Coastal Blue Space and Depression in Older Adults☆

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Abstract

This paper tests whether higher exposure to coastal blue space is associated with lower risk of depression using data from The Irish Longitudinal Study on Ageing (TILDA), a nationally representative longitudinal study of people aged fifty and over in Ireland. We contribute to the literature on blue space and health by (i) using scores from the Center for Epidemiologic Studies Depression Scale (CES-D) to measure depression outcomes (ii) using new measures of coastal blue space visibility (iii) studying the association in an older population (iv) using data from Ireland. Our results indicate that exposure to coastal blue space is associated with beneficial mental health outcomes: TILDA respondents with the highest share of sea view visibility have lower depression (CES-D) scores, while distance from coastline is not statistically significant when views and proximity are both included in the model. This finding supports the idea that the primary channel through which coastal blue space operates to reduce depression scores is visual rather than related to physical proximity.

Keywords: depression, CES-D scores, coastal blue space, blue space visibility, older adults, viewshed analysis

1. Introduction

Despite the historical development of urban areas alongside water bodies (e.g. inland waterways and coastal margins), the predominant focus of literature linking the natural environment to health outcomes, has related to the health benefits of green spaces (Gascon et al., 2017). However, against a backdrop of rapid urbanisation (UN, 2015), the health and well-being effects of *all* our environmental surroundings have become of increased relevance and importance to policy-makers. In recognition of the blue space gap in the environmental health literature the European Unions Horizon 2020 has allocated funding to the BlueHealth project in order to better understand how 'blue infrastructure' can be used to provide health and well being effects. Here blue space is defined by the BlueHealth project (Grellier et al., 2017) as "outdoor environments either natural or manmade that prominently feature water and are accessible to humans either proximally (being in, on or near water) or distally/virtually (being able to see, hear or otherwise sense water)". Our paper makes a unique contribution to the literature by examining the association of both proximal and visual measures of coastal blue space on the mental health outcome of depression in older people.

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2. Literature

2.1. Blue Spaces and Depression

As identified by Völker and Kistemann (2011, 2013) and Gascon et al. (2015) the health effects of blue spaces has been an under-explored topic in the literature. The emergent blue space literature borrows extensively from the pre-existing green space literature with relatively mixed evidence found regarding its health effects. Gascon et al. (2017) perform the first systemic review of this emergent blue space literature. Here they find evidence which suggests a positive association between blue space and outcomes relating to mental health, well-being and physical activity, but find the evidence to be more mixed when examining outcomes related to general health, obesity, and cardiovascular health. Overall Gascon et al. (2017) identify just 12 studies that examine the association between blue space and mental health and well-being. However, of these 12 studies, only 4 studies (Alcock et al., 2015; Triguero-Mas et al., 2015; White et al., 2013a,b) specifically examine the mental health outcome of depression. Since the systemic review of Gascon et al. (2017), we know of only one more study (Gascon et al., 2018) that has examined the link between blue spaces and depression.

Nutsford et al. (2016) outline the three main channels through which blue spaces can operate to create beneficial mental health effects. First, the availability of blue space can potentially increase the likelihood of engaging in physical activity (e.g. swimming, walking on beaches) which in turn will improve mental health. Second, blue space can facilitate increased social interaction which will generate positive mental health effects through fostering a sense of belonging and social cohesion. Third, blue space can confer positive mental health effects by acting as therapeutic or salutogenic (health and well-being promotion) places (Foley and Kistemann, 2015; de Bell et al., 2017; Hartig et al., 2014; Völker and Kistemann, 2013; MacKerron and Mourato, 2013). Much of the therapeutic landscape literature relates to the *biophilia* hypothesis (Wilson, 1984), a psycho-evolutionary theory, which posits that humans have an innate tendency to seek connections with nature and other forms of life. Bell et al. (2015) in particular examines the varied types of therapeutic experiences (symbolic, achieving, immersive and social) which coastal blue space might offer using data from residents of two towns in south west England, and suggests that the types of therapeutic experiences sought might change as an individual transitions through different stages of their life.

