Environmental influences on mental health: eight-year longitudinal data show a bi-directional association between residential mobility and mental health outcomes.

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Environmental influences on mental health: eight-year longitudinal data show a bi-directional association between residential mobility and mental health outcomes

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ABSTRACT

Evidence on the environmental determinants of mental health is often cross-sectional. This pre-registered longitudinal study examines the environmental determinants of mental health using eight years of data from the New Zealand Attitudes and Values Study. Among 44,051 adults, findings reveal age, body mass index, and exercise as key individual-level factors impacting mental health, while residential mobility and area-level deprivation emerged as key environmental-level determinants. Increased probability of moving correlates with higher prevalence of depression and anxiety, with subsequent moves worsening area-level deprivation for those with persistent mental health issues. Our findings underscore the significance of environmental factors for mental health, offering insights for population-level interventions.

1. Introduction

Globally, the burden of mental health conditions remains a significant public health challenge (World Health Organisation, 2019, 2020), with a 13% rise in mental health conditions and substance use disorders in the last decade to 2017 worldwide (World Health Organisation, 2024). For instance, suicide is now the second leading cause of death among 15–29 year-olds globally (World Health Organisation, 2024). In Aotearoa New Zealand (NZ), 24% of young people aged 15–24 years experienced high/very high levels of psychological distress in 2021/22, and New Zealand Health Survey data showed anxiety prevalence was 14% and depression was 19% in adults during the same period (Ministry of Health, 2022). This is coupled with unavailable professional mental health support, with 9% of adults reporting an unmet need for professional help for their emotions, stress, mental health or substance use in 2021/22. The causes of mental health conditions are multifaceted in aetiology, but evidence indicates that social and environmental determinants, such as access or exposure to different built and natural environments and residential mobility, are important influencing factors (Marek et al., 2021; Hobbs et al., 2021a, 2022; van der Wal et al., 2021).

Indeed, numerous studies have sought to link built and natural environment factors with mental health. The high prevalence of mental health conditions may be related to wider epidemiological transitions (McKeown, 2009) and in particular, urbanisation (van der Wal et al., 2021). Just under 80% of the global population in more developed regions now reside in urban areas, with the coupled impact of reduced access to "natural" spaces (Hancock et al., 2017), which are known to aid stress reduction (Hedblom et al., 2019), and increased access to health-constraining features such as liquor stores, gambling venues, and fast food outlets (Hobbs et al., 2021a, 2022). Despite this, evidence relating the built and natural environment to mental health is equivocal and is dominated by cross-sectional evidence (Hobbs and Atlas, 2019; Desjardins et al., 2023). A recent systematic review found inadequate evidence of an association between greenspace and a broad suite of mental health outcomes (de Keijzer et al., 2020), and a more recent meta-analysis showed little evidence of longitudinal associations

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between neighbourhood social, natural and built environments and adult mental health (Sui et al., 2022). However, longitudinal evidence from the British Household Panel Survey has demonstrated that moving to greener urban areas was associated with sustained mental health improvements (Alcock et al., 2014). Other longitudinal evidence has also highlighted that residential greenspace may be beneficial for the intellectual and the behavioural development in childhood, especially for children living in urban areas (Bijnens et al., 2020). Moreover, high levels of residential mobility may be an adverse factor influencing mental health alongside other factors, such as residing in or moving between highly deprived neighbourhoods (Morris et al., 2017; Tseliou et al., 2016).

Importantly, residential mobility is not just a geographical transition but may often be a response to other underlying social, economic, and psychosocial stressors (Coulter et al., 2016; Keene and Blankenship, 2023). These may be particularly important for individuals with pre-existing mental health conditions as it is known that safe, secure, appropriate and affordable housing is critical for recovery from mental ill-health and for being able to access appropriate support services (Brackertz et al., 2020). Moreover, factors such as financial hardship, eviction and forced relocation may exacerbate mental health challenges and contribute to a downward trajectory, resulting in relocation to more deprived areas (Brackertz et al., 2020). Previous research has highlighted the potential bi-directional nature of this association, where poor mental health increases the likelihood of residential mobility, particularly to disadvantaged areas, which in turn worsens mental health outcomes (Brackertz et al., 2020). For instance, people who experienced severe psychological distress had an 89% increased likelihood of financial hardship in the following year and people with a diagnosed mental health condition had a 39% increased likelihood of experiencing a forced move within one year (Brackertz et al., 2020). While such evidence is emerging, a better understanding of these mechanisms alongside consideration of wider built and natural environmental factors is required, and will be crucial for designing policies that address both housing security and mental health as interconnected public health concerns.

