



Can smartphone data identify the local environmental drivers of respiratory disease?

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ABSTRACT

Asthma and allergic rhinitis (or hay fever) are ubiquitous, chronic health conditions that seasonally affect a sizeable proportion of the population. Both are commonly triggered or exacerbated by environmental conditions including aeroallergens, air quality and weather. Smartphone technology offers new opportunities to identify environmental drivers by allowing large-scale, real-time collection of day-to-day symptoms. As yet, however, few studies have explored the potential of this technology to provide useful epidemiological data on environment-symptom relationships. Here, we use data from the smartphone app 'AirRater' to examine relationships between asthma and allergic rhinitis symptoms and weather, air quality and pollen loads in Hobart, Tasmania, Australia. We draw on symptom data logged by app users over a three-year period and use time-series analysis to assess the relationship between symptoms and environmental co-variables. Symptoms are associated with particulate matter (IRR 1.06, 95% CI: 1.04–1.08), maximum temperature (IRR 1.28, 95% CI: 1.13–1.44) and pollen taxa including *Betula* (IRR 1.04, 95% CI: 1.02–1.07), Cupressaceae (IRR 1.02, 95% CI: 1.01–1.04), Myrtaceae (IRR 1.06, 95% CI: 1.02–1.10) and Poaceae (IRR 1.05, 95% CI: 1.01–1.09). The importance of these pollen taxa varies seasonally and more taxa are associated with allergic rhinitis (eye/nose) than asthma (lung) symptoms. Our results are congruent with established epidemiological evidence, while providing important local insights including the association between symptoms and Myrtaceae pollen. We conclude that smartphone-sourced data can be a useful tool in environmental epidemiology.

1. Introduction

Allergic rhinitis (or hay fever) and asthma are two of the most common chronic inflammatory respiratory diseases worldwide (Pawankar et al., 2013). Their incidence and prevalence are shaped by a complex interaction of genetic, environmental and lifestyle risk factors (Fernandez et al., 2008; Abe et al., 2009; Makra et al., 2015; Wang et al., 2016; Barnish et al., 2017). Clinical symptoms fluctuate both day to day and seasonally, with these fluctuations depending on the severity of the illness, management interventions such as the use of asthma or allergy medications, and the presence of symptom triggers (Reddel et al., 2015). Many environmental factors including changes in air

temperature, humidity, respiratory viral illnesses, air pollution, airborne pollen and other aeroallergens can precipitate or worsen symptoms (Chen et al., 2006; Díaz et al., 2007; Kim et al., 2008; Medek et al., 2012; Makra et al., 2015; Davies et al., 2016; James et al., 2018).

Understanding which environmental conditions act as triggers can inform symptom management on both an individual and a population scale. Yet symptom-environment relationships are contingent on both individual and local geographical context, and untangling the complex mixture of interacting factors is challenging: for example, meteorological factors such as temperature, rainfall and humidity can both directly influence respiratory symptoms, as well as mediate other environmental determinants of symptoms, such as air quality and

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airborne pollen concentrations (Heinrich and Wichmann, 2004; Kim et al., 2008; Soyiri et al., 2013; Makra et al., 2015; Medek et al., 2015; Damialis et al., 2019). Air quality can act as both an adjuvant or amplify pollen allergenicity (D'Amato et al., 2010; Reinmuth-Selzle et al., 2017), while individuals may be sensitised to multiple (potentially co-occurring and/or cross-reactive) pollen types (Bastl et al., 2018).

Comprehensive, place-based studies incorporating multiple potential environmental stressors are critical if we are to (i) understand how these interacting factors drive asthma and allergic rhinitis symptoms; and (ii) provide sufferers with the information needed to minimise their exposure. Such holistic studies, however, remain limited in number and are frequently based on routinely collected health system data, such as hospital admissions and emergency department presentations (e.g. Atkinson et al., 2015; Osborne et al., 2017). While important, such high severity outcome measures fail to capture the most ubiquitous burden of asthma and allergic rhinitis: day-to-day symptoms that impact health and quality of life, but rarely lead to hospital or primary care presentations.

Smartphone technology provides new opportunities to fill this gap. In addition to supporting patient self-management (e.g. see Bousquet et al., 2019; Sleurs et al., 2019; Tan et al., 2019), smartphone health applications ('apps') can act as an epidemiological tool by collecting geo-located individual symptom reports in real-time. The ease of smartphone logging means that this method imposes a low burden on participants, can achieve high recruitment, and may support the collection of crowd-sourced symptom data on a large scale over periods of several years (Johnston et al., 2018; Chan et al., 2018; Ambrosini et al., 2018). While not without challenges—including selection, retention and reporting bias—a recent US validation study found coherent epidemiological trends that support the validity of asthma-related data obtained via crowd-sourcing app-based methods (Chan et al., 2018). The web and app-based 'Patient's Hayfever Diary' has also provided useful insights into relationships between hay fever symptoms and pollen dynamics in Europe (e.g. Bastl et al., 2014; Kmenta et al., 2016; Bousquet et al., 2017; Bastl et al., 2018).

Here we exploit this emerging technology to evaluate associations between meteorology, air quality and multiple pollen taxa with respiratory symptoms in Tasmania, Australia. Despite having amongst the highest rates of allergic respiratory disease globally (Australian Institute of Health and Welfare and Australian Bureau of Statistics, 2017), empirical evidence regarding asthma and allergy triggers in Australia remains scarce. In part, this reflects the challenges of a historical paucity of aerobiological monitoring (Haberle et al., 2014), poor air quality monitoring coverage, and the lack of diagnostic antigens for evaluating sensitisation to endemic plant species (Cook et al., 2007). Overall, this means that understandings of respiratory symptom drivers in Australia are in their infancy compared to much of the rest of the developed world.

