5210 (53.4 %) | 21,617 (22.6 %) | | 3240 (48.0 %) | 12,219 (18.5 %) | | 1970 (65.5 %) | 9398 (31.8 %) | |
| Household income: Low | 4190 (42.9 %) | 25,588 (26.8 %) | <0.001 | 2719 (40.3 %) | 16,760 (25.3 %) | <0.001 | 1471 (48.9 %) | 8828 (29.9 %) | <0.001 |
| Mid | 4149 (42.5 %) | 48,570 (50.8 %) | | 3034 (45.0 %) | 34,148 (51.6 %) | | 1115 (37.1 %) | 14,422 (48.9 %) | |
| High | 1418 (14.5 %) | 21,483 (22.5 %) | | 995 (14.7 %) | 15,225 (23.0 %) | | 423 (14.1 %) | 6258 (21.2 %) | |
| Mover: No | 4440 (45.5 %) | 46,957 (49.1 %) | <0.001 | 3105 (46.0 %) | 32,115 (48.6 %) | <0.001 | 1335 (44.4 %) | 14,842 (50.3 %) | <0.001 |
| Yes | 5317 (54.5 %) | 48,684 (50.9 %) | | 3643 (54.0 %) | 34,018 (51.4 %) | | 1674 (55.6 %) | 14,666 (49.7 %) | |

SD = standard deviation.

### 3.2. Correlations across exposure estimates

Supplementary Fig. S2 (top left) shows the pairwise Spearman correlation analysis. Distance to the coast and distance to the closest inland blue space were moderately correlated ($r = 0.37$; $p < 0.001$). Distance to the closest inland blue space was positively correlated with green spaces within 300 m buffers ($r = 0.51$; $p < 0.001$), while the correlations between distance to the coast and green spaces were minor ($r = 0.24$; $p < 0.001$). Urbanicity and green space were the strongest correlated exposures ($r = -0.73$; $p < 0.001$).

### 3.3. Associations between suicide risk and blue space exposure estimates

Unless stated otherwise, conditional logistic regressions results were based on environmental covariates with 300 m buffers as these fully adjusted models had lower Akaike information criterion scores than models using 1000 m buffers (Supplementary Table S5). GVIF values indicated no multicollinearity. Fig. 1 summarizes the estimated associations between suicide risk and blue space exposure estimates. Full numeric results are given in Supplementary Tables S6.