The equivocal nature of current evidence relating the broader built and natural environment to mental health outcomes may be due to several methodological limitations. First, as noted in a recent meta-analysis, the vast majority of research rely on cross-sectional designs and thus fails to capture residential mobility or movements between different areas, and to assess exposure or outcomes over time (Sui et al., 2022). Second, studies often only employ one measure of environmental influence such as greenspace. However, it is known that environmental influences can co-occur and thus accounting for the combined influence of distinct environmental features may be important (Hobbs et al., 2021a). Third, research often does not use multiple outcomes of mental health, but different mechanisms and pathways link environmental influences to disparate mental health outcomes (Hobbs et al., 2023a). Fourth, any association could be bidirectional; however, longitudinal study designs are required to test directionality or at least association over time (Desjardins et al., 2023). While greater area-level deprivation has been more consistently related to poorer mental health, evidence of a longitudinal association between exposure to environmental features such as green and blue spaces and/or residential mobility and mental health is less consistent and requires further research (Tseliou et al., 2016). Beginning to address these methodological limitations will lead to an enhanced understanding of the multifaceted determinants of mental health over time.

A longitudinal approach holds the potential to enhance our understanding of disease aetiology around exposure to the built and natural environment and mental health outcomes (Desjardins et al., 2023; Hobbs et al., 2021b, 2021c). Furthermore, research seldom explores whether the environment is linked to poor mental health, if deteriorating mental health precedes living in an unfavourable environment, or if the relationship is bidirectional (Huang et al., 2020; Pelgrims et al., 2021). Such potential selective migration effects (Engemann et al., 2019) might arise because healthier individuals move to areas that provide a health-promoting environment (Alcock et al., 2014; Hobbs et al., 2023b), or because people with better mental health tend to have higher incomes (De Neve and Oswald, 2012), enabling them to pay higher housing costs in what may be a health-promoting environment (Alcock et al., 2014). Our study has three aims. First, we aim to examine the association between sociodemographic (e.g., age) as well as broader social (e.g., area-level deprivation) and built/natural environmental factors (e.g., health-promoting features) and the mental health outcomes of depression, anxiety and psychological distress. Second, we aim to examine the association between residential mobility and changing area-level deprivation and the changes in mental health status. Finally, we use Monte-Carlo simulations to project the modelled effect of environmental changes in area-level deprivation on population-level mental health outcomes. This research aligns with the United Nations Sustainable Development Goals (SDG), particularly with SDG1 (no poverty) and SDG3 (good health and wellbeing), as well as contributing to SDG11 (sustainable cities and communities) by highlighting the need for supportive urban environments (United Nations, 2024).

2. Method

2.1. Study design

Our pre-registered study (see https://osf.io/m7qr5/?view_only=0dc4e788d07046e49afbc709913d376f) uses a longitudinal design leveraging data from the New Zealand Attitudes and Values Study.

2.2. The New Zealand attitudes and Values Study (NZAVS)

We used longitudinal data from eight waves of the NZAVS, from Year 6 (2014) to Year 13 (2021). The NZAVS is a nationwide panel study that began in 2009 based on a random sample of the Electoral Roll. The New Zealand Electoral Roll is publicly available for scientific research and includes all citizens and permanent residents over 18 years of age who are eligible to vote, regardless of whether they choose to vote, barring people who had their contact details removed due to specific case-by-case concerns about privacy. In the present longitudinal study, we used data comprising responses from n = 44,051 adults or n = 129,148 person-years of data. More details are provided in online supplementary materials or the NZAVS page (https://osf.io/75snb/).

2.3. Outcome measures

We included three mental health outcomes – (i) depression, (ii) anxiety, and (iii) psychological distress – at each time point. Diagnoses of depression or anxiety disorder were assessed by asking participants whether they had been diagnosed with a series of different health conditions, by a doctor, in the last five years (Lee et al., 2017). Psychological distress was measured using the Kessler-6 (Kessler et al., 2010). Participants rated on a scale from 0 to 4 how often they experienced six emotional states such as feeling worthless, or restless and fidgety over the past 30 days (scores were averaged, and thus ranged from 0 [low distress] to 4 [high distress]).

2.4. Other data

Relevant individual-level data extracted from the NZAVS database included age (What is your date of birth? [Years]), gender (What is your gender? [Male/Female]), ethnicity (Which ethnic group(s) do you belong to? [Māori, Pacific, Asian and European/other]), education-level (What is your highest level of qualification? [Ordinal-Rank 0–10 based on NZREG codes from 0 = no qualification through to 10 = Doctorate degree]), hours of exercise (Please estimate how many hours you spent doing each of the following things last week: exercising/physical

activity [number of hours]), relationship status (What is your relationship status? [Partner: 0 no, 1 yes]), being a parent (How many children have you given birth to, fathered, or adopted? [parent: 0 no, 1 yes]), socioeconomic status (2013 New Zealand Socioeconomic Index, NZSEI, reflecting the average education and income level associated with an occupation, with education given higher importance than income in the scoring and a higher score indicating higher socioeconomic position [range 10–90]), employment (What is your current employment situation [0 not employed, 1 employed]), and Body Mass Index (BMI, weight in kilograms divided by the square of height in metres).

