NOTE FROM EMMA: you’ll need to merge this doc with eric and paul’s version using the combine documents function (amber and stephanie had more comments on the actual analysis so I used theirs). Let me know if you need help with this as I only recently discovered this MS word functionality

Target journal: Landscape and Urban Planning, PLOS One, BMC Public Health, Canadian Journal of Public Health, Health Promotion and Chronic Disease Prevention in Canada… should we start SUPER ambitious with Lancet Planetary Health? YES, or Nature Sustainability?

**Biodiversity and mental health in Canadian cities**

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**Abstract**

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# Introduction

Urban growth is a major contributor to biodiversity loss (1, 2), yet for over 50% of the global human population that live in cities, urban biodiversity represents their predominant exposure to nature (3). Urban environments can increase stress (4) and reduce people’s engagement with the natural environment (5), which is problematic because exposure to nature is associated with a broad array of health and well-being benefits (6). As cities continue to grow, understanding the link between biodiversity and health within an urban context will be a key component of effective urban conservation and public health planning.

It is widely recognized that exposure to nature provides mental health benefits to people living in cities (7). The restorative effects of natural environments are tied to human evolution, throughout which our species has relied on nature for survival and reproduction. Thus, the biophilia hypothesis posits that humans have an innate affinity to connect with other species and nature (8). Two key psychological theories frame the biophilia hypothesis: ‘attention restoration theory’ (where nature facilitates the recovery from mental fatigue and replenishes attention through unconscious, cognitive processes; 9) and ‘stress recovery theory’ (where natural environments facilitate the recovery from physiological stress through autonomic response; 10). Moreover, natural environments can reduce exposure to urban stressors, such as heat, noise, and air pollution (11). Studies have explored the restorative properties of the amount of and proximity to ‘greenspace’, ‘urban nature’, and ‘parks’ (12, 13). Much of this research considers interactions with nature at large, considering the ‘dose’ of time spent in natural environments to generate positive mental health outcomes (14).

The role of biodiversity and different components of the natural environment in mental health outcomes is underexplored (15). Biodiversity encompasses the variety of species, from genes to ecosystems. Some studies have found relationships between the number and abundance of species and self-reported well-being, pleasure, connectedness to nature, overall health, stress, anxiety, and depression (16). At an urban park scale, psychological well-being was found to be related to higher bird and plant species richness (17), while lower depression, anxiety, and stress was associated with afternoon bird abundance (18). In larger national studies, in the UK, bird species richness was associated with the prevalence of good health (19) and in Germany, plant and bird species richness was positively related with mental health (20). However, other research has found a lack of association between standardized assessments of biodiversity and physiological well-being (21) and a positive association between well-being and perceived species diversity, rather than actual objectively-measured diversity (22).

Much of the research exploring the associations between biodiversity and health have measured bird diversity. For many people living in urban environments, interactions with birds constitute their predominant exposure to wildlife (23). Given their conspicuous vocal communication (which are known to benefit human well-being; 24), high density in urban areas (25), and rich symbolic value, birds have a great potential for providing restorative benefits for humans (26). Moreover, birds are important indicators of ecosystem health (27). Yet, avian populations are facing widespread declines across North America (28) and urbanization is a major driver (29). Thus, birds have increasingly become the focus of urban greening programs to restore landscapes for people and nature (30).

More than 50% of the population in middle- and high-income countries will suffer from at least one mental health disorder, and many environmental factors, including exposure to nature, play a role (Trautmann et al. 2016). Neighborhood characteristics and geographic inequalities have surpassed genetic factors in predicting mental health outcomes, in particular the characteristics of the urban environment (31). In Canada, approximately 1 in 5 Canadians are affected by mental illness, costing upwards of 50 billion dollars annually and driving higher rates of disability and mortality (32, 33). As the population continues to age and urbanize, it is estimated that within a generation, 8.9 million Canadians will be living with a mental illness (32). Mental health issues have become prevalent during the COVID-19 pandemic and demand for treatment has risen steeply (34). Because the ability to provide primary care to treat mental illness is insufficient to meet growing demand, public health approaches are increasingly being explored as alternatives (35).

