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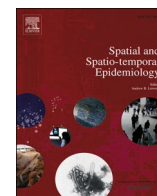
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## Exploring the feasibility of linking historical air pollution data to the Christchurch Health and Development study: A birth cohort study in Aotearoa, New Zealand

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### ABSTRACT

Spatial life course epidemiological approaches offer promise for prospectively examining the impacts of air pollution exposure on longer-term health outcomes, but existing research is limited. An essential aspect, often overlooked is the comprehensiveness of exposure data across the lifecourse. The primary objective was to meticulously reconstruct historical estimates of air pollution exposure to include prenatal exposure as well as annual exposure from birth to 10 years (1977–1987) for each cohort member. We linked these data from a birth cohort of 1,265 individuals, born in Aotearoa/New Zealand in mid-1977 and studied to age 40, to historical air pollution data to create estimates of exposure from birth to 10 years (1977–1987). Improvements in air quality over time were found. However, outcomes varied by demographic and socioeconomic factors. Future research should examine how inequitable air pollution exposure is related to health outcomes over the life course.

### 1. Introduction

Air pollution is one of the most important environmental factors affecting human health (Fairburn et al., 2019). Internationally, it contributes to millions of premature deaths (Manisalidis et al., 2020, Lu, 2020) including 940,000 child deaths each year (Landrigan et al., 2019). Air pollution exposure and the associated health risks are unequally distributed. Even in countries with reasonable overall air quality, concentrated hotspots of air pollution often exist, resulting in localised areas with elevated concentrations of air pollutants which potentially vary over time (Marek et al., 2018). Few studies have examined across-time changes in air pollution exposure and the extent to which social inequities exist in exposure to positive and/or negative change. From a public health perspective this issue is important in order to ensure equitable benefits from clean air policies, especially for those from disadvantaged or underserved groups who often experience the worst health outcomes (Mitchell et al., 2015).

Existing research is almost all cross-sectional which limits the ability

to examine changes in air pollution exposure over time or the effects of cumulative air pollution exposure on outcomes from conception through early and middle childhood (Sunyer, 2008, Myhre et al., 2018). Early exposure may be of particular concern given that this is a sensitive period of brain and behavioural development. Indeed, a recent review concluded that outdoor air pollution may be associated with increased risks of affective disorders and suicide in youth, and there is evidence for associated structural and functional brain abnormalities (Xie et al., 2023). Furthermore, evidence using high-resolution air pollution data with the Environmental-Risk Longitudinal Twin Study recently showed that those exposed to higher levels of outdoor NO<sub>x</sub> (outdoor nitrogen oxides) experienced greater psychopathology at the transition to adulthood, although there was no confirmed association with particulate matter (PM<sub>2.5</sub>) (Reuben et al., 2021).

Air pollution has long been recognised as an issue, especially in Ōtautahi Christchurch, Aotearoa New Zealand (NZ), which has a well-documented historical air pollution problem (McLeod, 1983, Sturman, 1985, Sturman, 1982). This includes significant disparities in the extent

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to which different population groups are exposed to varying levels of both ambient and extreme air-pollution episodes (Pearce et al., 2006). Further, in NZ, the importance of accounting for changes in air pollution exposure over time is especially relevant for Māori who, like many indigenous peoples, experience differential access to health determinants, whilst having an interest in the health of the environment as *tangata whenua* (people of the land).<sup>1</sup>

To examine these issues further, prospective data is urgently needed. Yet, few studies internationally have linked air pollution data to prospectively collected data (Reuben et al., 2021). Of the few studies that do exist, findings are often inconsistent and have not adequately adjusted for potential confounding factors (Park et al., 2021). However, it is now possible to combine innovations in spatial data science and historical environmental data with prospectively collected birth cohort data to examine inequity in exposure to air pollution over the lifecourse. This short communication, therefore, aims to highlight the feasibility of integrating historical air pollution data with birth cohort data in a spatial lifecourse epidemiological framework.

## 2. Methods

### 2.1. The christchurch health and development study birth cohort

The Christchurch Health and Development Study (CHDS) is a birth cohort study of 1265 individuals born in the Christchurch, NZ urban region over a 4-month period during 1977 (Fergusson et al., 1989, Fergusson and Horwood, 2001). This birth cohort has been studied regularly from birth to age 40 years using a combination of parent and participant interviews, standardised testing, teacher report, and medical record data. There are several previous publications that provide a full description of the cohort, the study design and how it has evolved over time. All phases of the CHDS were subject to ethical approval by the New Zealand Health and Disabilities Ethics Committee.