Relevant area-level data were also extracted from the NZAVS and other sources on four variables: i) health-constraining and health-promoting environments; ii) probability of moving address; iii) rurality; and iv) area-level deprivation (a more detailed description is provided in online supplementary materials). For this study, access to health-promoting and health-constraining environments was measured using the Healthy Location Index (see Fig. 1 for an example) (Marek et al., 2021). Exposure to health-promoting and health-constraining environments was defined based on the current residence and meshblock of each participant at the time of data collection wave.

2.5. Statistical analyses

Descriptive statistics are presented as n (%) or mean (standard deviation). To examine both static and dynamic associations between mental health, environmental covariates, and sociodemographic factors, we used random forests implemented via R package ranger (Wright and Ziegler, 2017). Random forests are gaining visibility in many fields including epidemiology for analysing complex datasets (Hamilton et al., 2021; Bellinger et al., 2017). First, we fitted a balanced random forest with the mental health status as the outcome variable and socioeconomic, demographic and environmental variables – both current and for the previous period (year), where applicable (i.e., with a one-year lag) – as inputs. We then fitted the model without the lag, and the model without any environmental covariates at all, and compared the respective model accuracies via the out-of-bag error. We fitted individual models for depression, anxiety, psychological distress and binarised psychological distress (categories with Kessler-6 scores from 0 to 3.5 vs. greater than 3.5 and up to 4).

We approached the question about associations between change in environment and change in mental health from two directions. First, we defined a new variable for the mental health status in two consecutive years as a response. For example, a person diagnosed with depression for both time points *t-1* and *t*, would have a combination '1-1' recorded for depression. We then fitted a balanced random forest to see whether the probability of having moved was associated with mental health status in the corresponding consecutive years, adjusting for sociodemographic variables. Second, for participants who have moved, we also fitted a random forest to see how the change in area-level deprivation decile linked to the move (if any) was associated with the mental health status in the corresponding consecutive years. The effects of individual variables can be assessed via an importance plot, which reflects the contribution of each variable to model accuracy. Another way to judge the effect size is to use partial plots where, for the observed sample, the value of the independent variable in question is varied across the range of interest while the other independent variables are kept constant, and the predicted average for the response variable is recorded. Finally, we used Monte-Carlo simulation to evaluate the effect of environmental improvements on mental health outcomes. For this purpose, we fitted a balanced random forest with the mental health status as the outcome variable and the sociodemographic variables as inputs. Deprivation decile was the only independent environmental variable fitted in the simulation model. We considered three different scenarios where 1%, 5% or 10% of all person-years in the recorded sample would have a deprivation improved by one decile. We simulated 100 realisations for each scenario and used the previously fitted random forest model to