This study draws on symptom data from the smartphone app, 'AirRater' in order to:

- i. Provide new knowledge about the triggers of symptoms of asthma and allergic rhinitis in Australia; and
- ii. Advance understandings of the utility of crowd-sourced app data in epidemiological studies of respiratory disease.

In this paper, we combine the symptoms logged by AirRater app users with environmental data to test the hypothesis that eye, nose and lung symptom reports from the app are associated with daily atmospheric environmental conditions (air pollution, pollen and meteorological conditions). The research was approved by the Tasmanian Health and Medical Human Research Ethics Committee (Reference number: H0015006).

2. Materials and methods

2.1. The AirRater smartphone app

AirRater (<https://airrater.org/>) was launched in October 2015. Described in detail in Johnston et al. (2018), AirRater is an integrated system that tracks exposure to air particles (PM_{2.5}), aeroallergens and temperature and communicates these to app users via interpolated maps. The primary aim of the app is to communicate environmental conditions that may trigger respiratory symptoms in vulnerable individuals as a public service, rather than to act as a coaching tool for clinical self-management (cf. Bousquet et al., 2018; Sleurs et al., 2019). The app also allows individuals to report their symptoms in real-time, collecting information on symptom location (eyes, nose or lungs) and severity. These symptom reports are archived with co-located exposure estimates, providing a novel database for epidemiological research.

The app is a public resource and freely available. It can be used by anyone although users are invited to register as study participants. Study participants are asked to provide some of their medical history and are blinded to environmental conditions until they have submitted a symptom report. They also receive a reminder prompt to log their symptoms every six days.

About 20% of people who download the app register as study participants. However, this group provides the vast majority of symptom reports (approximately 80%). A significant majority of these registered study participants identify as having allergic rhinitis, asthma or both (Johnston et al., 2018). This means that the app is mostly used by (and most symptom reports come from) the target group for whom the AirRater service was developed.

The app is set up to enable users to report information about symptoms commonly associated with exacerbations of allergic rhinitis and asthma rapidly and easily. The data collected are adapted from the Control of Allergic Rhinitis and Asthma Test (CARAT) (Azevedo et al., 2013). If a user wants to report symptoms they are taken to a screen and asked to identify the region affected (Eye, Nose, Lungs or Other). They are then able to specify the symptom or absence of particular symptoms for each region affected, and report the severity of that symptom (mild, moderate or severe, as an optional field to minimise reporting burden). They are taken to further screen where medication use is collected. The symptom data collection protocol is detailed fully in Section A1, Appendix A.

2.2. Symptom and environmental data

This paper evaluates associations between environmental conditions and symptom reports relating to the eyes, nose and lungs logged by AirRater app users located in Hobart, Tasmania (Fig. 1, population 204,000) over the first three years of the app's operation (October 29, 2015–October 29, 2018). Symptom reports were collected via the app as detailed in Section 2.1; and we sourced meteorological and air quality data from the Environment Protection Authority (EPA) of Tasmania's air quality monitoring network, known as the Base Line Air Network of EPA Tasmania (BLANKET). BLANKET stations measure particulate matter less than 2.5 µm in aerodynamic diameter (PM_{2.5}) using a DustTrak optical analyser; the stations also sample air temperature, relative humidity, precipitation, barometric air pressure, wind speed and wind direction every 10 min. The network does not measure gaseous pollutants because these occur at negligible levels in Tasmania and are therefore not routinely monitored by the Environment Protection Authority. For this study we aggregated meteorological and air quality data from the Hobart BLANKET station into daily observations including: rainfall (mm), maximum and minimum temperature (°C), mean relative humidity (percentage), and daily average concentration of PM_{2.5} (µg/m³). The pollen data were collected by our team using a Hirst-type volumetric spore trap (Burkard Manufacturing) fitted with a 24-h head using methods described in Johnston et al. (2018). The trap

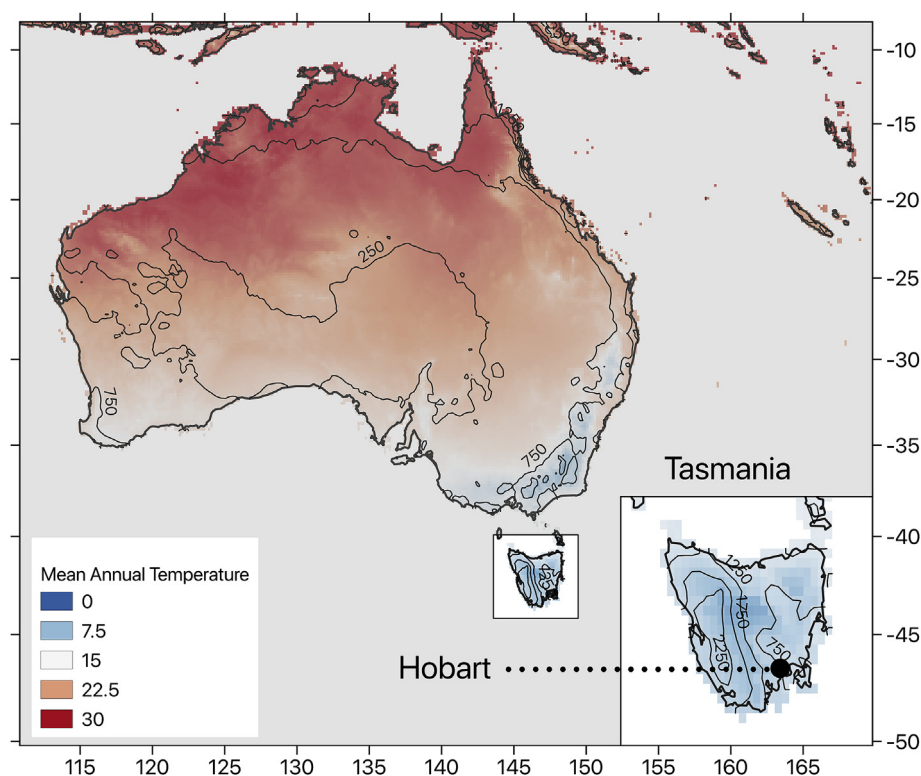


Fig. 1. Map showing the location of Hobart, Tasmania, Australia.

is located on the roof of the Sandy Bay campus, University of Tasmania and we collected daily pollen concentrations for 27 pollen taxa and one fungal spore (*Alternaria*, for all monitored taxa see [Table A1](#)).