Given the recognition of the link between health and nature, and mounting environmental and mental health crises, nature-based programs that address both of these issues are becoming increasingly important (36). Nature-based solutions aim to protect, restore, and create biodiversity while addressing societal challenges (37). For example, planting trees along streets can provide habitat for birds (38) while reducing the risk of depression (39). The Canadian government, like in many other jurisdictions, are increasingly investing in nature-based solutions in cities. For example, Canada’s government recently pledged to plant two billion trees over the next decade (<https://www.canada.ca/en/campaign/2-billion-trees.html>), to establish at least one new national urban park in each province and territory (<https://pm.gc.ca/en/mandate-letters/2021/12/16/minister-environment-and-climate-change-mandate-letter>), and to invest hundreds of millions of dollars into a ‘Nature Smart Climate Solutions fund’ (<https://www.canada.ca/en/environment-climate-change/services/environmental-funding/programs/nature-smart-climate-solutions-fund.html>). As interest increases in nature-based solutions, understanding the relationship between biodiversity and mental health can help guide national policy and planning.

Previous work has found that neighborhood ‘greenness’ (measured using the Normalized Difference Vegetation Index, NDVI) is associated with lower odds of poor self-rated mental health in Canadian cities (40). Although NDVI is a good indicator of vegetation cover, it is not a reliable predictor of species diversity (41). Yet, spatial data quantifying biodiversity across extensive areas such as cities is scarce. Thus, here we draw on the world’s largest biodiversity-focused community (aka citizen) science platform, eBird, and a national forestry inventory to quantify bird and tree species diversity across Canadian urban areas. We explore the relationship between biodiversity and mental health indicators, including perceived stress and psychological distress, from the nationally-representative Canadian Community Health Survey (CCHS). Additionally, we explore whether the association between biodiversity and mental health varies based on area-level socio-economic status (SES). We hypothesize that bird and tree diversity will have a positive influence on indicators of mental health, particularly for lower income populations (20).

# Methods

To focus on the urban population of Canada, we restricted our analyses to Canadian Census Metropolitan Areas (CMA, i.e., metropolitan areas with populations >100,000) designated as of 2021 (the year of the latest CCHS data). Because health data were georeferenced at the six-digit postal code level and many measures of SES (marginalization) and green and blue space were aggregated to this level, biodiversity metrics and other measures of green and blue space were aggregated by postal code, based on reference data from February 2021. We then used postal codes to link all data sources. To reduce within postal code variability, very large postal codes in CMAS with an area >16 km2 (>75th percentile) were excluded. All analyses were performed in R statistical software version 4.2.1 (42).

## Health data source

The CCHS is a repeated cross-sectional survey administered annually to collect data on the health status, health care use, and health determinants of Canadians. The CCHS uses computer and telephone assisted interview software and respondents provide detailed information on >1000 demographic and health-related variables. Survey participants are aged 12 years and older, excluding full-time members of the Canadian Armed Forces, residents of Indigenous reserves, and individuals living in institutions (the final sample is representative of ~98% of Canadians). From 2007 onwards, approximately 65,000 respondents were interviewed each year (43). Approval to access CCHS data was granted by the Carleton University Research Data Centre. All data were de-identified and kept in a secure computer facility on campus and thus did not require university ethics approval for use.

For the purpose of this study, data from the 2007 to 2021 CCHS were used. Because many of the health behaviour variables do not apply to participants under 17 (e.g., marital status, smoking, etc.), our analysis includes adults aged 18 years and older. This resulted in a pooled sample of n = 371,928 CCHS survey respondents in CMAs in postalcodes >16 km2. The CCHS underwent a redesign in 2015; thus we only use variables that were consistent before and after. As a further check, we visualized temporal model results to ensure there were not clear changes in patterns before and after 2015.

## Mental health indicators (dependent variables)

The CCHS includes several questions that assess the psychological condition of respondents, including questions related to psychological distress (44).

Perceived stress: To assess perceived stress, participants are asked “Thinking about the amount of stress in your life, would you say that most of your days are 1) not at all stressful, 2) not very stressful, 3) a bit stressful, 4) quite a bit stressful, or 5) extremely stressful”. Similarly to previous analyses (40) we created a binary variable, where values of 4 or 5 were considered ‘high perceived life stress’.

General mental health: Participants are asked about their perceived mental health: “In general, would you say your mental health is 1) Excellent, 2) Very good, 3) Good, 4) Fair, and 5) Poor”. A binary variable was created where values of 4 or 5 were considered ‘low perceived mental health’.