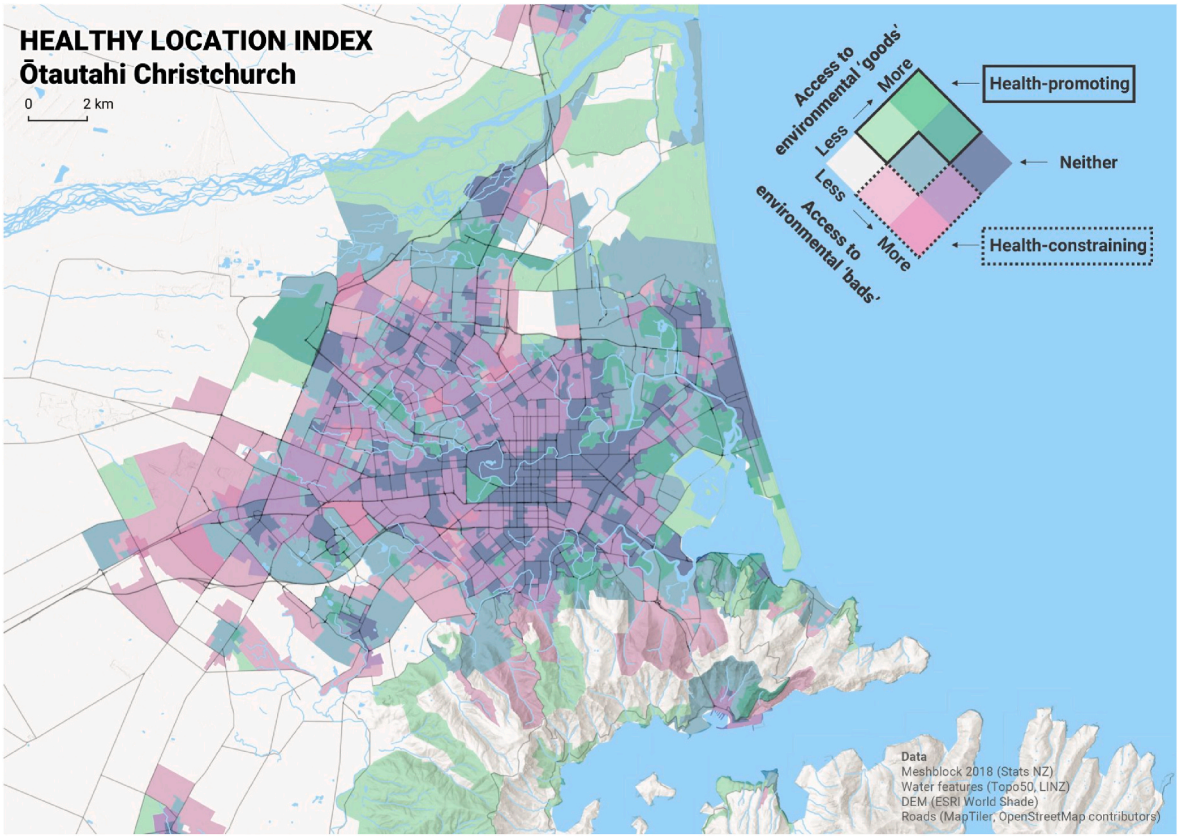

Fig. 1. Example of the nationwide Healthy Location Index (HLI) for Christchurch City, South Island, New Zealand.

predict the proportion of the sample with either depression or anxiety.

3. Results

3.1. Associations between sociodemographic and environmental factors with mental health outcomes

Table S1 (online supplementary materials) shows the study sample characteristics at each wave of data collection and across all waves included in this study. We used random forest to examine the relative importance of a range of sociodemographic and environmental factors for mental health at the concurrent wave of data collection as well as with a one-year lag effect. The longitudinal sample included 129,148 person-years across the study period and a total of 27% of the data within the NZAVS was pairwise complete and was included in the random forest models with the lag effect (see Table S2 online supplementary materials). Fig. 2 shows the relative importance of the sociodemographic and environmental determinants of mental health. Our study showed that the most important factors for mental health were age, body mass index, socioeconomic status and exercise. Other influencing factors were health-promoting and health-constraining environmental features, area-level deprivation, level of qualification, and residential mobility.

3.2. Residential mobility, anxiety, depression and psychological distress

In line with our hypothesis, an important component of environmental influences on mental health was residential location. Residential location data was available for 85.5% of the participants for all eight time points—Year 6 (2014) to Year 13 (2021)—and 96.9% of the participants for at least 2 time points. Among those for whom at least 2 time points were available, 54.7% have not moved at all, and 2.7% moved at least once every two years. A total of 42.0% of the participants had data available for Time 13 and were included in the random forest model exploring the possible effect of residential mobility on mental health outcomes. Accordingly, the probability of residential mobility was found to have a small effect on the estimated prevalence of depression, anxiety and psychological distress. The partial plot in Fig. 3 shows the prevalence of depression and anxiety, as well as the proportion of people reporting various levels of psychological distress on the Kessler-6 scale, for the sample estimated for the balanced random forest—assuming onlythe probability of moving annually changes, while all other factors remain constant. As the probability of moving increases from 0 to 0.5 (i.e., moving on average once every two years), the estimated prevalence of depression almost doubles from 29.41% to 56.04%. For anxiety, the numbers are similar with the estimated prevalence increasing from 29.35% to 50.98%. The out-of-bag prediction accuracy was 67.2%, 69.8%, and 39.49% (62.06%) for depression, anxiety and psychological

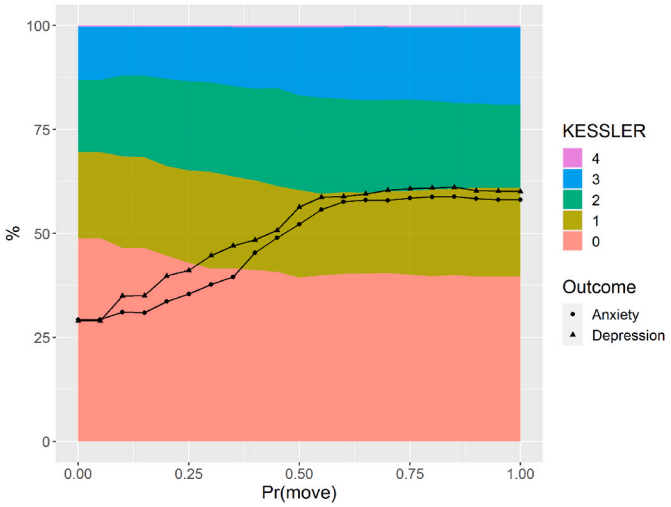

Fig. 3. Partial plot: the estimated effect of the probability of annual move on the prevalence of mental health conditions, other things being equal, based on a balanced random forest. (Note: Kessler refers to the measure used to assess psychological distress.)