2.3. Statistical analysis

We used time-series analysis to assess the association between symptoms and environmental conditions; specifically a negative binomial regression model because the distribution of the daily symptom counts was over-dispersed. We used the seven-day moving average of active users as an offset term to account for the shifting size of the app user base, which can fluctuate significantly day to day ([Salathé et al., 2012](#)). For this purpose, we defined an ‘active user’ as anyone who had interacted with the application in the previous seven days (regardless of whether they reported symptoms or not). We removed duplicate reports of the same symptom type by a single user on a single day so that the outcome measure for each individual was binary (symptoms or no symptoms on that day). Our overall model outcome measure was thus the daily proportion of active users reporting at least one symptom. Throughout this paper we refer to this as the ‘symptom reporting rate’.

We assessed the association between the symptom reporting rate and the following co-variables: daily maximum and minimum temperature, rainfall, average relative humidity, $PM_{2.5}$, and the atmospheric concentration (grains per m^3) of pollen. We adjusted for potential confounding by public holidays and day of week, as behaviour and exposure to environmental conditions can vary between working and non-working days ([Kim et al., 2008](#); [Chen et al., 2016](#)).

We implemented a seasonally stratified subgroup analysis (spring/summer vs autumn/winter) to assess the impact of seasonal variations in environmental conditions and user behaviour. The spring/summer analysis included the months from September–February and the autumn/winter analysis from March–August. In these analyses, only pollen taxa contributing at least 5% of the pollen load in the relevant time period were included. We implemented a separate second stratified analysis to investigate differences in environmental associations

between symptom reports related to the eyes/nose (more likely to be associated with allergic rhinitis) and those related to the lungs (more likely to be associated with asthma).

We conducted additional analyses to evaluate the sensitivity of our results to:

1. The definition of the active user base. These analyses explored the impact of defining the active user base over different time periods from 7 to 28 days (defining an active user as anyone who had interacted with the application over that time period, whether reporting symptoms or not). The choice of time period did not meaningfully impact the results (see [Table A3](#)); for our main analysis we opted to use the 7-day window as this most accurately reflected the sometimes sharp fluctuations in user numbers (for example, in response to media reports).
2. The inclusion or exclusion of anonymous users in our analysis. As noted in [Section 2.1](#), AirRater users may choose to use the app anonymously or to register as study participants. Study participants only are blinded to environmental conditions before symptom reporting; anonymous users are free to see the environmental conditions at any time. To test whether knowledge of environmental conditions introduced bias, we conducted a sensitivity analysis of registered (ie. blinded) users only. The results were very similar (see [Table A4](#)), we therefore retained symptom reports from all users in the analysis to maximise power.

We also performed a range of diagnostic evaluations; this included investigating quantile-quantile (QQ) and residual density distributions for abnormalities. All diagnostic tests were satisfactory (see [Figures A1–A3](#)).

For ease of interpretation, results are presented as the unit increase in the symptom reporting rate per 10 °C increase in temperature, 10 mm increase in rainfall, 10% increase in relative humidity, 10 $\mu g/m^3$ increase in $PM_{2.5}$ and 10 grains/ m^3 in pollen concentration. All analyses were performed in R version 3.4.4 ([R Development Core Team,](#)