### 2.2. Study design

A prospective longitudinal birth cohort study, representative of the Christchurch, NZ population in mid-1977 forms the basis of this work.

### 2.3. Participants

Residential address data were sourced from the 1265 cohort members at birth (1977), with 1220 (96.4%) successfully geocoded to a NZ address. Specifically, 1075 were resident in Christchurch, 140 in the rest of the South Island and 5 in the North Island. At age 4 years (1981), 1103 of the 1265 original cohort members (80.1%) were successfully geocoded to a NZ address including: 795 in Christchurch, 197 in the rest of the South Island and 111 in the North Island. Further details are provided in Table 1.

### 2.4. CHDS sociodemographic and socioeconomic characteristics

Several individual-level characteristics were extracted from the CHDS birth cohort database for this study. First, we extracted the cohort members' *age at each wave* of data collection. Second, *sex* was measured at the birth of the cohort member (male or female). Third, *ethnicity* at birth was defined as Māori/Pacific ethnicity or European/other and cohort members were classified as being either of European/other (85.4% of the cohort) or Māori/Pacific ethnicity (14.6%) based on parental reports of ethnic ancestry obtained at the time of birth. Fourth,

<sup>1</sup> Māori recognise their reciprocal relationships with, and responsibilities for, the sky, land, sea, plants and animals, as *kaitiaki* (guardians). *Kaitiakitanga* (guardianship) involves protecting and nurturing the environment so it in turn will protect and nurture people.

*maternal age* was assessed in whole years at the time of the cohort member's birth. *Maternal education* was assessed at the time of the child's birth using a 3-point scale that reflected the mother's highest level of educational attainment. This scale was: mother lacked educational qualifications (*none*); mother had secondary (high school) qualifications (*secondary*); and mother had tertiary (college) qualifications (*tertiary*). Family socioeconomic status at birth was based on *father's occupation* at the time of the child's birth. It was assessed using the Elley and Irving (W and I, 1976) scale of socioeconomic status for New Zealand. This index ranks families onto six levels on the basis of paternal occupation. For this analysis, the scale was reverse-coded and collapsed into three levels as follows: (a) Levels 1–2 (professional, managerial), (b) Levels 3–4 (clerical, technical, skilled), and (c) Levels 5–6 (semiskilled, unskilled, unemployed). *Family type* was defined as whether the cohort member was born into a single- or two-parent family. Finally, an area-level socioeconomic variable was linked to the CHDS cohort using *area-level deprivation* which was defined as NZDep91: a New Zealand index of deprivation available by meshblock (smallest geographic reporting unit) in 1991.

### 2.5. Exposure – air pollution

Historical estimates of air quality were problematic to obtain due to limited availability of specific suspended particulate matter measurements both locally and nationwide. Therefore, we used local historical records of the (black) smoke that was measured either in time-restricted campaigns (usually over Southern Hemisphere winters) or continually at a limited number of locations. Historical records during the late 1980's and 1990's were sparse due to changes of responsibilities and reorganisation of routine air pollution monitoring in NZ.

More specific, historical air pollution data (1971–1994) were obtained from the Canterbury Regional Council (ECAN) and included monthly (black) smoke estimates (micrograms (one-millionth of a gram) per cubic metre of air or  $\mu\text{g}\cdot\text{m}^{-3}$ ) from 30 monitoring stations across the wider Christchurch area. We restricted the period to 1977–1987 due to alignment with the birth cohort data and data availability, which was limited after 1987. We also did not consider 12 monitoring stations due to extremely sparse air pollution data over time. Missing data from the remaining 18 monitoring locations were individually imputed. For more details see online YUYU materials (Figure S1 and S2). Data for more complete monitoring stations were imputed using the seasonally splitted missing value imputation method (Moritz and Bartz-Beielstein, 2017). The less complete air pollution data were imputed using the fast imputation of missing values by chained random forests. We combined previously completed monitoring stations and additional time-related variables (year, month, season, usual order of monthly air pollution and average ratio of a month and the lowest-polluted month of the year).