Psychological distress: We attempted to use the Kessler Psychological Distress Scale (K-10) to assess generalized psychological distress (45). This involves a series of ten questions, each scored on a five-point scale from ‘none’ to ‘all of the time’ over the past four weeks: “how often did you feel 1) tired out for no good reason, 2) nervous, 3) so nervous that nothing could calm you down, 4) hopeless, 5) restless or fidgety, 6) so restless you could not sit still, 7) sad or depressed, 8) so depressed that nothing could cheer you up, 9) that everything was an effort, 10) worthless?” Responses are summed, yielding a total score of 10-50: a score under 20 indicates low distress, 20–24 indicates mild distress, and 25–29 indicates moderate distress, and scores above 30 indicate high distress. The psychometric properties of the K-10 scale have been examined extensively and shown to be reliable against other metrics of psychological distress and an accurate predictor of diagnosed mental disorders (46). Because K-10 scores were left-skewed, we explored cutoffs to make psychological distress a binary variable. Many cutoffs have been explored in the literature, typically, K-10 scores of 20 or higher have been recommended for clinical screening of mental disorders (47) whereas values of 22 and higher are associated with a higher likelihood of having a mental disorder. Given the differences were minor between cutoffs, we used a value of 22 to discretize this response. However, after discretization, the number of distress scale respondents experiencing high distress was so small within postal codes with sufficient eBird data that model results were almost entirely non-significant, and small sample size restrictions prevented us from releasing quantitative findings. Thus, all model results presented are for the mental health and stress outcomes.

## Bird and tree diversity (independent variables)

***Bird species diversity***

To extract estimates of bird species richness and diversity, we used eBird, a community science dataset with over 600 million users worldwide, representing one of the largest and most spatially comprehensive biodiversity datasets (48). Through the eBird app or website, volunteers submit ‘checklists’ with the number of individuals of each species observed, start time, duration, and distance covered. When bird sightings verified by regional reviewers and data are appropriately filtered, eBird checklists can provide data to understand ecological patterns at broad spatial extents (49, 50).

We downloaded eBird checklists from 2007-2021, corresponding to the CCHS cycles. To filter sampling events to the ‘best quality’ lists, we cleaned the checklist data using methods applied previously(51)(52), limiting checklists to those that were: (1) complete (where all birds seen and heard were recorded); (2) had a travel distance < 10 km; (3) were between 5 and 240 mins duration; and (4) were ‘stationary’, ‘travelling’, or ‘exhaustive’ (removing any incidental checklists). Further, we removed species that were recorded on fewer than 5% of checklists at each location to limit the impacts of vagrant birds or erroneous identification on the analysis (51). We used the *auk* package (53) to filter checklists. We note that community scientists involved in assembling eBird checklists in a given location need not live in that location. The association between an eBird checklist and a location simply means that a registered eBird user travelled to a particular location to perform that survey.

To explore the influence of bird diversity in neighborhood greenspaces we calculated the distance to and bird species diversity metrics of the nearest eBird “locality” to each postal code. eBird users can give their own names or choose from existing localities (e.g., eBird hotspots or locations that people regularly visit for birding; <https://ebird.org/ebird/hotspots>). We removed postal codes with no localities within 1.06 km from postal code edges, the largest estimate of the perceived size of a community in the U.S. (54). A previous study demonstrated that at least nine checklists were required to represent species diversity of bird communities with 90% confidence in 30 urban greenspaces across North America (51). Thus, we limited localities to those with a minimum of nine complete checklists in a year. To account for uneven sampling, we generated estimates of species richness and diversity using rarefaction (corresponding to a sample size of 17; 55) and nonparametric asymptotic estimation (56) in the *iNEXT* package (57).

Given eBird surveys occur at any time of year and checklists can vary in length, we created a generalized linear mixed model (GLMM) to standardize species diversity estimates. We created two models with species richness (with a Poisson error structure) and Shannon diversity (with a Gaussian error structure) as response variables. We included Julian date and checklist duration as fixed effects and year and locality as random effects. Models were run for each CMA separately (models would not converge with all data included). We then used these models to predict species richness and diversity for a 120 min checklist on June 5 (including breeding season but excluding spring migrants). We examined the sensitivity of our results to these diversity estimation methods.

To explore potential biases in eBird sampling effort by SES, we quantified the relationship between the number of checklists and a neighborhood-level index of marginalization. The Canadian Marginalization Index from the Canadian Urban Environmental Health Research Consortium (CANUE) was available at the postal code level, calculated for 2016, and describes material deprivation, residential instability, dependency, and ethnic concentration (58). Using a GLM with a Poisson error structure we found little evidence of a relationship between metrics of marginalization and number of checklists (R2 < 0.02, supplementary material S1).