2.2. Blue Space and Depression in Older Adults

Very few studies have examined the relationship between mental health and exposure to blue space in an ageing population. Finlay et al. (2015) examine the therapeutic impact of green and blue spaces for older adults (aged 65 to 86 years old) and find that blue space in particular embodies important therapeutic qualities for mental health. Similarly Coleman and Kearns (2015) examine the importance of blue space in informing experiences of place, being aged, and well-being in older adults in New Zealand. However, to the best of our knowledge this is the first paper which specifically examines the relationship between exposure to blue space and the mental health outcome of *depression* in an ageing population. We argue that this is an important outcome to examine, as although depression is less prevalent among older adults than younger adults, it can have serious negative consequences, including increased burden of physical illness, impaired functioning, and risk of suicide (Fiske et al., 2009).

The predominant approach used to measure depression in the studies outlined by the systemic review of Gascon et al. (2017) is the General Health Questionnaire-12 Items Scale, with Gascon et al. (2018) and Triguero-Mas et al. (2015) also using self-reported questionnaires on depression and related medication. As such, as far as we are aware, this paper is the first to use a different type of scale - the Center for Epidemiologic Studies Depression Scale (CES-D) scale (described in greater detail in Section 3.1.1) - in order to measure depression in our sample respondents of older people.

2.3. Irish Context

Despite the extensive coastline of Ireland and the substantial availability of other types of blue space (inland, freshwater, urban blue) relatively little research has been carried out on how blue space relates to health and well-being in an Irish context. Perhaps the most well known study is that of Brereton et al. (2008), who investigate the relationship between location-specific factors and life satisfaction. Here Brereton et al. (2008) find that proximity to coast has a significant association with life satisfaction, with those living within 2km of the coastline more likely to enjoy higher life satisfaction than those living more than 5km away. However, Brereton et al. (2008) find no evidence of a statistically significant association between proximity to beach and life satisfaction and suggest that given Ireland's climate, this finding could be indicative that the amenity value of coastal areas is not a function of the availability of a beach within an Irish context. Other contributions to Ireland's blue space literature includes Foley (2017, 2015) who investigates the relationship between well-being and swimming in blue spaces, and also Foley (2011) who explores the therapeutic impact of a more unconventional type of blue space, that of holy wells. More recently within the broader literature Gillespie et al. (2018) have also provided evidence using data from real estate transactions that blue space is valued by the Irish housing market. We therefore contribute to this nascent Irish literature on the well-being benefits of blue spaces by using data from Ireland.

3. Data

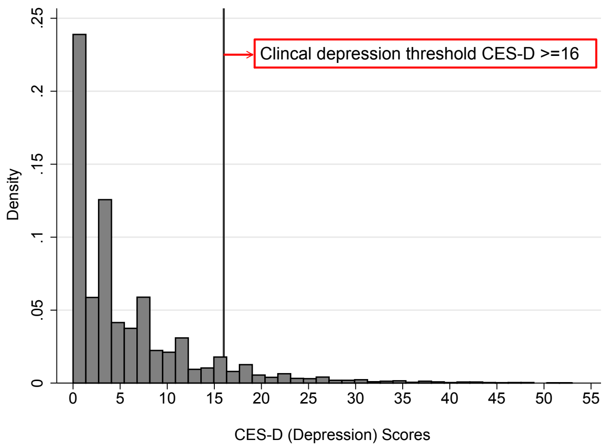
3.1. TILDA

This paper uses data from The Irish Longitudinal Study on Ageing (TILDA), a nationally representative longitudinal study of people aged fifty and over in Ireland. Data collection for Wave 1 was carried out between October 2009 and July 2011 on 8,175 individuals aged 50 and over, from the 6,279 households that participated in the study. Interviews were also conducted with the younger spouses and partners of TILDA participants (even if aged less than 50), leading to a total sample size of 8,504. Interviews were conducted by trained interviewers in each respondent's homes, and were carried out using Computer Assisted Personal Interviewing (CAPI). Participants were also given a self completed questionnaire (SCQ) with more potentially sensitive questions to fill out and return by mail. Lastly, TILDA respondents were invited to attend a nurse-led health assessment at specialised centres, or a modified partial assessment in their homes where travel was not practicable. The RANSAM sampling system (Whelan, 1979; Kenny et al., 2010), which uses the An Post GeoDirectory containing geocodes for all the addresses in Ireland, was used to construct the final sample of TILDA respondents. This means that the geo-code for each TILDA respondent's address is recorded, making TILDA a uniquely appropriate dataset for merging with other geo-coded spatial data on environmental factors (Dempsey et al., 2018a,b) such as blue space.