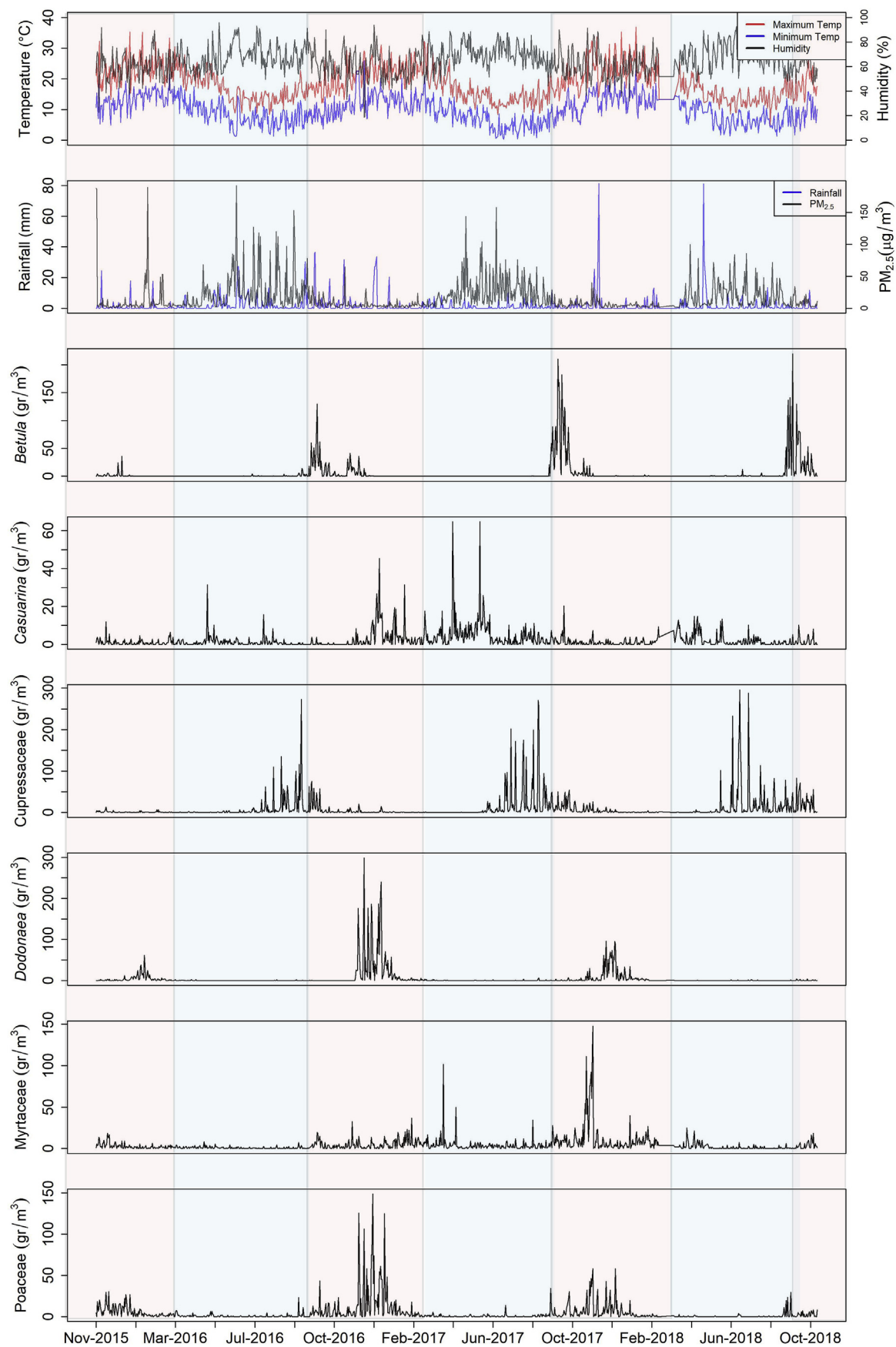


Fig. 2. Meteorological and pollen data for Hobart over the three-year study period (October 29, 2015 to October 29, 2018). Note that the pollen taxa have varying y-axes for ease of display.

2018) using the MASS and ggplot2 packages (Venables and Ripley, 2002; Wickham, 2009).

3. Results

3.1. Study population and environmental conditions

AirRater had 5141 unique users in Tasmania over the study period of October 29, 2015–October 29, 2018 (the first three years of the app's operation). A total of 6801 symptom reports were submitted through the app in the study area over this time, with the number of reports per day averaging 7.9 (range 0–65). Of the 6801 symptom reports, 6505 were classified as eyes (2045), nose (3306) or lung (1154) symptoms (additional reports of the same symptom type by the same user on the same day were removed). The number of reports submitted per user per year averaged 9.33 and varied from 1 to 427.

The meteorological, air quality and pollen data for Hobart over the study period are illustrated as a time-series in Fig. 2 (for summary statistics see Table A2). Maximum and minimum temperatures reflect Hobart's cool maritime temperate climate: maximums averaged approximately 20 °C in summer and 12 °C in winter; while minimums typically fluctuated between 10 and 15 °C in summer and 5–10 °C in winter. Relative humidity was generally higher in winter and lower in summer but rarely dropped below 50%. PM_{2.5} also showed clear seasonal variation with a higher mean through the winter as a result of domestic wood heater emissions (Reisen et al., 2013). In the summer, PM_{2.5} was generally very low apart from occasional peaks due to wildfires. *Betula* (birch), *Casuarina* (she-oak), Cupressaceae (cypress family, including both native and exotic taxa), *Dodonaea* (hop bush, primarily *D. viscosa*), Myrtaceae (includes *Eucalyptus*, *Leptospermum* and *Melaleuca*) and Poaceae (grasses) were the most commonly represented pollen taxa. All show seasonal trends in abundance as well as differences between years: for example, *Dodonaea* and Poaceae were most abundant in 2016/17, while *Betula* was most strongly represented in 2017/18 and 2018/19. No variables met our pre-determined criteria for multicollinearity (> 0.8 Pearson correlation coefficient).

3.2. Associations between environmental conditions and symptom reports

3.2.1. All symptom analysis

Fig. 3 shows the associations between the environmental variables and the daily symptom reporting rate for the full model (including eye, nose and lung symptoms reported in any month, for statistical table see Table A5). At the $p = 0.05$ level, there were significant positive associations between the daily symptom reporting rate and maximum temperature, PM_{2.5} and the pollen taxa *Betula*, Cupressaceae, Myrtaceae and Poaceae. Specifically, a 10 °C rise in the maximum temperature was associated with a 28% increase in all symptom reporting (IRR 1.28, CI 1.13–1.44), while a 10 µg/m³ increase in PM_{2.5} was associated with an increase of 6% (IRR 1.06, CI 1.04–1.08). For pollen, with every 10 grains/m³, the symptom rate increased with *Betula* by 4% (IRR 1.04, CI 1.02–1.07), Cupressaceae by 2% (IRR 1.02, CI 1.01–1.04), Myrtaceae by 6% (IRR 1.06, CI 1.02–1.10), and Poaceae by 5% (IRR 1.05, CI 1.01–1.09). There was a significant inverse association between symptom reporting rates and relative humidity (IRR 0.90, CI 0.85–0.95).