Point estimates at monitoring locations were interpolated into both monthly and annual air pollution surfaces in a  $100 \times 100$  m grid that was later aggregated into census area units so that the estimates are spatially aligned with the newer air pollution surveys data from HAPINZ studies (Kingham et al., 2008, Kuschel et al., 2022). Spatiotemporal random forest regression kriging, combining random forest prediction of smoke levels and the kriging prediction of the random forest residuals, was utilised as an interpolation method using implementation in *caret*, *randomForest* and *automap* R packages. Additional explanatory variables in the random forest part included year and consecutive year (and month/consecutive month), rasterised socioeconomic deprivation (1991), density of wood and coal burners (1991), elevation, and distances to main roads, buildings, and coast extracted from historical New Zealand Mapping Service Topographical Maps (NZMS1 1979, scale 1:63,360), and distance to a proxy for greenspace (pervious surface) in 1985. Air pollution exposure of CHDS cohort members was then approximated by spatial join of members' residential addresses and annual smoke/-aggregated area-level estimates. Data from 1977–1987 were linked to 1991 census area units.

**Table 1**

CHDS cohort members with air pollution records (AP) available and not available (NA) in childhood by family socioeconomic status at birth.

Parental employment	CHDS age (years)											
	Birth		2		4		6		8		10	
	AP	NA	AP	NA	AP	NA	AP	NA	AP	NA	AP	NA
Least skilled	306	36	255	87	234	108	223	119	213	129	203	139
	89%	11%	75%	25%	68%	32%	65%	35%	62%	38%	59%	41%
Medium skilled	603	65	497	171	449	219	444	224	430	238	411	257
	90%	10%	74%	26%	67%	33%	66%	34%	64%	36%	62%	38%
Most skilled	243	12	206	49	181	74	176	79	170	85	167	88
	95%	5%	81%	19%	71%	29%	69%	31%	67%	33%	65%	35%
Total	1152	113	958	307	864	401	843	422	813	452	781	484
	91%	9%	76%	24%	68%	32%	67%	33%	64%	36%	62%	38%

Note: % is of the total n at each wave of data collection by family socioeconomic status (SES). CHDS cohort members missing is due to: i) not followed up, ii) address unable to be geocoded (i.e. participant could be overseas), or iii) air pollution measure missing. Data are presented for the 6 out of 12 waves of data collection from birth to 10 years old. 13 individuals did not have SES at birth recorded.

## 2.6. Statistical analyses

We followed the Spatial Lifecourse Epidemiology Reporting Standards (ISLE-ReSt) Statement (Jia et al., 2020). With approximate N=900 the minimum detectable odds ratios ranged from 1.4–3.3 at 80% power ( $\alpha=0.05$ ). For the purpose of this short communication, we examined exposure to air pollution in relation to the sociodemographic and socioeconomic characteristics outlined above. Non-parametric two-way ANOVA with rank-transformed air pollution data was used to test differences in air pollution exposure by demographic and socioeconomic variables of individuals and time (represented by survey waves), as well as their interaction.

## 3. Results

### 3.1. Descriptive statistics

Table 2 describes the relationship between sociodemographic and socioeconomic background factors and median air pollution values (in  $\mu\text{g.m}^{-3}$ ) at two yearly age intervals from birth to age 10 years. Results show that the highest overall median levels of air pollution exposure for the cohort were at birth ( $24.1 \mu\text{g.m}^{-3}$ ) and age 2 years ( $24.3 \mu\text{g.m}^{-3}$ ), with exposure levels gradually decreasing until age 6 ( $20.6 \mu\text{g.m}^{-3}$ ), where it remained largely stable until age 10 years ( $20.5 \mu\text{g.m}^{-3}$ ). There were few differences by sex in median air pollution exposure at any age. Māori/Pacific were exposed to higher levels of air pollution across all ages. Specifically, Māori/Pacific children were exposed to higher levels of air pollution from birth ( $26.1 \mu\text{g.m}^{-3}$  vs.  $24.0 \mu\text{g.m}^{-3}$ ) to age 10 years of age ( $22.0 \mu\text{g.m}^{-3}$  vs.  $20.4 \mu\text{g.m}^{-3}$ ) compared to children of European/Other ethnic background. Cohort members born to younger mothers were exposed to higher air pollution at birth (<20 years= $26.0 \mu\text{g.m}^{-3}$  vs. >35 years= $23.1 \mu\text{g.m}^{-3}$ ) through to age 10 years (<20 years= $21.5 \mu\text{g.m}^{-3}$  vs. >35 years= $19.8 \mu\text{g.m}^{-3}$ ). Children born to less educated mothers were also exposed to higher levels of air pollution from birth (None= $24.5 \mu\text{g.m}^{-3}$  vs. Tertiary= $23.2 \mu\text{g.m}^{-3}$ ) to age 10 (None= $20.9 \mu\text{g.m}^{-3}$  vs. Tertiary= $19.8 \mu\text{g.m}^{-3}$ ). Differences were also noted for father's occupation, with the least skilled, exposed to higher levels of air pollution at birth ( $25.7 \mu\text{g.m}^{-3}$  vs.  $23.2 \mu\text{g.m}^{-3}$ ) through to 10 years ( $21.5 \mu\text{g.m}^{-3}$  vs.  $19.6 \mu\text{g.m}^{-3}$ ). Finally, cohort members with a single parent (compared to two parents) experienced higher levels of air pollution exposure at birth ( $24.9 \mu\text{g.m}^{-3}$  vs.  $24.1 \mu\text{g.m}^{-3}$ ) through to age 10 years ( $21.9 \mu\text{g.m}^{-3}$  vs.  $20.4 \mu\text{g.m}^{-3}$ ) and the largest difference was seen for area-level deprivation. Cohort members born into the most deprived areas (compared to least deprived) at birth ( $26.3 \mu\text{g.m}^{-3}$  vs.  $23.0 \mu\text{g.m}^{-3}$ ) through to age 10 years ( $22.0 \mu\text{g.m}^{-3}$  vs.  $19.5 \mu\text{g.m}^{-3}$ ).