3.1.1. Outcome Variable: Depression

Scores from The Center for Epidemiologic Studies Depression Scale (CES-D) scale are used to proxy depression in our sample of TILDA respondents. The CES-D scale is a self-reported scale designed to measure depressive symptomatology in the general population (Radloff, 1977). Its validity as a measure of depression in older adults has been well documented (Hertzog et al., 1990; Lewinsohn et al., 1997) and it has been used extensively in studies of later life depression (Beekman et al., 1997; Santini et al., 2015). Administered during the CAPI section of the TILDA questionnaire, each respondent is asked a total of 20 questions based on a four point scale to measure the prevalence of depressive symptoms during the past week, leading to a total CES-D score of 60 (O'Regan et al., 2011). A cut-off score of $\geq$ 16 is generally used to determine clinically significant depressive symptoms, with 9.64% of TILDA respondents in our final sample falling into this category (see Figure 1). This is consistent with the baseline finding that 10% of the cohort suffer from clinically depressive symptoms (Regan et al., 2013). Subsequent research of the cohort at Wave 3 has also shed light on the fact that two-thirds of depressed TILDA respondents have not been prescribed antidepressant/antipsychotic therapy (Briggs et al., 2018). An advantage therefore of using this measure, is that it is a validated tool for capturing clinically significant depression and will not be affected by undiagnosed depression (as would be the case with a self-reported question on whether the individual was ever diagnosed with depression).

Figure 1: Distribution of CES-D scores amongst TILDA respondents



3.1.2. Covariates

A significant problem with the blue/green space literature is the difficulty of estimating causal relationships due to the potential occurrence of self-selection (whereby individuals with low depression scores also choose to live in areas with greater blue space exposure). If self-selection occurs, then this would mean that our blue space exposure variables are simply acting as a proxy for some unobserved factor which impacts depression scores. While the structure of our data does not allow us to completely eliminate the possibility that these selection effects are occurring, the richness of the TILDA dataset does allow us to control for a wide range of variables which could potentially be determining both the location decision of an individual (and thus their blue space exposure), and also their depression scores. In choosing these variables we draw upon the previous analysis of O'Regan et al. (2011) who identified several socio-economic and demographic factors which were independently associated with higher CES-D scores in TILDA respondents. The following characteristics are therefore included in the model: self-rated vision, whether or not they take anti-depressant medication, age (50-64, 65-74, $\geq$ 75), gender (male, female), marital status (married, never married, separated/divorced, widowed), employment status (employed, retired, other), income, smoking status (never, past, current), alcohol problem[1], social connectedness score[2] and population density of electoral division.[3] Table 1 shows the descriptive statistics for each of these variables.[4]

3.2. Explanatory Variable: Exposure to Coastal Blue Space

Although the type of blue space we examine, coastal blue space, is the most common type of blue space examined in the pre-existing health effects literature, we contribute to the literature by using a novel method to develop proxies for exposure to coastal blue space. Two measurements are used to calculate coastal blue space exposure in our sample of respondents. First we follow a conventional approach used in the literature (Wüstemann et al., 2017), and calculate the Euclidean distance between each of our TILDA respondents and the Irish coastline (see Appendix A). For all respondents within 10 km of the coast we categorise respondents into quintiles, and those living further away from the coast comprise a sixth category. Second,

[1]TILDA respondents were described as having an alcohol problem if their CAGE score (Ewing, 1984) was ≥ 2. All missing observations were recoded to a separate 'non-reported' drinking category.

[2]Derived TILDA variable with a total score of four. A single point is added if the TILDA respondent is: a member of church, married/living with partner as if married, a member of an organisation excluding the church and, has at least one close relative or friend.

[3]We calculated the population density of each electoral division by dividing the population of each electoral division by the number of hectares in each electoral division, using data from the CSO Census 2011 Small Area Population Statistics.