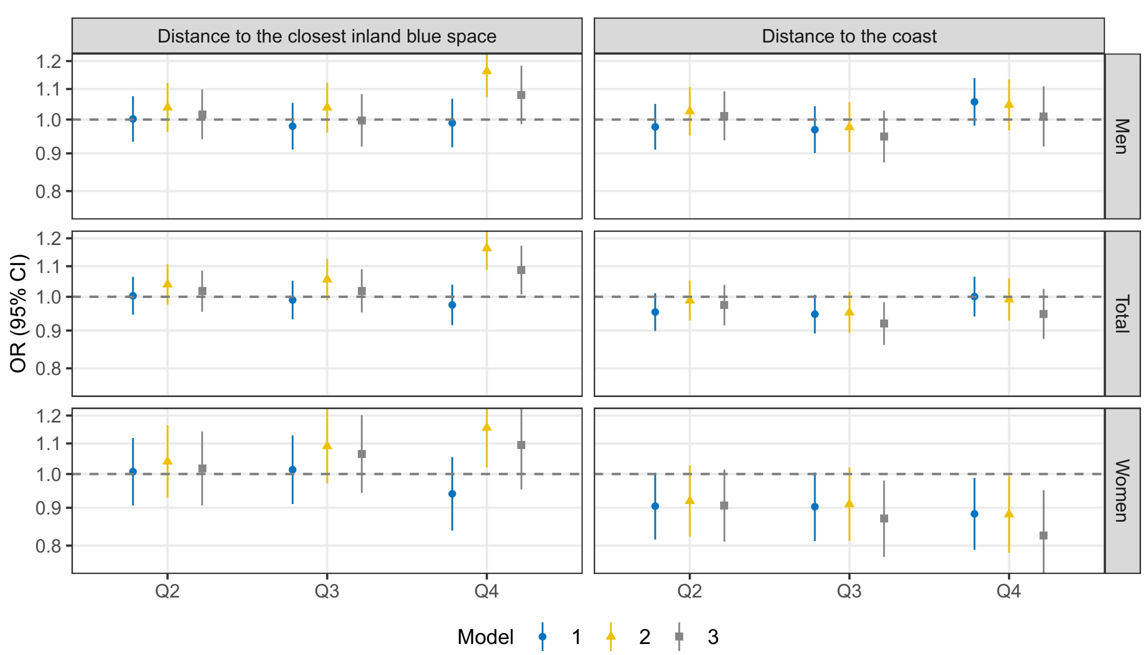


**Fig. 1.** Associations between suicide risk, distance to the closest inland blue space (Q2: >580–960 m, Q3: >960–1591 m, Q4: >1591–9843 m), and distance to the coast (Q2: >11–27 km, Q3: >27–61 km, Q4: >61–172 km). Odds ratios (OR) and 95 % confidence intervals (CI) are shown for quartiles of exposures across a ten-year residential address history among the total study population, among only men, and among only women. ORs are relative to the lowest quartiles (Q1). Effect estimates were obtained through conditional logistic regressions. Model 1 was adjusted for age. Model 2 was additionally adjusted for ethnicity, household income, employment status, mover, marital status, and household type. Model 3 was additionally adjusted for $PM_{2.5}$, green spaces, urbanicity, deprivation, and social fragmentation. The environmental covariates were measured based on 300 m buffers.

Distance to the coast was statistically significantly associated with suicide among women. Women in the 3rd and 4th quartile of distance to the coast had lower suicide risk than women in the lowest quartile. The magnitude of the effect estimates between distance to the coast and suicide were stronger after covariate adjustments (Models 1 vs. 3). Fully adjusted effect estimates for men and the total population were nonsignificant (Model 3). Model 3 for the total study population showed that people living farthest away from inland blue space (4th quartile) had greater suicide risk than those living closer-by (1st quartile). Distance to the closest inland blue space showed null associations with suicide among men and women (Model 3).

Secondary analyses showed no evidence of heterogeneity in effect estimates for distance to the coast and the closest inland blue space across income categories. The likelihood ratio tests did not reach significance ($p > 0.05$).

Sensitivity tests confirmed the robustness of the significant association between blue space exposures and suicide across levels of adjustments, stratifications, and exposure assessments. The results of rerunning Model 3 with 1000 m buffer sizes for the environmental covariates were like those with 300 m buffer sizes (Supplementary Table S7) as were the results with other coastal distance classes (i.e., <6 km, 6–15 km, >15–25 km, and >25 km) (Supplementary Table S8). There was no indication that distance to the coast and distance to the closest inland blue space were nonlinearly related with suicide in Model 3 (e.g., Supplementary Fig. S3). In agreement with the quartile-specific estimates, the splines had effective degrees of freedoms of approximately 1.0 and supported linear associations. Additional adjustments for antidepressants did not alter the significance of the distance to the coast associations nor the distance to the closest inland blue space associations (Supplementary Table S9). Distance to the coast associations did not change markedly when using the latest address rather than the ten-year residential address history, but distance to the associations of closest inland blue space with suicide risk became insignificant in these models (Supplementary Tables S10–S11).

Suicide risk among the total population and women was higher with increased concentrations of $PM_{2.5}$ regardless of the buffer size. Social fragmentation was identified as another risk factor for women. Green spaces were positively associated with suicide risk but only among women and the association was inconsistent across buffer sizes.

## 4. Discussion

This nationwide study of >105,000 adults is the largest evaluation of potential associations between blue spaces and suicide and the first assessment of long-term exposure to blue spaces over a ten-year residential address history.

### *4.1. Main findings and interpretation*

In contrast to our expectations, women who live closer to the coast had a higher risk of suicide. These associations remained statistically significant and became more pronounced after comprehensive model adjustments for air pollution, green spaces, urbanicity, deprivation, and social fragmentation. Such findings substantiate the importance of co-exposure assessments that would otherwise bias environment-health associations (Klompmaker et al., 2021). Reasons for our gender-specific findings are difficult to establish but could relate to trends in women spending more time at home (e.g., Dutch women predominantly work part-time) and the potential for women having different perceptions of coastal areas than men. Importantly, our findings imply that the slowly converging notion of mental health benefits of coastal areas (Smith et al., 2021) may not hold for women being suicidal. Evidence that suicide-distance to the coast associations varied across socioeconomic and geographic strata was inconclusive. We saw no significant differences in risk estimates across income groups.