***Tree species diversity***

We extracted tree species richness and diversity from the publicly available National Forest Inventory (NFI), which employs a combination of ground-survey plots, photo identification plots, and MODIS remote sensing data in a k-Nearest Neighbour modelling approach to produce countrywide maps of tree species volume (at 250 m resolution). We extracted the mean Shannon diversity and richness of tree species within each postal code polygon using the *diversity* function within the *vegan* package (59). We note that the kNN model was validated against NFI plots in forested areas, and therefore cannot fully identify the set of tree species present in Canada’s urban areas. This is especially true in the case of non-native tree species, which are common in urban areas but are not assessed within the NFI. This likely resulted in an underestimation of tree species diversity within urban areas. This inaccuracy is expected to affect all CMAs and therefore not lead to biases in our conclusions, but may reduce the observed impact of tree diversity on mental health.

***Other metrics of green and blue space***

We examined the effect of overall greenness (NDVI, not green space) from MODIS data. These data are compiled as the mean from May 1st through August 31st (growing season) by CANUE in 500m and 1000m circular buffers around each postal code centroid in Canada. We assigned greenness values based on the closest years of greenness data available (i.e., a two-year mean, corresponding to, or closest to, the two years of the survey cycle). To calculate the influence of access to green space, we calculated the percentage of and mean distance to the nearest green space (comprising all vegetated land use classes), and the percentage of and mean distance to the nearest blue space (all water classes, including wetlands), from the North American Land Change Monitoring System at 30m from Landsat imagery. NDVI values of NA were assumed to take a value of 0, as they likely pertained to cells that could not contain green space (e.g., water).

***Covariates***

Health behaviours and contextual variables

We analyzed other characteristics of survey participants collected using the CCHS questionnaire known to affect mental health. This included socio-demographic characteristics: age, sex, marital status, employment, total household income (ordinal classes treated as a continuous variable), highest level of education attained (treated as a categorical variable), and binary ethnicity (white, non-white, derived from the more complex Cultural/Racial Background variable within the CCHS). We included relevant health behaviours from the CCHS questionnaire known to affect mental health (Fig. 1): total daily fruit and vegetable servings consumed per day (60), type of smoker (every day, occasionally, or not at all; 61), binary smoking cessation (62), alcohol consumption (63), and an energy expenditure function calculated using the *cchsflow* package (64) in R statistical software version 4.1.3 (various R 4.1.x versions at the Carleton University Research Data Centre; Fig. 1 in 65). The energy expenditure function estimates the number of minutes per week each respondent spent engaging in leisure physical activity. Finally, we included a 6-level categorical variable representing immigration, generated using *cchsflow* (see Fig. 1 in 65): White Canadian-born, non-white Canadian born, white immigrant born outside of Canada (0-9 years in Canada), non-white immigrant born outside of Canada (0-9 years in Canada), white immigrant born outside of Canada (10+ years in Canada), non-white immigrant born outside of Canada (10+ years in Canada). Missing or ‘I don’t know’ responses were included as separate levels of categorical variables to increase the number of complete cases with which to fit the model.

## Effect Modifiers

To account for evidence suggesting the health benefits from nature can be larger for those residing in more deprived neighborhoods (11), we stratified our analysis by neighbourhood marginalization. We explored the relationship between metrics of biodiversity and indicators of mental health in neighborhoods with low and high values of Canadian Marginalization Index from CANUE. Because there are four dimensions of marginalization (instability, deprivation, dependency, and ethnic concentration), to select the dimension with the highest likelihood of modifying the relationship between mental health and biodiversity, we explored the relationship between species diversity of birds and trees and each marginalization dimension. We fitted 16 GLMs, 8 with a Poisson error structure with species richness of birds or trees as the response and 8 with a Gaussian error structure with Shannon diversity of birds or trees as the response. We selected the “instability” marginalization dimension, as these models had the best fit with both tree and bird species diversity (tree species richness R2 = 0.4). We then considered high marginalization as values in the top two quintiles of instability among Canadian postal codes (values of 4 or 5).

## Analysis

All code and derived data are available at a GitHub repository [here](http://www.github.com/emmajhudgins/equitablecities) (data privacy restrictions notwithstanding).