[4]The majority (n=329) of dropped observations are under 50 years of age, while a further small number were deleted due to missing values on the outcome variable (CES-D) or population density.

Table 1: Descriptive Statistics

Variable	Categories	Frequency	Percent
Distance to coast	>10km to coast	3,196	39.76
	Furthest Quintile	955	11.88
	4th Quintile	971	12.08
	3rd Quintile	972	12.09
	2nd Quintile	972	12.09
	Closest Quintile	973	12.1
Sea view	None	4,913	61.11
	Least Sea View Tertile	1,032	12.84
	2nd Tertile	1,059	13.17
	Greatest Sea View Tertile	1,035	12.87
Self-rated vision	Excellent	1,523	18.95
	Very good	3,010	37.44
	Good	2,721	33.85
	Fair	642	7.99
	Poor	127	1.58
	Registered Blind	16	0.2
Antidepressants	No	7,503	93.33
	Yes	536	6.67
Population Density	Least Dense Quintile	1,583	19.69
	2nd Quintile	1,617	20.11
	3rd Quintile	1,600	19.9
	4th Quintile	1,647	20.49
	Most Dense Quintile	1,592	19.8
Age Category	50 - 64	4,606	57.3
	65 - 74	2,120	26.37
	≥ 75	1,313	16.33
Gender	Male	3,688	45.88
	Female	4,351	54.12
Income Category	Lowest Quintile	637	7.92
	2nd Quintile	1,622	20.18
	3rd Quintile	2,671	33.23
	4th Quintile	1,544	19.21
	Highest Quintile	696	8.66
	Unknown	869	10.81
Marital Status	Married	5,563	69.2
	Never married	776	9.65
	Sep/divorced	537	6.68
	Widowed	1,163	14.47
Employment Status	Employed	2,901	36.09
	Retired	2,991	37.21
	Other	2,147	26.71
Social Connectedness Score	1	433	5.39
	2	1,819	22.63
	3	2,813	34.99
	4	1,742	21.67
	Missing	1,232	15.33
Alcohol Problem	No	5,851	73
	Yes	802	9.98
	Non-response	1,386	17
Smoking Status	Never	3,517	43.75
	Past	3,068	38.16
	Current	1,454	18.09
Total		8039	100

we use an innovative measure of blue space exposure in which estimates of blue space visibility (sea view) are constructed using viewshed analysis. Including measures of blue space visibility has been less commonly used in the literature, with Nutsford et al. (2016) being a notable exception. The measure used in this paper is the share of coastal blue space in total space visible from each respondents home, and it is estimated for all TILDA respondents living within 10km of the coastline. We categorise respondents with some coastal view into three equally-sized categories, and those without a view or at least 10km away are assigned to a fourth category (see Appendix A for a more formal description).

By including two different types of blue space exposure measurements (distance to coast and share of visible sea view) we increase the likelihood of capturing the total blue space exposure of each TILDA respondent. This is important if the types of blue space exposure (proximal versus visual) vary for each individual. For example it could be the case that those living close to the sea might have relatively low sea view visibility if they are at a lower elevation whereas those living further away at a higher elevation might experience a greater share of sea view. In addition to increasing the likelihood of capturing total blue space exposure, the inclusion of two types of blue space measurements allows us to test whether or not these different types of exposures have independent associations with depression outcomes in older people.

Most importantly, the inclusion of two types of blue space exposure measurements allows us to come closer to understanding the ways in which blue space might be operating to impact depression outcomes. With regard to the proximity measure, those who live closer to the coastline may find it easier to physically interact with the blue space than those who live further away. We therefore hypothesise that our distance variable is more likely to capture the potential underlying mechanisms of increased physical activity and social interaction as discussed in Section 2.1 through which proximal blue space exposure might be operating to reduce depression scores. With regard to the visual measure, we suggest that our sea view variable is more likely to pick up on the effects from underlying mechanisms related to the therapeutic salutogenic influence of the landscape. While we acknowledge that the underlying mechanisms behind these two channels (proximity versus visual) are not necessarily exclusive, allowing for both types of factors should provide some insight as to which transmission mechanisms might be the most important in mediating the relationship between blue spaces and depression outcomes in older people.