Our results partly conflict with the only other study on blue spaces and suicide, though that study used cross-sectional and ecological data (Helbich et al., 2018). The authors reported nonsignificant associations between coastal proximity and suicide risk for 398 Dutch municipalities. In support of our findings, a study in Australia (Lawes et al., 2021) and one in the United Kingdom (Middleton et al., 2008) found striking patterns of heightened suicide rates in census areas near the coast. Such findings could have been the result of increased stigmatization to mental health problems in these small and isolated coastal communities as well as the attraction to these areas by elderly people with elevated suicide risk (Whitty, 2021). Parts of the Dutch Bible Belt communities (i.e., those with a high concentration of conservative orthodox Protestants) are also located more inland, where people tend to believe that human life has spiritual and religious meaning (Gearing and Lizardi, 2009). Therefore, suicidal ideation and behavior may be less likely in these non-coastal areas within the Bible Belt. We additionally contemplate that a closer connectedness with the ocean may provoke stimuli to reflect upon the meaning of life and intensify emotions, which may lead to psychological distress and suicide ideation. Supported by the integrated motivational–volitional model of suicidal behavior (O'Connor and Kirtley, 2018), such effects are thought to operate in the motivational phase through distal factors (e.g., environmental influences across the lifespan) as well as proximal factors (e.g., entrapment) leading to suicide. In the volitional phase, access to suicide means (e.g., drowning in the sea) may confer greater risk.

Our individual-level data uncovered that living >1.5 km away from an inland blue space may be a suicide risk factor. Of note, this effect was only observed for the total population, and was not significant in either gender. Explanations for these results remain speculative. Like an ecological Dutch study (Helbich et al., 2018), gender-specific null findings like ours could be attributed to a lack of statistical power and/or insufficient numbers of blue spaces around our study populations' homes, which may have affected our estimates.

Due to a rather limited evidence base, the health effects of blue spaces are inconclusive when looking at mental health and mortality studies in general (Smith et al., 2021; White et al., 2020). In a pooled multi-cohort study from the Netherlands (Generaal et al., 2019) and registered patients of Dutch general practitioners (Zock et al., 2018), blue space of total land use was, as in our case, not associated with the prevalence and severity of depressive symptoms. In contrast, another Dutch study on adults reported a protective association between the available blue space within 1 km of the participant's home and mood disorders (de Vries et al., 2016), while small inland lakes in the United States were associated with higher rates of mood disorder hospitalizations (Pearson et al., 2019). Our nonsignificant results conflict with those in Canadian cities, which found a reduced mortality risk of people living within 250 m of blue space (Crouse et al., 2018). Yet Spanish evidence showed that all-cause premature mortality risk increased with greater blue space exposure, which was predominantly observable in deprived areas (Nieuwenhuijsen et al., 2018). Depending on how blue space exposure was estimated, an Australian study of elderly men found that residential proximity to blue spaces was associated with lower mortality risk, while a higher number of residential blue spaces seemed to increase mortality risk (Zijlema et al., 2019). Of note, directly contextualizing these previous results with ours is difficult since only a small share of deaths is caused by suicide.

### *4.2. Strengths and limitations*

A clear strength of our study was full access to individual-level data on 14 million people aged 18–64 years. This allowed us to randomly draw controls from the eligible full population, which minimized the risk of selection bias while being nationally representative. These high-quality register data also provided vast resources of accurate and reliable person, household, and area-level factors with ample power to detect even weak associations. We advanced existing research by taking advantage of people's long-term exposure history through reconstructing their ten-year residential address history, thus making exposure estimates less error-prone. We acknowledged the lengths of stay at each address to refine these long-term exposure assessments. With a biennial relocation rate of approximately 22 % in the

Netherlands (own calculation), disregarding moving patterns would have otherwise yielded substantial exposure misclassification.