To explore the effect of environmental covariates on mental health metrics we used generalized additive models (GAMs) for very large datasets in the *bam* package (66). The GAM approach is flexible, including each covariate as a smooth function that allows for non-linear relationships, while avoiding overfitting (67). Because model selection likely would not remove entire smooth terms from a model, analogous to GAM, *bam* andallows for the specification of a “select” option that assesses the optimal number of knots in each smoother term. We fit models with the bam default method fREML (“fast REML”), and discretized covariates for efficiency (68). To further avoid fitting overly complex smoother terms, we capped the maximum knots fit by any model at five. Because our goal was to understand relationships among our dependent variables and our predictor variables, rather than to understand average Canadian wellbeing, we use unweighted CCHS data throughout our analyses (69).

We fitted two sets of logistic GAMs (binomial models with a logit link) using the following response variables: 1) high/low self-perceived life stress; and 2) high/low self-perceived mental health. To control for unexplained spatial variability and nonlinear temporal variability in mental health, each model had a basic structure containing CMA as a random effect, as well as a continuous smoother fit to CCHS survey year and postal code area. For each response variable we fitted four models: 1) only biodiversity and bluespace/greenspace exposures; 2) adding in age and sex; 3) adding in other socio-demographic characteristics (marital status, income, education, ethnicity, and immigration status); and 4) adding in health behaviours. All continuous covariates were centred and scaled by subtracting the mean and dividing by the standard deviation. All covariates apart from survey year and CMA were included as parametric terms (i.e., were included in the model without a smoother) to allow comparison of the relative influence of categorical and continuous predictors and penalizing models against overfitting complex smoothers. Different amounts of missing data meant that each of these models contained a different sample size of complete cases.

For the first model, we chose the most parsimonious combination of NDVI, tree and bird diversity metrics, and distance to and density of bluespace/greenspace by fitting models with different combinations and selecting the model with the lowest AIC for each response variable (24 possible models). We fitted these model sets for all data, data from low marginalization neighborhoods, and data from high marginalization neighborhoods. This resulted in a total of 27 possible models for each marginalization stratification/response variable combination, or 162 total models. To assess collinearity among independent variables (including covariates), we computed a Spearman’s correlation matrix. For independent variables with a correlation coefficient (R) greater than 0.7 (70) we included one of each covariate in a separate model (where it was the only term) and chose the covariate with the model that resulted in the lowest Akaike’s Information Criterion (AIC). Each *BAM* fit was further assessed for concurvity (the GAM equivalent of multicollinearity; 71), which can persist among smoothed terms even in the absence of strongly collinear variables. When high concurvity was detected for survey year (worst case concurvity of >0.8 in the *concurvity* function), the number of knots associated with the smoother term for survey year was iteratively reduced until concurvitydecreased below 0.8. If concurvity persisted, survey year was converted to a parametric term.

In the fourth model set (with health behaviours) we found evidence of complete separation (response variable separates the categorical predictor variables perfectly) due to large amounts of missing CCHS data, leading to large parameter and confidence interval estimates. To ensure robustness in our parameter estimates, we compared the results from this model to models where 1) some health behaviour predictors that had particularly high levels of missingness (alcohol consumption and time spent exercising) were removed, 2) missing values were imputed to the median, and 3) missing values were imputed with multiple imputation by chained equations via the *mice* R package following the approach outlined in (72), where we performed 50 imputations and used our full model equation as our imputation structure.

## Sensitivity analysis.

To explore whether socioeconomic factors were suitably controlled in our models, we tested the relationship between our biodiversity metrics and a proxy of wealth. We selected having entirely missing teeth as our proxy due to its high correlation with SES while being theoretically unrelated to nature exposure (73). We used the CCHS question “Do you have at least one of your own teeth?” as a binary response variable in a GAM that followed the same structure as our 4th model in our model-building structure for each best set of terms in each stratification and response variable tested (9 total models).

# Results

**Descriptive results**

Life stress had greatest number of respondents (n = 370025 respondents in CMA postal codes), followed by general mental health (n = 362836). As mentioned before, psychological distress sample sizes were too small to allow release. When restricted to postal codes with adequate bird diversity samples, there were n= 47623 non-missing responses for mental health and n=48693 non-missing responses for stress outcomes. The probability of poor self-reported mental health was 0.08 (SD=0.27) within this subset as a whole, as well as within high-marginalization postal codes (SD=0.08), while it was 0.07 in low-marginalization postal codes (SD=0.26). The probability of high self-reported life stress was 0.20 (SD=0.40) for the entire subset, 0.21 within high-marginalization postal codes (SD=0.41), and 0.19 (SD=0.41) within low marginalization postal codes.