3.2.2. Seasonal stratification

The results from the stratified spring/summer and autumn/winter analyses are presented in Table 1. At the $p = 0.05$ level, the spring/summer model found significant positive associations between the daily symptom reporting rate and, maximum temperature (IRR 1.19, CI 1.00–1.38) and PM_{2.5} (IRR 1.06, CI 1.03–1.10), similar to the unstratified model. This model also found a significant positive association between the symptom reporting rate and *Betula*, *Dodonaea* and *Rumex* pollen, for which a 10 grain/m³ increase was associated with a 3% (IRR

1.03, CI 1.01–1.05), 2% (IRR 1.02, CI 1.00–1.04), and 13% (IRR 1.13, CI 1.04–1.22) respectively. There was an association with Myrtaceae pollen of borderline statistical significance. The results for Poaceae and Cupressaceae pollen were attenuated and lost statistical significance in the spring/summer compared with the full year analysis.

In the autumn/winter model, maximum temperature was not significantly associated with symptom reporting (Table 1), in contrast to both the overall and the spring/summer analyses. However, the association between the symptom reporting rate and PM_{2.5} remained consistent, with a 10 µg/m³ rise in PM_{2.5} associated with an 8% (IRR 1.08, CI 1.04–1.11) increase in symptom reporting. The autumn/winter model also found a significant inverse association between the symptom reporting rate and relative humidity (IRR 0.85, CI 0.76–0.94); and a significant positive association with both Cupressaceae pollen, the most abundant pollen taxon in the cooler months (IRR 1.03, CI 1.00–1.05) and Myrtaceae pollen (IRR 1.09, CI 0.98–1.22).

3.2.3. Symptom group stratification

Table 2 shows the results stratified by symptom group (also displayed as Figure A5). Pollen taxa were prominent amongst the predictors of eye and nose symptoms, with five pollen taxa showing a significant positive association (at $p \leq 0.05$). For every 10 grains/m³ increase, for these specific symptoms, the reporting rate increased with *Betula* by 4% (IRR 1.04, CI 1.02–1.06), Cupressaceae by 2% (IRR 1.02, CI 1.01–1.04), *Dodonaea* by 2% (IRR 1.02, CI 1.00–1.04), Myrtaceae by 6% (IRR 1.06, CI 1.02–1.10), and Poaceae by 6% (IRR 1.06, CI 1.01–1.10). Maximum temperature (IRR 1.343 CI 1.16–1.51) and PM_{2.5} (IRR 1.05, CI 1.02–1.07) were also significant. Relative humidity showed a significant inverse association with the eye and nose symptom reporting rate (IRR 0.89, CI 0.84–0.94); there was also a significant inverse association with *Casuarina* pollen (IRR 0.88, CI 0.78–0.97). No significant associations were found with rainfall or minimum temperature.

Lung symptoms were primarily predicted by meteorological and air quality variables (Table 2). PM_{2.5} and maximum temperatures were both positively associated with lung symptoms. A 10 µg/m³ rise in PM_{2.5} was associated with an increase of 11% (IRR 1.11, CI 1.09–1.14), and a 10 °C increase in daily maximum temperature was associated with a 40% increase in lung symptom reporting (IRR 1.40, CI 1.18–1.63). Relative humidity was again inversely associated with lung symptom reporting (IRR 0.92, CI 0.85–0.99). Cupressaceae and *Betula* pollen were significantly associated with lung symptoms at the $p = 0.05$ level, with an IRR of 1.02 (CI 1.00–1.04) and 1.03 (IRR 1.00–1.05 respectively). Poaceae was positively associated at the $p = 0.1$ level, with a p -value of 0.07.

4. Discussion

AirRater-logged symptoms were clearly associated with air quality, pollen and meteorological conditions. We found an association between symptoms and PM_{2.5} in all model variants, and seasonally-variable associations with maximum temperature, relative humidity and several pollen taxa. Our seasonally-stratified models highlight that there are differences in the pollen taxa associated with symptoms in the warmer versus cooler months; the contrasts we found are in line with each taxon's seasonal abundance (see Fig. 2). Our symptom type stratification highlights differences in triggers between eye and nose symptoms (most likely associated with allergic rhinitis) and lung symptoms (more likely related to asthma); however eye, nose and lung symptoms were all associated with air quality, meteorological conditions and at least some pollen taxa. This underlines the importance of a holistic epidemiological approach when attempting to understand environmental triggers.

With respect to PM_{2.5}, the positive associations in our data are consistent with a large body of epidemiological and mechanistic literature linking particulate matter (including biomass-derived