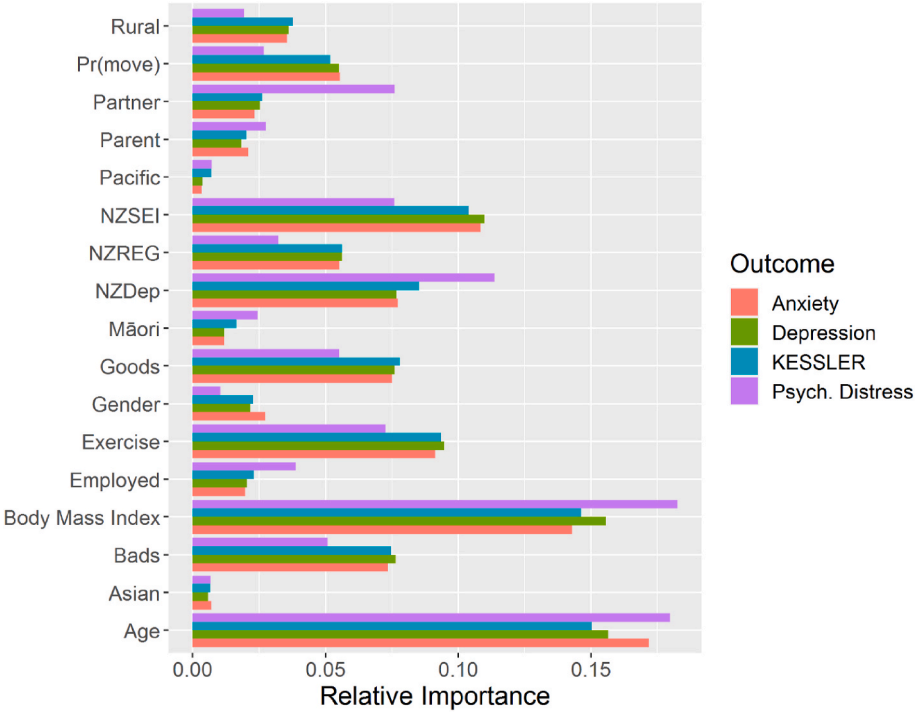

Fig. 2. The relative importance of sociodemographic and environmental factors in the balanced random forest model by mental health outcomes of depression, anxiety and psychological distress.

distress (binarised), respectively.

3.3. Mental health, residential mobility and area-level deprivation

As the patterns of residential mobility and environmental change were very similar for depression and anxiety, we decided to focus on the joint outcome "depression or anxiety" across the study period. Of all the pairs of time points for which data were available (n = 129,139 person-years, N = 44,044 unique individuals), 103,071 (79.0%) stayed free of depression or anxiety, 4628 (3.6%) became depressed or anxious, 4635 (3.6%) became either depressed and/or anxious, and 17,805 (13.8%) had either depression or anxiety in both the consecutive years. For those who had either depression or anxiety in both the consecutive years, a total of 13,338 (11.2%) moves were recorded, of which 12,307 (9.5% of the total) had a change in area-level deprivation decile. The corresponding average change in area-level deprivation is shown in Table 1.

We found no difference between the models with and without the mental health dynamics as an explanatory variable and moving as the outcome (out-of-bag-errors of 0.2521 and 0.2528, respectively). Likewise, the mental health dynamics did not appear to explain the probability of moving (out-of-bag errors 0.4584 and 0.4655, respectively). We also found no difference between the models with and without mental health dynamics as explanatory variables and with area-level deprivation decile change as the outcome variable (out-of-bag errors of 11.34 and 11.33, respectively). However, both the sample statistics and the partial plot (Fig. 4) showed that the average change in deciles of area-level deprivation for those who had stayed depressed or anxious for two consecutive years (1-1) was higher (i.e., moving towards more deprived areas) than for the other combinations (i.e., becoming not depressed/anxious).

Based on the balanced, random forest model, we found that, after adjustment, people with either depression, anxiety or both were more likely to move than people (at time + 1) without these mental health conditions. The decile change for those who had persistent mental health conditions was estimated at 0.156, while for those who had neither depression nor anxiety in one of the two consecutive time periods, the change in decile was only 0.02. In real terms, a 0.156 change in decile per year for those with persistent mental health conditions equates to a full decile change in area-level deprivation after approximately six years; for example, someone who started in decile six would move to decile seven. In summary, those individuals with persistent mental health (depression/anxiety) conditions progressively moved on average into higher deprivation.