Additional statistical testing using two-way ANOVA confirmed differences for all individual characteristics, except sex at birth (see supplementary materials Table S1). We also examined differences by time represented by survey waves. No interactions were found between

individual characteristics and wave of data collection (time). This means that while there were significant differences by characteristics and time, effects were independent of each other suggesting that temporal trends (often decreases in air pollution) were similar regardless of the group. For instance, if there were existing differences by area-level deprivation at birth and air pollution improved over time, these improvement levels were similar regardless of area-level deprivation category over time (Table S1).

## 4. Discussion

This study used recent innovations in spatial data science to integrate historical air pollution data with data from a well-defined birth cohort to examine historical inequities in exposure to air pollution over the first 10-years of life. The first ten years of life is an important period of rapid brain growth and development, as well as child socioemotional, behavioural and cognitive development. Our study design and data respond to recent calls to integrate environmental exposure data within a lifecourse spatial epidemiological framework to examine long-term changes in air pollution exposure and associations between the extent of exposure and outcome (Hobbs and Atlas, 2019).

Study findings provide evidence to support the feasibility of utilising historical birth cohort data to characterise patterns of air pollution exposure over time and during an important period of childhood when environmental factors may be especially salient. We successfully linked birth cohort data from the 1970's and 1980's to estimated air pollution exposure from birth in 1977 to age 10 in 1987. Encouragingly, exposure to air pollution decreased slightly from birth to age 10 years which may have been due to air quality control strategies implemented in 1970s and 80 s under the Clean Air Act 1972 and associated Clean Air Zone Orders (1974 and 1984), which included greater controls on industrial and domestic sources of air pollution. These Orders restricted the type of domestic fuel burners that could be used as well as the fuels that could be burnt in them. This period marked the start of an improvement in air quality in Christchurch, although smoke concentrations did not show much of a decline until the late 1980s (Graham and Narsey, 1994). Stricter controls were put in place following the 1991 Resource Management Act, resulting in a steady decline in air pollution concentrations that has continued to improve since the early 2000s (Spronken-Smith et al., 2002, Appelhans et al., 2013). However, during the 1970s to the early 2000s variations in the dominant weather patterns during the winter period also likely contributed to significant inter-annual variability in air pollution concentrations often making it difficult to identify a clear trend (Appelhans et al., 2013).

Despite this, our findings did show that inequity existed in air pollution exposure by several individual sociodemographic factors such as ethnicity, early motherhood, family socioeconomic adversity and area-level deprivation. This supports previous evidence demonstrating inequities in exposure to air pollution (Fairburn et al., 2019, Landrigan

**Table 2**  
Socio-demographic characteristics of the study sample by median air pollution exposure (black smoke measured in  $\mu\text{g}\cdot\text{m}^{-3}$ ).