While those who live closest to the sea have the largest view share, these variables are not perfectly correlated. For example, of those living in the quintile closest to the coast, almost 40% fall into the highest view share category but more than 20% have no sea view. These differences provide enough statistical variation for us to distinguish between these two variables.

4. Methodology

As shown in Figure 1, the outcome variable (CES-D scores) has a highly skewed distribution of non-negative integer values in which a large number of zero observations are recorded. This suggests that a count model is the most appropriate model to use, as an OLS regression would not only assume a normally distributed error term but would also predict negative values for the dependent variable. The Poisson regression model assumes equidispersion (where the mean and variance are equal). However, Table 2 shows that this assumption does not hold for our data. As such, we employ a negative binomial model. This relaxes the equidispersion assumption and instead allows overdispersion (where the variance and mean differ) to occur.

Table 2: Summary Statistics of CES-D scores

	Observations	Mean	Variance	Std. Dev	Min	Max
CES-D score	8039	7.21	51.95	7.21	0	53

We estimate three versions of the model, each varying according to the type of blue space exposure included in the model. Model (1) first includes distance to coast as the blue space exposure variable hypothesised to have an effect on CES-D scores. The distance to coast variable is split into a reference category of those who live more than 10km from the coast, with the remaining TILDA respondents who live within 10km of the coastline, split into five quintiles. While Model (1) might be able to capture the overall association between blue space exposure from living near the coast and CES-D scores, Model (1) cannot cast light on what might be the potential mechanism (proximity or visual aspect) underpinning this relationship. This is due to the fact that distance to coastline could simply be acting as a proxy for increased sea view.

The second version of the model, Model (2), includes only sea view as the explanatory blue space exposure variable. Here sea view captures the share of area around the TILDA respondent's residence which is visible sea. The reference category for this variable is those who either have no sea view or live more than 10km from the coastline, with the remaining TILDA respondents split into tertiles of increasing sea view. However, while Model (2) suggests that sea view visibility could be an important mediating factor in the relationship between blue space exposure and CES-D scores, it could inadvertently be suffering from the same omitted variable bias as Model (1). In the case of Model (2), sea view might be acting as a proxy for distance to coastline and as such, Model (2) fails to pinpoint the exact channel through which blue space exposure might be operating to reduce depression scores. The third and final version of our model, Model (3), includes both types of blue space exposure variables (distance and sea view). This overcomes the previous problems presented by Model (1) and Model (2) and allows us to unpack more fully the different types of transmission mechanisms which might be at play. All analyses were performed using Stata 9.

5. Results

Table 3 presents the results from estimation of the negative binomial model. Here Model (1) shows that there is a beneficial association between living close to the sea and depression risk. Those living nearest to the coastline (1st quintile of distance) are shown to have lower CES-D scores relative to those who live more than 10km from the coastline, with the relationship shown to be statistically significant at the 5% level. Respondents who live in the 2nd quintile of distance also have marginally significantly lower CES-D scores, at the 10% level. In sum, Model (1) indicates that those living near the coastline have lower depression scores as measured by CES-D.

Model (2) in Table 3 also shows a negative relationship between sea view and CES-D scores. Those who live in the 3rd tertile of sea view, ie. with the highest share of sea view, are estimated to have lower CES-D scores than TILDA respondents who have no sea view. This coefficient is significant at the 1% level. Like proximity, coastal views show a beneficial association with depression risk.

Finally we include both coastal proximity and sea view in the model together. The results in Table 3 for Model (3) show that while the third tertile of sea view continues to be statistically significant when both types of blue space exposure measures are included, distance to coast is no longer significant. This suggests that the association between sea visibility and depression risk is independent to how close one lives to the sea.

Note also that the categorical representation we use for sea view allows for the possibility of a non-linear relationship. This is indeed what we observe, with only the highest sea view category showing a significant association with depression risk. This result may indicate that there is a threshold relationship rather than a constant marginal trade-off. We do not have the data to explore the mechanism behind this association further, but a threshold could arise for example if the extent of views needs to be sufficiently large to confer positive mental health benefits on those living in these areas.