This study also had limitations. Landsat imagery enabled us to map blue spaces objectively in a consistent manner over two decades, yet due to sensor-specific technical limitations (e.g., spatial resolution, minimum mapping unit), smaller blue spaces (e.g., canals) that are ubiquitous in the Netherlands remained unrecognized. This potential limitation was inevitable, since finer-grained remotely sensed data over two decades were unavailable. Despite capturing blue spaces with remotely sensed imagery over time, there was no way to represent how cases/controls perceived the quality of and actively used blue spaces (White et al., 2020). In keeping with other register studies (Hagedoorn et al., 2020; Qin et al., 2003), these factors would have required population-wide self-reported data, which were unavailable. While we made comprehensive covariate adjustments, we may have missed important ones that biased our results. For example, we lacked information on previous suicide attempts, but this limitation was to some extent accounted for by medical treatments for mental illness the year before death. Therefore, we believe that incorporating previous suicide attempts into our models would have had minimal impacts on our results. Similarly, we did not account for the likelihood that the observed associations were influenced by other environmental factors, such as meteorological conditions (Frangione et al., 2022). Due to the small number of blue space-related suicides, we were also unable to conduct robust statistical analyses on suicide means (e.g., suicide by drowning). To the extent our findings are generalizable to other (European) countries remains open and warrants further research, given the homogenous and flat Dutch coastline. Finally, our analyses precluded causal inferences that are difficult to infer from observational studies.

## 5. Conclusions

We found suggestive evidence that women (but not men) living closer to the coast are at greater risk of suicide. This finding implies that the health-supportive effects coastal areas may not hold for woman facing suicide risk. For the total population, our results partially supported that living at a distance from inland blue spaces may diminish resilience against suicide. If future research supports our main findings, than blue space interventions for women with severe mental illness or propensities to engage in self-harm should be approached with caution. More broadly, our findings support the need for additional research on suicide and long-term environmental exposures.

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## Ethics

The study protocol (Helbich, 2019) was approved by the Ethics Review Board of Utrecht University (FETC17–060). Data records were fully anonymized. As there was no interaction with subjects, the need for informed consent was waived.

## Data sharing

Dutch privacy legislation permits the use of linked microdata for research purposes under strict conditions. Register data are non-publicly accessible for scientific research in accordance with Dutch privacy legislation through Statistics Netherlands. Data access requests should be directed to Statistics Netherlands. The environmental exposure maps are available on request from the corresponding author.

## CRediT authorship contribution statement

**Marco Helbich:** Conceptualization, Methodology, Formal analysis, Data curation, Resources, Writing – original draft, Visualization, Project administration, Funding acquisition. **Matthew H.E.M. Browning:** Writing – review & editing. **Mathew White:** Writing – review & editing. **Paulien Hagedoorn:** Conceptualization, Methodology, Formal analysis, Writing – review & editing.

## Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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## Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.scitotenv.2022.157329.

## References

Bakker, B.F.M., Van Rooijen, J., Van Toor, L., 2014. The system of social statistical datasets of Statistics Netherlands: an integral approach to the production of register-based social statistics. Stat. J. IAOS 30, 411–424.

Braithwaite, I., Zhang, S., Kirkbride, J.B., Osborn, D.P.J., Hayes, J.F., 2019. Air pollution (particulate matter) exposure and associations with depression, anxiety, bipolar, psychosis and suicide risk: a systematic review and meta-analysis. Environ. Health Perspect. 127, 126002.

Cairns, J.-M., Graham, E., Bambra, C., 2017. Area-level socioeconomic disadvantage and suicidal behaviour in Europe: a systematic review. Soc. Sci. Med. 192, 102–111.

Chang, S.-S., Gunnell, D., 2018. Natural environments and suicide. Lancet Planet. Health 2, e109–e110.

Crouse, D.L., Balram, A., Hystad, P., Pinault, L., van den Bosch, M., Chen, H., Rainham, D., Thomson, E.M., Close, C.H., van Donkelaar, A., et al., 2018. Associations between living near water and risk of mortality among urban Canadians. Environ. Health Perspect. 126, 77008.

Essebag, V., Platt, R.W., Abrahamowicz, M., Pilote, L., 2005. Comparison of nested case-control and survival analysis methodologies for analysis of time-dependent exposure. BMC Med. Res. Methodol. 5, 5.

Frangione, B., Villamizar, L.A.R., Lang, J.J., Colman, I., Lavigne, E., Peters, C., Anisman, H., Villeneuve, P.J., 2022. Short-term changes in meteorological conditions and suicide: a systematic review and meta-analysis. Environ. Res. 207, 112230.