As we expected, the postal codes containing sufficient eBird data for biodiversity analysis were a biased subset of all postal codes, where respondents tended to have higher income (Δ=0.48 semi-quantitative ranks, ~$ 4,800 per year), and to be slightly older (Δ=1.94 years), more active (Δ=2.24 hours of activity per week), and consume less alcohol (Δ=0.20 drinks per week) than the overall set of CCHS respondents (Table S1), though they also consumed slightly fewer fruits and vegetables (Δ=-0.25 servings per day). Counter to expectations, the postal codes with sufficient data tended to have lower NDVI (Δ=-0.14 to -0.15 across buffer sizes) and tree diversity (Δ=-0.29 int tree species richness and Δ=-0.04 in tree diversity). These patterns largely persisted even within the two stratifications by marginalization index (Table S2-S3), though the bias towards and increase in SES and health behaviours was more pronounced in low-marginalization postalcodes, and the bias changed direction to higher tree diversity in high-marginalization postalcodes with sufficient eBird data. As such, our survey likely does not capture the impacts of biodiversity on the most at-risk Canadians if its effects on these groups are not consistent with those of the individuals we were able to assess. We note, however, that there were only small differences in our response variables across all subsets, where the probability of poor self-reported mental health remained around 0.07-0.08 and the probability of high self-reported life stress ranged only from 0.19-0.22 across stratifications and before and after subsetting to postalcodes with sufficient eBird data.

**Model results**

Throughout this section, we refer to effect as positive on mental health if they decrease the incidence of poor mental health outcomes (negative terms in our models) and positive on stress if they increase the incidence of high stress (positive terms in our models).

## General mental health

The best biodiversity, blue and greenspace variables for the self-reported poor mental health model applied to all data was the model including NDVI measured at a 500m buffer, tree species richness, and modeled bird Shannon diversity, where the year term was linearized to minimize concurvity (AIC=26 188.02, deviance explained=1.52%, n=47623, Table S52). The most influential term beyond the intercept and time in model 1(including only biodiversity and bluespace/greenspace exposures), was tree species richness, which had a strong positive effect on self-reported mental health (interpreted as a negative term in a model for the incidence of poor self-reported mental health, β=-0.11, SE=0.026, p<0.0001,Table SX). Bird diversity had a positive effect on self-reported general mental health (β=-0.092, SE=0.018, p<0.0001). Increased distance to blue space had a strong negative effect on self-reported mental health (β=0.085, SE=0.020, p<0.0001). No other variables were significant.

Adding age and sex in model 2 made the effect of greenness (NDVI) significant (β=-0.11, SE=0.026, p<0.0001,Table SX), but did not appreciably change the effect of bird and tree diversity (β= -0.090, SE=0.026, p<0.0001), tree species richness (β= -0.090, SE=0.018, p<0.0001), or distance to blue space (β= 0.076, SE=0.020, p=0.00012).

After adjusting for socioeconomic covariates in model 3, the effect of modelled bird diversity remained relatively stable (β= -0.075, SE=0.018, p<0.0001), while the effect of tree diversity weakened more and became only marginally significant (β= -0.057, SE=0.027, p=0.032).

When adding in health behaviours in model 4, we observed similar parameter estimates after interpolation by the *mice* function compared to subsetting to complete cases, removing problematic terms, and compared to replacing missing data with the median (Tables S7-S10). In the MICE model, modelled bird and tree diversity both persisted as significant terms (β= -0.069, SE=0.018, p=0.00019 for bird diversity and β= -0.055, SE=0.027, p=0.040 for tree species richness, Table S7), while distance to blue space became nonsignificant.

**Figure 1.** Model results for the logistic GAM for biodiversity and green and blue space on the incidence of poor mental health, adjusting for age, sex, SES covariates and health behaviours across all CCHS respondents included in our analysis. Marriage contrasts are compared to married respondents, Employment contrasts are compared to unemployed respondents, Ethnicity contrasts are relative to non-white ethnicity, immigration contrasts are compared to white, Canadian-born respondents, Education contrasts are compared to respondents who did not graduate high school, Smoking cessation contrasts are relative to respondents who have quit smoking, and smoking frequency contrasts are relative to respondents who smoke daily. The random effect term for CMA had empirical degrees of freedom of 26.77, Χ2=188.02, p<2E-16, while the year term was linearized due to high concurvity in model 1 (>0.8). Model AIC=24156.15, R2adj=0.049, deviance explained=7.43% (n=46522). Significant terms are coloured in black while unsignificant terms are coloured in grey. Parameter estimates are displayed as an odds ratio, which indicates the relative risk of perceived poor mental health for a particular covariate level relative to a baseline in the case of categorical predictors, or for an increase of one standard deviation away from the mean value for continuous predictors. The “Immigrant (White, <10 years)” term had very large confidence intervals spanning 0 that are not fully displayed. See Table S7 for exact parameter estimates.