Characteristic	Birth <sup>1</sup>	Year 2 <sup>1</sup>	Year 4 <sup>1</sup>	Year 6 <sup>1</sup>	Year 8 <sup>1</sup>	Year 10 <sup>1</sup>
<b>Overall</b>	24.1 (3.3)	24.3 (3.7)	22.0 (3.6)	20.6 (2.8)	20.7 (2.7)	20.5 (2.5)
<b>Sex at birth</b>						
Male	24.1 (3.4)	24.3 (3.7)	22.2 (3.7)	20.7 (2.7)	20.9 (2.8)	20.5 (2.6)
Female	24.2 (3.2)	24.3 (3.7)	21.8 (3.6)	20.3 (2.5)	20.7 (2.9)	20.5 (2.5)
<b>Ethnicity</b>						
European/Other	24.0 (3.4)	24.1 (3.5)	21.8 (3.5)	20.2 (2.7)	20.4 (2.8)	20.4 (2.5)
Māori/Pacific	26.1 (3.2)	25.6 (3.0)	23.6 (3.3)	21.6 (1.8)	22.2 (2.2)	22.0 (1.8)
<b>Mother's age (years)</b>						
≤20	26.0 (3.9)	24.8 (3.6)	23.4 (4.4)	21.3 (3.5)	21.7 (3.7)	21.5 (3.4)
21–25	24.6 (3.1)	24.8 (3.7)	22.6 (3.9)	20.8 (3.0)	21.3 (3.2)	21.3 (3.3)
26–30	23.6 (3.2)	24.1 (3.5)	21.4 (3.1)	20.2 (2.5)	20.4 (2.5)	20.3 (2.2)
31–35	23.5 (2.5)	23.6 (3.0)	21.2 (2.8)	19.5 (2.6)	19.8 (2.4)	19.6 (2.4)
>35	23.1 (2.6)	24.2 (3.7)	21.3 (3.3)	20.1 (2.5)	20.2 (2.7)	19.8 (2.5)
<b>Mother's education</b>						
None	24.5 (3.5)	24.8 (3.7)	22.6 (4.1)	21.1 (3.4)	21.5 (3.5)	20.9 (3.2)
Secondary	24.2 (3.2)	24.2 (3.5)	21.8 (3.4)	20.3 (2.6)	20.7 (2.7)	20.5 (2.3)
Tertiary	23.2 (2.4)	23.6 (2.7)	20.9 (2.2)	19.4 (1.9)	19.8 (1.6)	19.8 (1.7)
<b>Father's occupation</b>						
Least skilled	25.7 (3.5)	25.2 (3.3)	23.5 (4.1)	21.3 (3.0)	21.8 (3.4)	21.5 (3.2)
Medium	24.0 (3.4)	24.1 (3.7)	21.8 (3.7)	20.6 (3.1)	20.7 (3.0)	20.5 (2.8)
Most skilled	23.2 (2.5)	23.7 (2.8)	21.1 (2.2)	19.6 (1.6)	19.7 (1.6)	19.6 (1.4)
<b>Family type</b>						
Single-parent	24.9 (3.1)	24.8 (3.2)	23.5 (3.9)	21.5 (3.8)	21.8 (2.7)	21.9 (2.2)
Two-parent	24.1 (3.3)	24.2 (3.7)	21.8 (3.6)	20.3 (2.5)	20.7 (2.6)	20.4 (2.5)
<b>Deprivation</b>						
1 (least deprived)	23.0 (1.9)	23.3 (2.3)	20.5 (1.4)	19.3 (1.5)	19.5 (1.7)	19.5 (1.5)
2	23.5 (3.2)	23.6 (2.9)	21.2 (3.8)	20.2 (3.5)	20.4 (3.3)	20.4 (3.4)
3	24.5 (3.2)	25.1 (3.4)	23.2 (4.8)	21.4 (3.7)	22.4 (3.5)	21.5 (3.5)
4	25.6 (3.2)	25.6 (3.6)	23.9 (3.2)	21.8 (3.2)	22.3 (3.3)	22.0 (2.9)
5 (most deprived)	26.3 (3.7)	26.2 (2.9)	24.1 (3.4)	21.8 (2.6)	22.3 (3.0)	22.0 (3.0)

<sup>1</sup> median (median absolute deviation)

et al., 2019, Pearce et al., 2006, Brajer and Hall, 2005). More contemporary UK based evidence has shown that decreases over time in air pollution from 2001 to 2011 were concentrated in the least deprived areas of Great Britain (Mitchell et al., 2015). However, our findings showed that decreases, at least in the first ten years of life from 1977 to 1987, were relatively uniform across different sociodemographic and socioeconomic factors. Uniformity may also relate to relatively low levels of migration rates in the early years (Murray et al., 2021, Norman and Boyle, 2014) however, high levels of residential mobility have been seen in NZ especially in childhood (Marek et al., 2023, Morton et al., 2014, Morton et al., 2017). It remains to be seen if these patterns persist in more contemporary estimates of air pollution such as  $\text{PM}_{2.5}$  or  $\text{PM}_{10}$ .