6. Conclusions

Our results lend support to the hypothesis that there are salutogenic health effects from the visual aspect of blue space and that it is mainly through this channel that exposure to coastal blue space operates to lower depression outcomes. The magnitude of the association between visual blue space exposure and

Table 3: Negative binomial models esimating the relationship between exposure to blue space and CES-D scores.

Dependent Variable: CES-D Score		Model 1		Model 2		Model 3	
		dy/dx	St. Error	dy/dx	St. Error	dy/dx	St. Error
Distance to coast	>10km to coast [ref]						
	Furthest Quintile	-0.46	(0.25)*			-0.39	(0.26)
	4th Quintile	-0.25	(0.28)			-0.07	(0.30)
	3rd Quintile	-0.06	(0.27)			0.12	(0.29)
	2nd Quintile	-0.47	(0.25)*			-0.21	(0.29)
	Closest Quintile	-0.56	(0.26)**			-0.24	(0.31)
Sea view	None [ref]						
	Least Sea View Tertile			-0.39	(0.24)	-0.29	(0.26)
	2nd Tertile			-0.22	(0.24)	-0.17	(0.27)
	Greatest Sea View Tertile			-0.76	(0.23)***	-0.69	(0.27)**
Self-rated vision	Excellent [ref]						
	Very good	0.79	(0.19)***	0.79	(0.19)***	0.79	(0.19)***
	Good	1.64	(0.20)***	1.63	(0.20)***	1.63	(0.20)***
	Fair	3.57	(0.35)***	3.54	(0.35)***	3.55	(0.35)***
	Poor	4.60	(0.71)***	4.58	(0.70)***	4.59	(0.70)***
	Registered Blind	3.27	(2.18)	3.02	(2.08)	3.14	(2.1628)
Antidepressants	No [ref]						
	Yes	4.27	(0.41)***	4.31	(0.41)***	4.31	(0.41)***
Pop. Density	Least Dense Quintile [ref]						
	2nd Quintile	-0.25	(0.22)	-0.28	(0.22)	-0.28	(0.22)
	3rd Quintile	-0.13	(0.24)	-0.16	(0.23)	-0.15	(0.24)
	4th Quintile	0.52	(0.25)**	0.51	(0.25)**	0.54	(0.25)**
	Most Dense Quintile	1.09	(0.28)***	1.19	(0.28)***	1.20	(0.29)***
Age Category	50 - 64						
	65 - 74	-0.92	(0.21)***	-0.91	(0.21)***	-0.91	(0.21)***
	≥75	-1.11	(0.24)***	-1.08	(0.24)***	-1.09	(0.24)***
Gender	Male [ref]						
	Female	1.16	(0.16)***	1.15	(0.16)***	1.16	(0.16)***
Income Category	Lowest Quintile [ref]						
	2nd Quintile	-0.73	(0.33)**	-0.72	(0.33)**	-0.74	(0.33)**
	3rd Quintile	-1.14	(0.32)***	-1.11	(0.32)***	-1.14	(0.32)***
	4th Quintile	-1.56	(0.35)***	-1.54	(0.35)***	-1.56	(0.35)***
	Highest Quintile	-2.41	(0.37)***	-2.34	(0.38)***	-2.36	(0.38)***
	Unknown	-0.93	(0.37)**	-0.90	(0.37)**	-0.92	(0.37)**
Marital Status	Married [ref]						
	Never married	0.57	(0.28)**	0.56	(0.28)**	0.56	(0.28)**
	Sep/divorced	1.18	(0.34)***	1.20	(0.34)***	1.19	(0.34)***
	Widowed	0.85	(0.26)***	0.85	(0.26)***	0.85	(0.26)***
Employment Status	Employed [ref]						
	Retired	0.81	(0.21)***	0.80	(0.21)***	0.81	(0.21)***
	Other	1.89	(0.2119)***	1.88	(0.21)***	1.88	(0.21)***
Social Score	3 [ref]						
	1	1.08	(0.37)***	1.03	(0.37)***	1.04	(0.37)***
	2	0.88	(0.21)***	0.88	(0.21)***	0.87	(0.21)***
	4	-0.21	(0.21)	-0.19	(0.21)	-0.19	(0.21)
	Missing	-0.017	(0.48)	-0.01	(0.49)	-0.03	(0.49)
Alcohol Problem	No [ref]						
	Yes	1.93	(0.31)***	1.93	(0.31)***	1.95	(0.31)***
	Non-response	0.96	(0.50)*	0.94	(0.50)*	0.96	(0.51)*
Smoking Status	Never [ref]						
	Past	0.20	(0.16)	0.21	(0.16)	0.21	(0.16)
	Current	1.08	(0.23)***	1.11	(0.23)***	1.10	(0.23)***