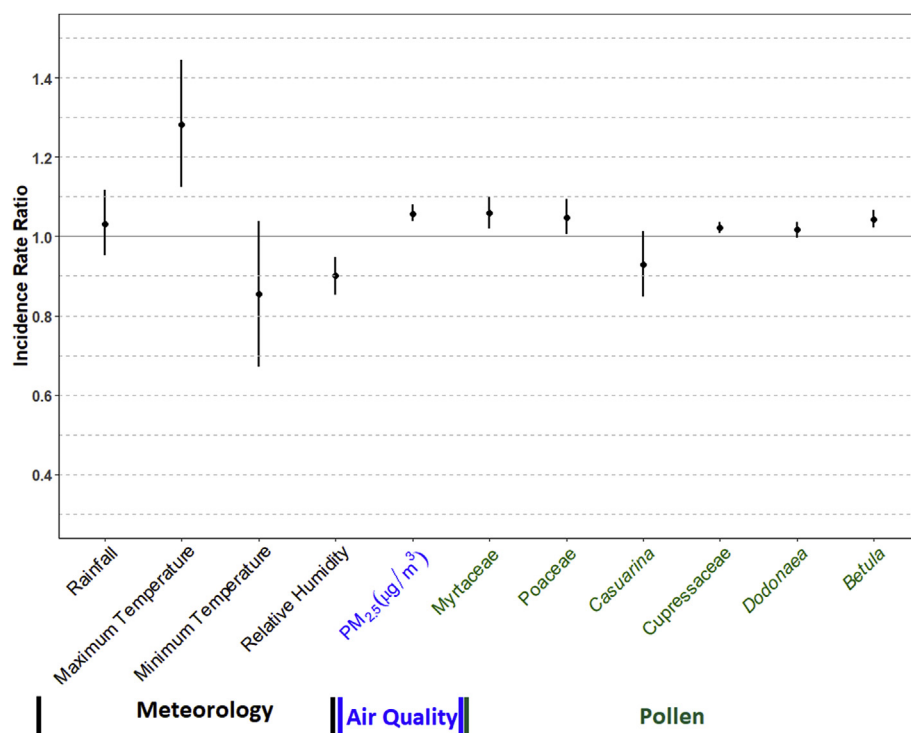


Fig. 3. Incidence rate ratios from a negative binomial for determinants predicting AirRater reported symptoms from October 29, 2015 to October 29, 2018 in Hobart. Note that day of the week and public holiday status were also included in the model; these are not shown here for clarity of presentation. For full statistical results, see [Table A5](#).

Table 1

Results of negative binomial time series models evaluating associations between symptoms logged using the AirRater smartphone app and environmental covariates. The data-set covers eyes, nose and lung symptoms logged by AirRater users in Hobart between October 29, 2015 and October 29, 2018, stratified into two groups: spring/summer (September–February) and autumn/winter (March–August). Only pollen taxa contributing at least 5% of the pollen load in the relevant period were included; the taxa therefore vary slightly between models. All models were adjusted for public holiday and day of week. IRR = Incidence Rate Ratio.

	IRR	SE	CI 2.5	CI 97.5	p-value	Signif. code ^a
Spring/summer						
PM _{2.5}	1.064	1.016	1.034	1.097	< 0.001	***
Max. Temp	1.185	1.095	0.995	1.379	0.053	*
Min. Temp	0.835	1.112	0.619	1.056	0.134	
Rel. Humidity	0.957	1.028	0.904	1.011	0.131	
Rainfall	0.984	1.049	0.894	1.080	0.743	
<i>Betula</i>	1.029	1.010	1.009	1.051	0.002	**
Cupressaceae	1.015	1.010	0.995	1.037	0.150	
<i>Dodonaea</i>	1.019	1.010	1.000	1.038	0.052	*
Myrtaceae	1.034	1.019	0.996	1.074	0.084	.
Poaceae	1.018	1.019	0.979	1.059	0.360	
<i>Rumex</i>	1.127	1.046	1.038	1.221	0.006	**
Autumn/winter						
PM _{2.5}	1.075	1.016	1.042	1.108	0.000	***
Max. Temp	1.118	1.130	0.857	1.388	0.365	
Min. Temp	0.855	1.164	0.541	1.178	0.368	
Rel. Humidity	0.848	1.047	0.759	0.938	0.001	**
Rainfall	1.055	1.076	0.903	1.222	0.469	
<i>Alnus</i>	0.976	1.057	0.870	1.088	0.668	
<i>Casuarina</i>	1.058	1.053	0.942	1.184	0.266	
Cupressaceae	1.026	1.011	1.004	1.050	0.015	*
Myrtaceae	1.093	1.047	0.976	1.222	0.050	*

^a Signif. codes: '***' = < 0.001, '**' = 0.001–0.01; '*' = 0.01–0.05, '.' = 0.05–0.1.

particulate matter) to asthma and a range of other respiratory symptoms (McGowan et al., 2002; Chen et al., 2016; Mirabelli et al., 2016; Pope et al., 2017). Notably, the association in our data is of similar strength both in winter—when wood smoke burning results in consistently high exposure—and summer, when PM_{2.5} levels are mostly

Table 2

Results of negative binomial time-series models evaluating associations between symptoms logged using the AirRater smartphone app and environmental covariates. The data-set covers eye, nose and lung symptoms logged by AirRater users in Hobart between October 29, 2015 and October 29, 2018, stratified into two groups: eyes/nose and lungs. Only pollen taxa contributing at least 5% of the pollen load were included. All models were adjusted for public holiday and day of week. IRR = Incidence Rate Ratio.

	IRR	SE	CI 2.5	CI 97.5	p-value	Signif. code ^a
Eyes/nose						
PM _{2.5}	1.046	1.012	1.023	1.069	< 0.001	***
Max. Temp.	1.332	1.083	1.161	1.506	< 0.001	***
Min. Temp.	0.842	1.101	0.646	1.041	0.111	
Rel. Humidity	0.888	1.026	0.837	0.938	< 0.001	***
Rainfall	1.042	1.045	0.954	1.134	0.354	
<i>Casuarina</i>	0.873	1.048	0.781	0.966	0.008	**
Cupressaceae	1.022	1.007	1.007	1.038	0.003	**
<i>Dodonaea</i>	1.022	1.010	1.002	1.044	0.033	*
Myrtaceae	1.060	1.019	1.020	1.103	0.002	**
Poaceae	1.055	1.021	1.011	1.102	0.009	**
<i>Betula</i>	1.041	1.010	1.018	1.064	< 0.001	***
Lungs						
PM _{2.5}	1.112	1.013	1.086	1.137	< 0.001	***
Max. Temp.	1.399	1.109	1.179	1.625	< 0.001	***
Min. Temp.	0.817	1.132	0.565	1.076	0.161	
Rel. Humidity	0.919	1.034	0.853	0.985	0.016	*
Rainfall	1.052	1.059	0.929	1.165	0.381	
<i>Betula</i>	1.025	1.013	0.998	1.051	0.054	*
<i>Casuarina</i>	1.049	1.054	0.940	1.152	0.360	
Cupressaceae	1.021	1.009	1.002	1.039	0.027	*
<i>Dodonaea</i>	1.005	1.012	0.981	1.029	0.659	
Myrtaceae	1.022	1.021	0.980	1.063	0.290	
Poaceae	1.041	1.023	0.993	1.089	0.071	.