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**Figure 2.** Modelled estimates of the relative risk of incidence poor self-reported mental health across our set of model adjustments for **a.** modeled bird Shannon diversity, **b.** tree species richness, and **c.** distance to blue space. Means and standard errors are shown. Model 1 was fit only to biodiversity and green and blue space predictors, model 2 was further adjusted by age and sex, model 3 was further adjusted by SES covariates, and model 4 was further adjusted by health behaviours. Parameter estimates are displayed as odds ratios, which indicate the relative risk for an increase of one standard deviation from the mean value for continuous predictors.

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The counterfactual analysis suggested that model 4 was well controlled for SES covariates and therefore provided further support for a causal relationship between biodiversity and mental health, as this model did not show a residual significant relationship among biodiversity variables and missing teeth (Table S11).

Results were qualitatively similar for models 1-4 applied to the low and high marginalization stratifications separately, albeit with decreased variable significance (Tables S12-S51), and evidence of poorer control of residual SES correlations in the counterfactual analyses. In the low-marginalization stratification, tree species richness and modeled bird diversity both remained significant across models 1-4, albeit with larger p-values than in the unstratified set (β= -0.083, SE=0.059, p=0.040 in model 4 for tree diversity, and β= -0.068, SE=0.028, p=0.016 in model 4 for bird diversity). Distance to blue space had a negative effect on mental health in models 1-2 (β= 0.076, SE=0.020, p=0.00012 in model 2) that disappeared in models 3-4. The counterfactual analysis for the low-marginalization stratification showed a near-significant positive relationship between bird species diversity and missing teeth (β= 0.15, SE=0.076, p=0.0501), which was in the opposite direction as would be expected if there were residual positive correlations between bird diversity and SES, which suggests an underestimation of the true effect of bird diversity on mental health. The proportion of green space variable was nearly significant and positive in this model, again showing poorer control of residual SES correlations in this subset in the opposite direction than expected (β= 0.18, SE=0.096, p=0.057).

Modeled bird Shannon diversity had significant positive effects on mental health that persisted throughout models 1-4 in the high marginalization stratification (β= -0.064, SE=0.024, p=0.0087 in model 4). The high-marginalization stratification showed support for improved mental health due to higher tree diversity in models 1-2 (β= -0.068, SE=0.028, p=0.014 in model 2), but this term became non significant in models 3-4. The counterfactual of this model showed that bird and tree diversity metrics were well controlled (p>0.05), but that proportion of blue space and NDVI variables had residual effects on missing teeth (β= 0.11, SE=0.047, p=0.020 for proportion of blue space, β= -0.50, SE=0.025, p=0.043 for greenness within a 500m buffer).

## Perceived Life Stress

The best perceived life stress model variables for the unstratified dataset were greenness within the postal code (NDVI), tree species Shannon diversity, and modeled bird species richness (AIC=49025.92, deviance explained=0.442%, n=48963, Table S52). In model 1, tree diversity did not have a significant effect on the incidence of high perceived life stress, while bird diversity had a near-significant negative effect (i.e. decreasing the chance of high stress, β= -0.021, SE=0.012, p=0.083). Distance to blue space had a weak positive effect on stress in this model (i.e. increasing stress, β= 0.029, SE=0.014, p=0.035), and greenness appeared to increase stress (β= 0.051, SE=0.016, p=0.0014). These effects all disappeared in models 2-4 except the effect of greenness, which remained positive in model 4 (β= 0.081, SE=0.0527, p=0.0024). However, the effect of greenness was shown to be poorly adjusted for SES in the counterfactual, where it showed a residual negative correlation with missing teeth (β= -0.34, SE=0.17, p=0.047). The results were weaker across stratifications, with greenness remaining only marginally significant in the low marginalization stratification beyond model 1 (β=0.086, SE=0.041, p=0.038 in model 4). Bird diversity was nearly significantly negatively related to stress in models 1 and 2 in the high diversity stratification, while distance to blue space was nearly positively related to stress in model 1, and greenness (NDVI) was marginally positively related to stress in models 1-4 (β= 0.074, SE=0.035, p=0.033 in model 4).