***p <0.01, **p <0.05, *p <0.10

reduced depression risk is not inconsiderable, with a coefficient comparable to being in the second quintile of income rather than the first quintile of income, or 9.58% of a standard deviation in the CES-D scores. It is also worth noting that the models control for use of anti-depressant medication by respondents, so the associations found between blue space and lower depression risk are additional to the average effects of medication.

6.1. Limitations

The main limitation of this paper relates to the fact that our measures of blue space exposure can only approximate both the type and level of blue space exposure received by each TILDA respondent. For example, the distance to coastline metric makes no distinction among the different types of use values that different parts of the coastline might encapsulate (e.g. beaches, cliffs). As a consequence, this variable could under-estimate the association between distance to some types of coastline and depression outcomes, since the mediating factor of physical activity might be more or less pertinent depending on the type of coastline available. Similarly, our metric of sea view does not distinguish between different types of sea view but instead treats all views as the same. Furthermore, we have no data on actual blue space exposure which could vary according to the personal preference of each TILDA respondent. For example, it could be the case due to personal preference, that those furthest from the coastline might be more likely to engage in blue space physical activity than those living relatively closer. Similarly, those with more extensive sea views might still be less likely to look at their sea view and thus have less blue space exposure than those with a less extensive sea view. In addition, we use Euclidean distances rather than road distances or travel time.

An additional concern with our proxy of sea view relates to the fact that we did not compute the individual view-sheds for each TILDA respondent's residence but rather proxied it with 10m grid squares (see Appendix A), and second, that our data implicitly assumed that the landscape was smooth and thus did not account for buildings and individual trees. However, further additional models which interacted urban areas (with increased likelihood of buildings blocking views) with our sea-view metric did not produce significant results, leading us to believe that the measurement error from the smoothing of the landscape is relatively minor in magnitude.[5] A final limitation of the paper, in common with much of the environmental health literature, relates to the cross-sectional nature of our dataset, which prevents a claim of causality from being made. However, given that the unit of analysis is at the level of the individual, and as such, confounding variables for each individual are controlled for, this approach represents an improvement on prior approaches which may have used a more aggregated area-based unit of analysis.

6.2. Discussion

Older adults in Ireland whose dwellings are exposed to coastal blue space have lower depression risk as proxied by CES-D scores. From our empirical results it seems that the visual aspect of blue space exposure could have a stronger association than physical proximity does with depression among this group. These findings underline the public health value of policies to protect and enhance coastal blue spaces, and they suggest that urban planners should take such benefits into account. There could also be equity implications, to the extent that visual blue space exposure is not evenly distributed across different socioeconomic groups.

The main contribution of our paper is in testing the relationship between coastal blue space and depression risk in older adults while controlling for a wide range of individual-level confounders. Further analysis of other population groups is required in order to test whether these relationships may be moderated by life stage (for example, the salutogenic effects of blue space may be different for younger adults who spend greater proportions of their time away from home). Another contribution is in defining and illustrating a metric for sea views that can be generated at dwelling level without undue computational requirements (see Appendix A for further details). We think this method could readily be applied in other jurisdictions. We also contribute to the literature by more fully exploring the different types of channels through which blue space exposure can operate to provide mental health benefits. Our results suggest that the visual aspect

[5] Results available on request from the authors

of coastal blue space may have a stronger relationship with depression risk than physical proximity alone. Future research into the mechanisms behind this relationship would be useful (for example, by ascertaining the potential associations with mediators such as social engagement, physical activity and stress).