^a Signif. codes: '***' = < 0.001, '**' = 0.001–0.01; '*' = 0.01–0.05, '.' = 0.05–0.1.

low but punctuated by extreme landscape fire-related peaks (see Fig. 2). This suggests that app-sourced data such as ours may be capable of detecting associations between both chronic and acute particulate exposure, and detect responses to both domestic heating and landscape fire-derived smoke. This is congruent with the Asthma Mobile Health

Study, which found that in-app reports were able to detect symptom peaks responding to acute increases of PM_{2.5} during the 2015 Washington fires (Chan et al., 2018). Also notable is the positive association we found between PM_{2.5} and eye and nose symptoms—those symptoms most likely related to allergic respiratory disease. Although less pronounced than the association with lung symptoms, this finding is in line with a growing—if not yet conclusive—body of evidence linking particulate pollution to allergic rhinitis (Sheffield et al., 2011; Baldacci et al., 2015; Teng et al., 2017; Wu et al., 2018; Chen et al., 2018), including by acting as an adjuvant that promotes a pro-allergic immune response (see Reinmuth-Selzle et al., 2017 for a detailed review).

Our meteorological associations are likewise in directions consistent with the wider literature. We found a positive association between symptoms and maximum temperature in all models except the winter stratification. This implies that in our study population, both asthma and allergic rhinitis symptoms increase during times of high temperature. This is congruent with previous studies linking high temperatures to asthma symptoms and other adverse respiratory outcomes (including allergic rhinitis) locally, nationally and internationally (Michelozzi et al., 2009; Xu et al., 2013; Li et al., 2014; Ching-yu Lam et al., 2016; Upperman et al., 2017; Ehelepola et al., 2018; Campbell et al., 2019). An area for future research is to clarify the underlying mechanisms underlying this apparently widespread effect (De Sario et al., 2013; Ching-yu Lam et al., 2016). Although we did not find a statistically significant relationship between symptom reporting and minimum temperature, in all of our models the direction of association was inverse, consistent with the broadly-established link in the wider literature between cold temperatures and poor respiratory outcomes - including both asthma and allergic rhinitis (Abe et al., 2009; Guo et al., 2012; Xu et al., 2013; Zhang et al., 2014; Ehelepola et al., 2018; Kim et al., 2018).

Relative humidity can have a variety of effects on asthma and allergy symptoms. Previous studies have found asthma and/or allergy exacerbations to be associated with both high and low relative humidity, with the direction of association largely climate-dependent (May et al., 2011; Delamater et al., 2012; Ching-yu Lam et al., 2016; Silver et al., 2018). Here, we found a negative (inverse) association between relative humidity and symptoms that was strongly significant ($p < 0.001$) in our overall model. However, when stratified into spring/summer and autumn/winter data-sets, the relationship was significant only for the autumn/winter model (Table 2). Overall, this suggests that there is a negative association between symptoms and humidity in our study population that is strongest when the air is both cool and dry. On this basis, the predominant pathway by which relative humidity affects allergy and asthma symptoms in Tasmania may be the impact of cool dry air on the humidity of the mucosal membrane—an effect that can increase susceptibility to airway infections and irritation by allergens and other irritants. The seasonal difference in our data is congruent with a recent finding of a seasonally variable effect of humidity on asthma presentations on Hong Kong (Ching-yu Lam et al., 2016) and highlights the need to account for seasonality—and the multiple mechanisms by which humidity can impact respiratory symptoms—when considering humidity in epidemiological studies.

Of the pollen types analysed we found positive associations between symptoms with *Betula*, Cupressaceae, *Dodonaea*, Myrtaceae, Poaceae and *Rumex* in one or more models. Of these, *Betula* and *Rumex* are introduced taxa, Myrtaceae (e.g. *Eucalyptus*, *Leptospermum* and *Melaleuca*) is native, while Poaceae and Cupressaceae include both native and introduced species. All of these pollen types except *Dodonaea* have been previously implicated as allergic rhinitis and/or asthma triggers (Hanigan and Johnston, 2007; Panzner et al., 2014; Gibbs, 2015; Domínguez-Ortega et al., 2016; Kam et al., 2016; Le et al., 2017; Guilbert et al., 2018). Of note, the positive association between *Betula*, Cupressaceae and Poaceae pollen with lung symptoms (noting that Poaceae was only marginally significant) is consistent with studies that

have found these pollen types to be associated with asthma related hospital admissions (Calderon-Ezquerro et al., 2018; Guilbert et al., 2018; Olstrup et al., 2019).

The status of the native Myrtaceae as an allergen is somewhat controversial. Very few studies have investigated Myrtaceae as a potential aeroallergen; and a US study concluded that *Melaleuca quinquinervia* was not an important aeroallergen in Florida (Stablein et al., 2002). However, Myrtaceae is commonly a significant contributor to the pollen load in Australia (Haberle et al., 2014) and Hanigan and Johnston (2007) found a strong association between Myrtaceae pollen and respiratory hospital admissions in Darwin (Australia). Gibbs (2015) also found high rates of sensitisation to *Eucalyptus* pollen amongst asthmatic children in Queensland. Our findings add to these studies to provide further evidence that Myrtaceae may be a potential respiratory trigger in Australia and other regions in which it is abundant; given this taxon's ubiquity, we suggest that this body of evidence warrants further attention. The significant association we found between *Dodonaea* pollen and eye/nose symptoms (and all symptoms in spring/summer) also merits further investigation. Overall, our findings highlight the need for further work to enhance the poor knowledge base regarding the allergenicity of Australasian plant taxa.