Garrett, J.K., Clitherow, T.J., White, M.P., Wheeler, B.W., Fleming, L.E., 2019. Coastal proximity and mental health among urban adults in England: the moderating effect of household income. Health Place 59, 102200.

Gearing, R.E., Lizardi, D., 2009. Religion and suicide. J. Relig.Health 48, 332–341.

Generaal, E., Hoogendijk, E.O., Stam, M., Henke, C.E., Rutters, F., Oosterman, M., Huisman, M., Kramer, S.E., Elders, P.J.M., Timmermans, E.J., et al., 2019. Neighbourhood characteristics and prevalence and severity of depression: pooled analysis of eight Dutch cohort studies. Br. J. Psychiatry 1–8.

Gunnell, D., Lewis, G., 2005. Studying suicide from the life course perspective: implications for prevention. Br. J. Psychiatry 187, 206–208.

Hagedoorn, P., Helbich, M., 2022. Longitudinal effects of physical and social neighbourhood change on suicide mortality: a full population cohort study among movers and non-movers in the Netherlands. Soc. Sci. Med. 294, 114690.

Hagedoorn, P., Groenewegen, P.P., Roberts, H., Helbich, M., 2020. Is suicide mortality associated with neighbourhood social fragmentation and deprivation? A Dutch register-based case-control study using individualised neighbourhoods. J. Epidemiol. Community Health 74, 197–202.

Hajat, A., MacLehose, R.F., Rosofsky, A., Walker, K.D., Clougherty, J.E., 2021. Confounding by socioeconomic status in epidemiological studies of air pollution and health: challenges and opportunities. Environ. Health Perspect. 129, 65001.

Helbich, M., 2019. Dynamic urban environmental exposures on depression and suicide (NEEDS) in the Netherlands: a protocol for a cross-sectional smartphone tracking study and a longitudinal population register study. BMJ Open 9, e030075.

Helbich, M., de Beurs, D., Kwan, M.-P., O'Connor, R.C., Groenewegen, P.P., 2018. Natural environments and suicide mortality in the Netherlands: a cross-sectional, ecological study. Lancet Planet. Health 2, e134–e139.

Helbich, M., O'Connor, R.C., Nieuwenhuijsen, M., Hagedoorn, P., 2020. Greenery exposure and suicide mortality later in life: a longitudinal register-based case-control study. Environ. Int. 143, 105982.

Jiang, B., Shen, K., Sullivan, W.C., Yang, Y., Liu, X., Lu, Y., 2021. A natural experiment reveals impacts of built environment on suicide rate: developing an environmental theory of suicide. Sci. Total Environ. 776, 145750.

Kaplan, S., 1995. The restorative benefits of nature: toward an integrative framework. J. Environ. Psychol. 15, 169–182.

Klompmaker, J.O., Janssen, N.A.H., Bloemsma, L.D., Marra, M., Lebret, E., Gehring, U., Hoek, G., 2021. Effects of exposure to surrounding green, air pollution and traffic noise with non-accidental and cause-specific mortality in the Dutch national cohort. Environ. Health 20, 1–16.

Kuh, D., Ben-Shlomo, Y., Lynch, J., Hallqvist, J., Power, C., 2003. Life course epidemiology. J. Epidemiol. Community Health 57, 778.

Lawes, J.C., Peden, A.E., Bugeja, L., Strasiotto, L., Daw, S., Franklin, R.C., 2021. Suicide along the Australian coast: exploring the epidemiology and risk factors. PLoS One 16, e0251938.

Li, Z., Page, A., Martin, G., Taylor, R., 2011. Attributable risk of psychiatric and socio-economic factors for suicide from individual-level, population-based studies: a systematic review. Soc. Sci. Med. 72, 608–616.

McDougall, C.W., Quilliam, R.S., Hanley, N., Oliver, D.M., 2020. Freshwater blue space and population health: an emerging research agenda. Sci. Total Environ. 737, 140196.

McFeeters, S.K., 1996. The use of the normalized difference water index (NDWI) in the delineation of open water features. Int. J. Remote Sens. 17, 1425–1432.

Middleton, N., Sterne, J.A.C., Gunnell, D.J., 2008. An atlas of suicide mortality: England and Wales, 1988–1994. Health Place 14, 492–506.