**Figure 3.** Model results for the logistic GAM for biodiversity and green and blue space on the incidence of high perceived life stress, adjusting for age, sex, SES covariates and health behaviours across all CCHS respondents included in our analysis. Marriage contrasts are compared to married respondents, Employment contrasts are compared to unemployed respondents, Ethnicity contrasts are relative to non-white ethnicity, immigration contrasts are compared to white, Canadian-born respondents, Education contrasts are compared to respondents who did not graduate high school, Smoking cessation contrasts are relative to respondents who have quit smoking, and smoking frequency contrasts are relative to respondents who smoke daily. he random effect term for CMA had empirical degrees of freedom of 15.38, Χ2=42.03, p=5.2E-06, while the year term was linearized due to high concurvity in model 1 (>0.8). Model AIC=46207.20, R2adj=0.038, deviance explained=4.07 % (n=47543). Significant terms are coloured in black while unsignificant terms are coloured in grey. Parameter estimates are displayed as an odds ratio, which indicates the relative risk of perceived poor mental health for a particular covariate level relative to a baseline in the case of categorical predictors, or for an increase of one standard deviation away from the mean value for continuous predictors. The “Immigrant (White, <10 years)” term had very large confidence intervals spanning 0 that are not fully displayed. See Table S31 for exact parameter estimates. Means and standard errors are shown

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**Figure 4.** Modelled estimates of the relative risk of incidence high self-reported life stress across our set of model adjustments for **a.** modeled bird species richness, **b.** greenness in postalcode (NDVI) and **c.** tree Shannon diversity. Means and standard errors are shown. Model 1 was fit only to biodiversity and green and blue space predictors, model 2 was further adjusted by age and sex, model 3 was further adjusted by SES covariates, and model 4 was further adjusted by health behaviours. Parameter estimates are displayed as odds ratios, which indicate the relative risk for an increase of one standard deviation from the mean value for continuous predictors.

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## Covariate results

In the unstratified dataset, perceived mental health was significantly poorer for individuals who were younger, female, white, unmarried, unemployed, lower-income, less educated individuals who smoked, had not quit smoking, and those who consumed fewer fruits and vegetables. Self-reported mental health significantly declined over time across all models. The effect of ethnicity became non-significant when examining only respondents in the low-marginalization stratification (Table S15), but not within the high-marginalization stratification (Table S23). There was no significant relationship between self-reported mental health and immigration status, activity level, alcohol consumption, or postal code size in this set of respondents (Tables S4-S51). In the unstratified set, perceived life stress was higher for individuals who were younger, female, white, employed, who smoked, had only high school education, and those who consumed fewer fruits and vegetables. There was no significant temporal trend in self-reported life stress across models. There was no significant relationship between self-reported life stress and immigration status, activity level, smoking cessation, alcohol consumption, immigration status, postal code size or income. The effect of ethnicity, education, and fruit and vegetable consumption became non-significant when examining only respondents in the low-marginalization stratification (Table S39), but not within the high-marginalization stratification (Table S47).

# Discussion

* Support for bird and tree diversity playing a unique role on mental health not explainable by SES.
* Bird diversity effects appear more robust
* Tree diversity effects are likely in part weaker due to the poorer-resolved urban tree diversity data underlying them – a research need for the future
* Many correlates of biodiversity are more related to SES than directly related to mental health (greenness)
* Fairly consistent effects of diversity across levels of marginalization, even though many covariates change sign/importance
* Greenness is not all created equal – people respond to plant diversity whether they know they do or not – implications for urban planning for healthy cities
* Biodiversity also provides co-benefits for other forms of health not captured in this analysis that may themselves alter mental health (e.g. cooling)
* Acuteness of stress and distress may make them less reliably linked to biodiversity
* eBird data are rich and useful!
* Blue space benefits are underexplored compared to green space
* Marginalization appears to make mental health outcomes less modifiable through behaviours (as evidenced for decreased significance/nonsignificance of fruit and veg, education) [if we want to get into the covariates]
* Because our responses are self-reported, there are likely relationships between our covariates and likelihood of self-reporting as being in poor mental health (any previous evidence this explains our sex and ethnicity results?)
* Reiterating that our sample didn’t capture the most marginalized communities because they do not have adequate bird diversity effort.

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