Geospatial studies in health research are often limited by utilizing spatial and temporal cross sections that do not capture true spatiotemporal dynamics (Deng et al., 2024). For instance, change in residence or change in exposure over space and time, or longitudinal measures of health behaviours and outcomes. This study is an important first step in examining the environmental determinants of health, and particularly how air pollution may relate to health across the lifecourse within a spatial lifecourse epidemiological framework. While we have addressed some of these questions, any lifecourse analyses in the future will remain challenging. For instance, it is often difficult to investigate changes in air quality over time and space as air pollution measurements have changed with the use of more advanced measurement techniques, resulting in improvements in accuracy and differences in the pollutant characteristics measured. In this case, air pollution data from childhood was only available for Christchurch and relied on measurements of black smoke, not the more contemporary metrics of air pollution (suspended particulate material, such as  $\text{PM}_{10}$  and  $\text{PM}_{2.5}$ ). Moreover, we also only have a static cross-sectional area-level deprivation measure although air pollution and individual variables are time varying (Mitchell et al., 2015). However, as highlighted as a major limitation of evidence in a recent meta-analysis, our data are largely now better able to understand, amongst other things, the role of both individual- and area-level confounders of the air pollution-health association (Park et al., 2021). By successfully integrating longitudinal air pollution exposure data with longitudinal data from a prospectively studied birth cohort, we are now able to begin to robustly explore the associations between air pollution and health.

In this brief contribution, we highlight how innovations in spatial data science can progress our understanding of the environmental determinants of health by enabling us to combine historical environmental data with prospectively assessed birth cohort data. Using a lifecourse spatial epidemiological framework means we can now better capture cumulative air pollution exposure over early stages of the lifecourse, a changing dynamic that may drive health outcomes throughout the whole lifecourse. We believe this research lays a platform for more effectively disentangling the links between health and place by accounting for the spatial processes that underlie observed patterns, including cumulative effects of air pollution exposure over time. When combined with contemporary air pollution measurements, future research could now use health data to examine the cumulative impact of air pollution over the lifecourse on both physical and mental health in a well-studied birth cohort.

#### Data availability statement

The CHDS data are not freely available as we do not currently have ethical approval to upload these data to any repository and this prevents us from sharing this data in this way. However, data are available on request, subject to approval by the Christchurch Health and Development Study Director: chds.uoc@otago.ac.nz The change in the food environment data used in this study are freely available at the Geo-Health Laboratory website under the data tab: <https://www.canterbury.ac.nz/science/research/geohealth/>

#### Ethical approval

All phases of the CHDS were subject to ethical approval by the New Zealand Health and Disabilities Ethics Committee.

#### CRediT authorship contribution statement

**M. Hobbs:** Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Resources, Data curation, Writing – original draft, Writing – review & editing, Visualization, Supervision, Project administration, Funding acquisition. **L. Marek:** Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation,



Resources, Data curation, Writing – original draft, Writing – review & editing, Visualization. **G.F.H. McLeod:** Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Resources, Data curation, Writing – original draft, Writing – review & editing, Visualization. **L.J. Woodward:** Conceptualization, Writing – review & editing, Supervision, Funding acquisition. **A. Sturman:** Conceptualization, Methodology, Investigation, Resources, Data curation, Writing – review & editing, Supervision. **S. Kingham:** Conceptualization, Resources, Writing – review & editing. **A. Ahuriri-Driscoll:** Conceptualization, Methodology, Investigation, Writing – review & editing, Funding acquisition. **M. Epton:** Conceptualization, Writing – review & editing, Funding acquisition. **P. Eggleton:** Validation, Formal analysis, Investigation, Resources, Data curation, Writing – review & editing. **B. Deng:** Validation, Formal analysis, Investigation, Resources, Data curation, Writing – review & editing. **M. Campbell:** Conceptualization, Writing – review & editing. **J. Boden:** Conceptualization, Methodology, Formal analysis, Investigation, Resources, Data curation, Writing – review & editing, Supervision, Funding acquisition.

### Declaration of competing interest

All authors declare no conflicts of interest.

### Data availability

The authors do not have permission to share data.

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### Supplementary materials

Supplementary material associated with this article can be found, in the online version, at [doi:10.1016/j.sste.2024.100675](https://doi.org/10.1016/j.sste.2024.100675).

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