Finally, in order to see how the changes in the environment might affect mental health at the population level, we used Monte-Carlo simulations as follows. We considered situations in which 1%, 5% and 10% of the person-years selected randomly from the original sample would shift to a better decile every year for 50 years in the future. We then used a balanced random forest model to predict the resulting percentage of the sample with either depression or anxiety. The initial distribution of deciles and the partial plot for predicted decile-specific probabilities of depression and/or anxiety, adjusted for sociodemographic covariates, are shown in Figs. 5 and 6. Essentially, in Fig. 6, our data shows that in the first 10 years, depression or anxiety is predicted to get 0.1% [0.0–0.2], 0.5% [0.4–0.6] and 1.0% [0.9–1.2] lower for 1%, 5%, and 10% change in deciles, respectively. In 50 years, depression or anxiety is predicted to get 0.5% [0.4–0.6], 2.2% [2.1–2.4] and 3.4% [3.3–3.5] lower for 1%, 5% and 10% change in deciles, respectively.

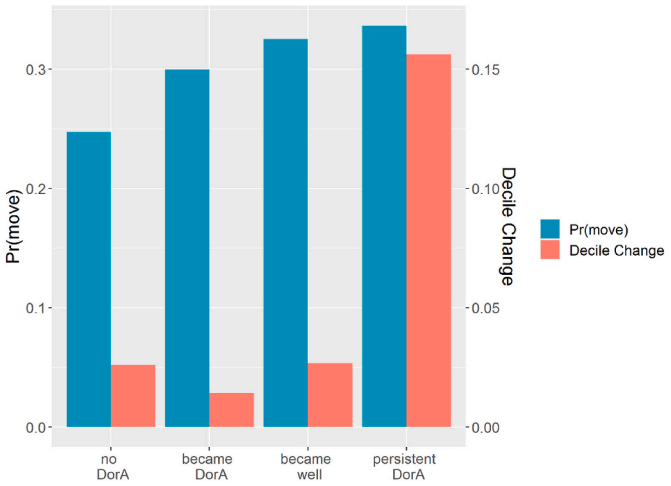

Fig. 4. Partial plot: the estimated effect of the mental health dynamics (Depression or Anxiety DorA) on the probability of moving (left-hand y-axis) and the change in deprivation decile (right-hand y-axis) for those who have moved, other things being equal, based on the balanced random forest. [The combinations 0-0 (not depressed or anxious at both time points), 0–1 (becoming depressed or anxious), 1-0 (becoming depression or anxiety free), and 1-1 (staying depressed or anxious) refer to the mental health state (whether or not the person had either anxiety, depression or both) at two consecutive time points.]

4. Discussion

This eight-year pre-registered longitudinal study in Aotearoa New Zealand explored connections between sociodemographic and environmental factors with mental health outcomes (depression, anxiety and psychological distress). The study found two main insights. First, a higher likelihood of moving was associated with an increased probability of experiencing a mental health condition. Second, individuals consistently experiencing mental health conditions were more prone to moving, often relocating to areas with higher deprivation levels. Findings reveal age, body mass index, and exercise as key individual-level factors impacting mental health, while residential mobility and area-level deprivation emerged as key environmental-level determinants.

Table 1
Examining the dynamics between change in mental health status (anxiety or depression) and change in decile of area-level deprivation across concurrent observations (n = 129,139 person-years).

Depression or Anxiety	Observed				Predicted by the Model	
	Total, n (%)	Have moved, n (%)	Have changed Decile, n (%)	Difference in Deciles if moved, mean (sd)	Have moved	Mean difference in deciles if moved
0–0	102,071 (79%)	10,489 (10.3%)	8900 (8.7%)	0.0187 (3.27)	24.7%	0.0261
0–1	4628 (3.6%)	644 (13.9%)	549 (11.9%)	0.0016 (3.39)	30.0%	0.0143
1–0	4635 (3.6%)	636 (13.7%)	538 (11.6%)	−0.0330 (3.23)	32.6%	0.0269
1–1	17,805 (13.8%)	2679 (15.0%)	2320 (13.0%)	0.2087 (3.36)	33.7%	0.1563
All	129,139	14,448 (11.2%)	12,307 (9.5%)	0.0509 (3.29)		

Observed numbers and proportions of people who moved and changed deciles as well as the difference in deciles for those who moved are based on the longitudinal sample. The predicted numbers are based on the balanced random forest.