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Appendix A. Coastal Proximity and Views

To calculate proxy variables for coastal proximity and views we use data from Ordnance Survey Ireland (OSi). The method used here draws heavily on prior work reported in Gillespie et al. (2018).

Appendix A.1. Distance to coast

This metric is based on the Euclidean distance between the survey respondents home and the nearest high-tide watermark (outside of a transitional water body) for all respondents within 10km of the coast. In the modelling we divide households within this zone into quintiles based on their distance score, and this categorical representation of the data is used to protect confidentiality. An additional categorical variable denoting households more than 10km from the coast is also included.

Appendix A.2. Coastal Seaviews

We apply viewshed analysis to estimate the share of view from each respondents residence that is coastal blue space. Again this is employed in categorical form to protect confidentiality, with variables representing three tertiles of sea view percentage plus another category for dwellings within 10km of the coast but no view of the sea. The viewshed analysis involves carrying out a 3D simulation of the view from each point on land by combining its (x,y) spatial coordinate with data on local topology. Ireland's topology is represented by a 10m resolution DEM (Digital Elevation Model), generated by converting the OSi's contour line data into raster[6] format. This implicitly assumes that the landscape is smooth, omitting buildings and individual trees. It thus yields a proxy for the local sea view rather than a direct measurement. The proxy takes the following form:

$$seaview = \frac{simulated\ visibile\ sea\ area}{total\ area\ within\ local\ horizon} \tag{A.1}$$

The denominator of Equation A.1 is explained in Equations (A.2) to (A.4). Equation A.2 assumes a viewpoint 1.8m above the local terrain elevation, in line with Gillespie et al. (2018). Regarding Equation A.3, detailed distance to horizon formulas can be found in Bohren and Fraser (1986). As such, the figure 2637100 in Equation A.3 simply represents the radius of the earth multiplied by two. Atmospheric refraction affects the distance to visible horizon as discussed in Proctor and Ranyard (1895). We use a standard multiplicative factor of 1.08 in Equation A.3 in order to correct for this.

$$eye\ level = elevation + 1.8 \tag{A.2}$$

$$horizon\ distance = (((eyelevel^2) + (26371000 * eyelevel))^{0.5}) * 1.08 \tag{A.3}$$

$$total\ area\ within\ local\ horizon = \pi(horizon\ distance)^2 \tag{A.4}$$

The numerator of Equation A.1 requires more complex GIS modelling. To keep the computational burden manageable, we simulate the visible sea area from each point on land by dividing the sea into grids of even density and then measuring the viewshed on to the land from each of these grid squares. Employing this viewshed methodology yields a 10 meter resolution raster which represents, for every 10 meter square pixel of land within 10 km of the coast, the number of sea grid cells which can be seen from that point. This therefore creates a metric indicating the area of sea which can be seen from each 10 meter cell on land.

This is illustrated in Fig A.1 below. Buffers are created from the coast out to sea with the spatial resolution declining with distance: 0-500m from the coastline at 250m resolution (area A); 500m-10km at

[6] A raster can be described as matrix of cells or pixels with each cell containing information on local conditions such as the area of sea visible from that position.

500m resolution (area B) and 10km-30km at 3km resolution (area C). The total visible areas from each grid square on land is then aggregated up from the set of sea grid squares from which it is visible. To allow for the possibility that are locations with views extending beyond 30km from the coast (places at higher elevation and near the coast), we include an additional extrapolation factor. Using a Digital Elevation Model with a resolution of 10m, we map the area of sea more than 30km from the coast that might be visible from each residence given its local horizon. We then assume that the fraction of this sea area that is actually visible is equal to the share of the 10-30km zone also within the local horizon that was predicted to be visible in our earlier analysis. In essence, we gross up the area of visible sea in the 10-30km zone to the extent that the local horizon extends beyond 30km (area D). However, although there were 120 addresses which could have potentially had a view $\geq$ 30km from the coastline, none of these addresses in our dataset could see beyond 10km from the coast.

Because this method provides an estimate of the visible sea area for every grid square on land within 10km of the Irish coastline, it can be used to obtain a proxy of coastal sea views for datasets of any size with no additional computational burden.

Figure A.1: Calculation of share of visible sea area in local horizon circle (not to scale)