Mitchell, R., Popham, F., 2008. Effect of exposure to natural environment on health inequalities: an observational population study. Lancet 372, 1655–1660.

Naghavi, M., 2019. Global, regional, and national burden of suicide mortality 1990 to 2016: systematic analysis for the Global Burden of Disease Study 2016. BMJ 364, l94.

Nieuwenhuijsen, M.J., Gascon, M., Martinez, D., Ponjoan, A., Blanch, J., Ramos, R., Foraster, M., Mueller, N., Espinosa, A., et al., Garcia-Gil, M.del M., 2018. Air pollution, noise, blue space, and green space and premature mortality in Barcelona: a mega cohort. Int. J. Environ. Res. Public Health 15, 2405.

Nordt, C., Warnke, I., Seifritz, E., Kawohl, W., 2015. Modelling suicide and unemployment: a longitudinal analysis covering 63 countries, 2000–11. Lancet Psychiatry 2, 239–245.

O'Connor, R.C., Kirtley, O.J., 2018. The integrated motivational–volitional model of suicidal behaviour. Philos. Trans. R. Soc. B 373.

Pearson, A.L., Shortridge, A., Delamater, P.L., Horton, T.H., Dahlin, K., Rzotkiewicz, A., Marchiori, M.J., 2019. Effects of freshwater blue spaces may be beneficial for mental health: a first, ecological study in the North American Great Lakes region. PLoS One 14, e0221977.

Qin, P., Agerbo, E., Mortensen, P.B., 2003. Suicide risk in relation to socioeconomic, demographic, psychiatric, and familial factors: a national register-based study of all suicides in Denmark, 1981–1997. Am. J. Psychiatry 160, 765–772.

Smith, N., Georgiou, M., King, A.C., Tieges, Z., Webb, S., Chastin, S., 2021. Urban blue spaces and human health: a systematic review and meta-analysis of quantitative studies. Cities 119, 103413.

Statistics Netherlands, 2017. Statline: overledenen; zelfdoding (inwoners), diverse kenmerken [WWW Document]. URL http://statline.cbs.nl/Statweb/publication/?DM=SLNL&PA=7022gza&D1=a&D2=0&D3=0&D4=30,60,64-65&HDR=G1,G2&STB=T,G3&VW=T.

Turecki, G., Brent, D.A., Gunnell, D., O'Connor, R.C., Oquendo, M.A., Pirkis, J., Stanley, B.H., 2019. Suicide and suicide risk. Nat. Rev. Dis. Prim. 5, 1–22.

Ulrich, R.S., Simons, R.F., Losito, B.D., Fiorito, E., Miles, M.A., Zelson, M., 1991. Stress recovery during exposure to natural and urban environments. J. Environ. Psychol. 11, 201–230.

de Vries, S., ten Have, M., van Dorsselaer, S., van Wezep, M., Hermans, T., de Graaf, R., 2016. Local availability of green and blue space and prevalence of common mental disorders in the Netherlands. Br. J. Psychiatry Open 2, 366–372.

White, M.P., Elliott, L.R., Gascon, M., Roberts, B., Fleming, L.E., 2020. Blue space, health and well-being: a narrative overview and synthesis of potential benefits. Environ. Res. 110169.

Whitty, C., 2021. Chief Medical Officer's Annual Report 2021: Health in Coastal Communities.

Wood, S.N., 2003. Thin plate regression splines. J. R. Stat. Soc. Ser. B (Stat Methodol.) 65, 95–114.

Woodward, M., 2013. Epidemiology: Study Design and Data Analysis. CRC Press.

World Health Organization, 2021. Suicide Worldwide in 2019: Global Health Estimates Geneva.

Zijlema, W.L., Stasinska, A., Blake, D., Dirgawati, M., Flicker, L., Yeap, B.B., Golledge, J., Hankey, G.J., Nieuwenhuijsen, M., Heyworth, J., 2019. The longitudinal association between natural outdoor environments and mortality in 9218 older men from Perth, Western Australia. Environ. Int. 125, 430–436.

Zock, J.-P., Verheij, R., Helbich, M., Volker, B., Spreeuwenberg, P., Strak, M., Janssen, N.A.H., Dijst, M., Groenewegen, P., 2018. The impact of social capital, land use, air pollution and noise on individual morbidity in Dutch neighbourhoods. Environ. Int. 121, 453–460.