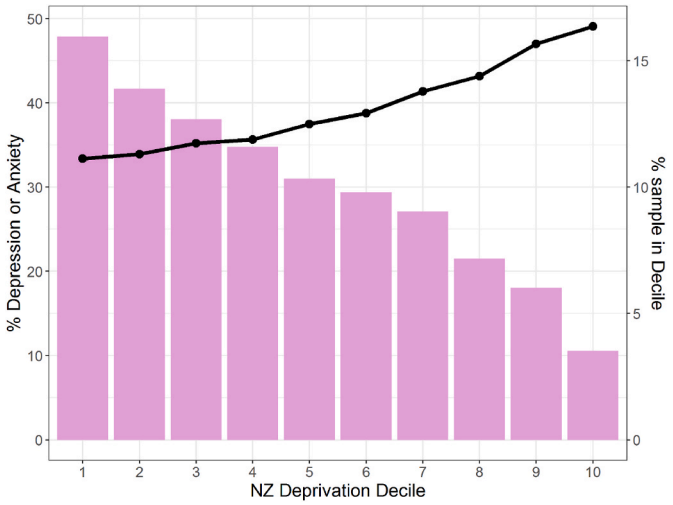

Fig. 5. Observed distribution by NZ Deprivation Decile (purple bars) in % of person-years and the predicted decile-specific % of depression or anxiety predicted by a balanced random forest model adjusted for sociodemographic covariates (black line).

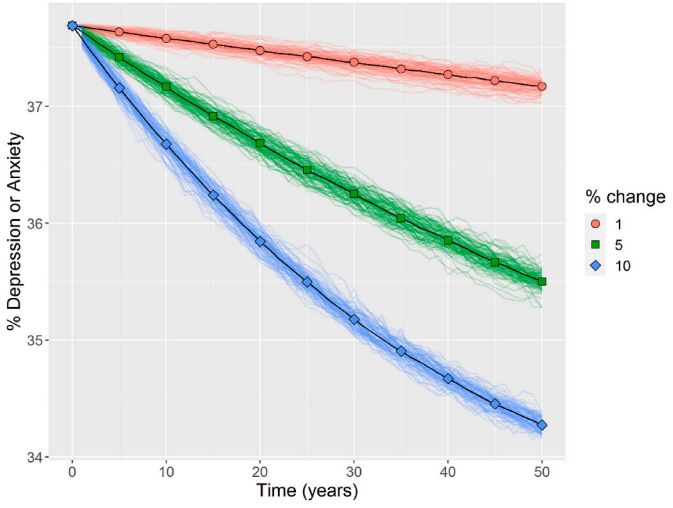

Fig. 6. Predicted proportion of depression or anxiety based on the balanced random forest predictions for the original sample when 1%, 5% and 10% of the original sample respectively move 1 decile up each year.

Our study reinforces the importance of residential mobility and area-level deprivation as important determinants in the analysis of socio-environmental influences on mental health (Egli et al., 2020; Hobbs et al., 2019). Importantly, individuals with persistent mental health conditions were found to have a higher propensity to relocate over time, often shifting towards areas characterised by higher levels of area-level deprivation (Lee et al., 2020; Greene et al., 2020). The observed association between persistent mental health conditions and adverse changes in subsequent area-level deprivation alongside higher residential mobility further emphasises the ongoing need to prioritise initiatives aimed at reducing inequalities (Marmot, 2005).

In terms of implications of these findings, it is clear that efforts to improve mental health must be integrated with broader strategies that address social and economic disparities including a range of policies from income support, healthcare accessibility, educational initiatives, housing policies, continued efforts to recognise specific needs of indigenous communities, as well as economic development programs aimed at reducing disparities (Minister of Health, 2023). Given the strong association between residential mobility and mental health, which is consistent with previous literature (Ahlberg et al., 2023), particularly for individuals with pre-existing mental health conditions, policy initiatives aimed at promoting housing stability are essential (New Zealand Government, 2023; Reynolds et al., 2021). For instance, stricter tenancy rights could help prevent forced relocations due to eviction (Chisholm et al., 2022), while tenancy support services may assist individuals facing financial difficulties that threaten their housing (Chisholm et al., 2017; Krishnan, 2001). Mental health outreach services embedded in communities, especially those at higher risk of instability, could offer crucial support before individuals are forced to move (Ministry of Health NZ, 2024). In addition, housing-first models, which prioritise securing stable housing as a fundamental step in treating mental health issues, can break the cycle of instability and poor mental health (Peng et al., 2020). Brokerage services that help individuals manage loan or rent repayments during stressful life events, such as job loss or family crises, could preclude the need for sudden moves, reducing the associated mental health strain (Clark, 2016). By addressing both housing stability and mental health in a coordinated manner, these policies can support long-term wellbeing for underserved or vulnerable populations.

Although we employed a novel Healthy Location Index to measure built and natural environmental influences on mental health, its relationship with mental health in this longitudinal analysis was inconclusive. Our study confirmed much previous evidence which has shown that factors such as age, body mass index, socioeconomic status, physical activity, area-level deprivation and residential mobility are important for determining mental health (Hobbs et al., 2021c; Helbich, 2018a, 2018b). However, effects for health-constraining and health-promoting features were often very small to negligible in size and most likely not meaningful at a population-level which contrasts with previous cross-sectional research (Hobbs et al., 2021a, 2022). Nevertheless, this supports previous evidence including a recent systematic review and meta-analysis of 30 studies that found little evidence of longitudinal associations between neighbourhood social, natural, and built environments and adults' mental health (Sui et al., 2022). In addition, another reason for this could be the limitation of our data, which measures proximity or availability of built/natural environmental resources but does not capture whether individuals used or engaged with them. Research that employs methods such as GPS tracking or survey data on individuals' perceptions and usage of their environments might provide a more nuanced understanding of these relationships.

Our study also supports previous research demonstrating the importance of area-level deprivation in Aotearoa New Zealand and internationally (Egli et al., 2020; Hobbs et al., 2019). Despite this, evidence from a citywide cluster randomised trial showed how greening of vacant lots can result in meaningful reductions in psychological distress (South et al., 2018). Further longitudinal research is required to unpick the association between the built and natural environment and mental health.

Environmental contributions to mental health are complex and longitudinal data are required to capture the dynamics between our health and the places we reside. Our study shows that a higher probability of moving is associated with a higher probability of having mental health conditions. This supports previous evidence demonstrating that the number of times an individual has moved is associated with poorer mental health (Choi and Oishi, 2020). In addition, while our study saw few associations, better accounting for residential mobility may create varying levels of exposure to healthy and unhealthy living environments with downstream implications for mental health (Norman et al., 2005). From a theoretical perspective, any effect of environmental change on mental health is not straightforward. On the one hand, research on habit discontinuity argues that behaviour change is easier during life course changes such as moving house because of the disruption between specific cues that activate particular habits (Carden and Wood, 2018; Gardner et al., 2022). In the context of moving from a less healthy environment to one that is healthier, for example, this could mean that previous habits are disrupted, and new habits emerge (e.g., taking a

walk in the nearby park). In doing so, one may start to establish 'healthier' habits that benefit mental health. But on the other hand, habits are slow to change as these involve implicit or nonconscious processes that emerge due to activation of learned associations between specific cues and behaviour (Gardner et al., 2022). Such habits may take weeks or even many months to retrain, so people may not necessarily adopt new behaviours following a change in environment (Harvey et al., 2022). Nevertheless, future research should consider such dynamic processes when considering its impact on mental health (Desjardins et al., 2023; Choi and Oishi, 2020; Campbell et al., 2021; Oishi and Talhelm, 2012).

Several limitations should be considered when interpreting findings from this study. First, the NZAVS is not fully representative of the New Zealand population and the longitudinal data are influenced by dropout and/or attrition (Satherley et al., 2015). Second, we only had measures of access to the environment and not what study participants actually did in their locale. Consequently, this study suffers from the uncertain geographic context problem where the causally relevant area for health is unknown (Kwan, 2012, 2018). Even when speaking of association rather than a causal effect, most statistical models, random forests included, postulate the response or dependent variable and a number of input or independent variables. Although often the direction is obvious, sometimes it is not. For example, in this study, we have considered both: (i) how the change in mental health may induce a change in the living environment (moving to a more or less deprived area) and (ii) how change in the living environment may induce a change in mental health. An alternative way to model such data with a lot of interrelationships, some of which are obvious others less so, is Bayesian networks. Implementation of a Bayesian network is thus one of our future objectives. Future research should also consider examining how the impact of changes in environmental features are related to changes in health outcomes accounting for longer-term residential histories. Future work is also needed to examine and complement this research by examining how specific environmental indicators individual features within the Healthy Location Index contribute to mental health when isolated from the co-located features. Moreover, whilst we were able to consider residential mobility, we were not able to consider housing tenure or type. Given this may be related to both residential mobility (Ong ViforJ et al., 2022) and the type of area (Wood et al., 2022) an individual may move to or from, this is an important area for future research. By better contextualising housing moves with socioeconomic contexts, housing markets, and other pressures, a more holistic picture of the influences will be captured (Clark, 2016).

5. Conclusion

This study examined the impact of sociodemographic, social, and environmental factors on mental health in adults. Notably, we discovered elevated anxiety and depression rates among those who moved, potentially revealing a connection between ongoing mental health challenges and subsequent negative shifts in area-level deprivation. While our innovative methods including the use of the Healthy Location Index aimed to capture environmental influences on mental health, analyses were inconclusive.

CRediT authorship contribution statement

M. Hobbs: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **E. Moltchanova:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **L. Marek:** Writing – review & editing, Writing – original draft, Methodology. **K. Yogeeswaran:** Writing – review & editing, Writing – original draft, Methodology, Conceptualization. **T.L. Milfont:** Writing – review & editing, Writing – original draft, Conceptualization. **B. Deng:** Writing – review & editing, Writing – original draft, Methodology. **C.G. Sibley:** Writing – review & editing, Writing – original draft, Funding acquisition, Data curation, Conceptualization.

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Conflicts of interest

None to declare.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.healthplace.2025.103487.

Data availability

The authors do not have permission to share data.

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