The strengths of this study include the multi-year time-series and the wide range of environmental co-variables assessed. Our use of real-time symptom reporting as an outcome measure allows for more precise temporal matching between symptoms and environmental conditions than can be obtained with more traditional outcome measures such as hospital admissions and pharmacy sales. In addition, this method has allowed us to capture the dynamics of the many less severe asthma and allergy symptoms that do not lead to a quantified health system outcome. While pharmacoepidemiological and panel studies are also capable of capturing such day to day, less severe, symptom information (Johnston et al., 2009; Li et al., 2014; Grundström et al., 2017), crowd-sourced app-based reporting offers a lower cost and highly accessible way to examine daily symptom dynamics cheaply on a population scale. In this way our approach provides an important complement to traditional epidemiological data-sets, which can offer a valuable perspective on the day-to-day dynamics of allergic and respiratory conditions.

The key limitation is our reliance on self-reported data from a self-selected and shifting user base; a pervasive issue for crowd-sourcing app-based studies that requires further investigation to understand impacts on study validity and generalisability (Chan et al., 2018). In particular, in the context of our study, most users of the app identify as having allergic rhinitis, asthma or both (Johnston et al., 2018). This means that our results are not generalisable to the wider population, but could be applicable to those with a history of asthma or allergic rhinitis. In the absence of demographic information about our user base, we were unable to control for individual factors (such as age or smoking status), nor were we able to control for the presence of other potential symptom triggers (such as animals or dust), or the use of symptom-reducing medications. All are factors with the potential to mediate environment-symptom relationships (Ching-yu Lam et al., 2016), but we were not able to examine their impact here. While we found no seasonal bias in symptom reporting, an additional caveat is that the identity and characteristics of the study population may have varied over time.

Notwithstanding these caveats, our results are highly congruent with existing mechanistic and epidemiological understandings of the triggers of allergic and respiratory disease. Well-known allergens such as *Betula* and Poaceae feature prominently as pollen predictors, and our study clearly captures the well-known linkage between respiratory symptoms and PM_{2.5}. As expected, our lung-only model found stronger associations with air quality and meteorology; while our eye and nose symptom model revealed stronger linkages with pollen. Overall, this congruence provides confidence that our app derived data-set provides useful insights into the environmental triggers of asthma and allergic rhinitis in Australia, a previously little studied region.

While further work is needed to address challenges such as selection bias, reporting bias and retention, our study adds to a body of literature supporting the validity of crowd-sourced app-based data as a novel tool in epidemiological research (Stieb et al., 2017; Chan et al., 2018; Ambrosini et al., 2018). An important note is that data derived from different apps will have different strengths and weaknesses: as noted by Kenner (2016), m-health apps are designed for a multiplicity of purposes, ranging from clinical management, to data collection for controlled cohort studies, to apps such as AirRater, which are designed to be low burden participatory epidemiology tools that collect data from an uncontrolled but very large study cohorts. Each type of app will provide data with its own caveats and limitations. In our study, we show that data from AirRater, an app that collects minimal information from a shifting user base, yields epidemiological associations that are consistent with the established epidemiological and mechanistic literature on the environmental triggers of asthma and allergic rhinitis. This supports the capacity of data from such apps to provide useful insights, despite some important caveats on interpretation.

While not the focus of this paper, integrated smartphone tools such as AirRater simultaneously offer opportunities in environmental health management; for example by delivering easily accessible health information, creating potential for personally-targeted notifications, and providing new possibilities for public health surveillance (Johnston et al., 2018; D'Antoni et al., 2019). Together, this constitutes a strong case for the extended application of smartphone technology in epidemiological and public health research.

5. Conclusion

In Tasmania, Australia, there is a strong association between respiratory symptoms logged by AirRater app users and particulate matter, maximum temperature and several pollen taxa. Particulate matter appears to be a pervasive symptom driver, being strongly associated with symptoms year-round. Pollen taxa and meteorological factors have more seasonally-nuanced effects. Importantly, Myrtaceae and *Dodonaea* pollen are associated with symptom reporting; these linkages warrant further investigation. Our results are congruent with both mechanistic and established epidemiological evidence and we conclude that smartphone-sourced data can be a useful tool in environmental epidemiology.

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Ethics declaration

This research was approved by the Tasmanian Health and Medical Human Research Ethics Committee (Reference number: H0015006).

CRedit authorship contribution statement

Penelope J. Jones: Writing - original draft, Writing - review & editing, Project administration. **Iain S. Koolhof:** Writing - original draft, Methodology, Formal analysis. **Amanda J. Wheeler:** Conceptualization, Project administration, Funding acquisition, Writing - review & editing. **Grant J. Williamson:** Methodology, Software, Visualization. **Christopher Lucani:** Software. **Sharon L. Campbell:** Project administration, Writing - review & editing. **David M.J.S. Bowman:** Conceptualization, Writing - review & editing, Funding acquisition. **Fay H. Johnston:** Conceptualization, Methodology, Supervision, Funding acquisition, Writing - review & editing.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.envres.2020.109118>.

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Can smartphone data identify the local environmental drivers of respiratory disease?

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Supplementary Information

Appendix A

Section A1: AirRater symptom reporting protocol

Symptom reporting questions

AirRater app users are invited to report any health symptoms they are experiencing via the questions in the box below.

The questions were based on Azevedo et al., 2013, with simplification to facilitate ease of logging in a smartphone app context.

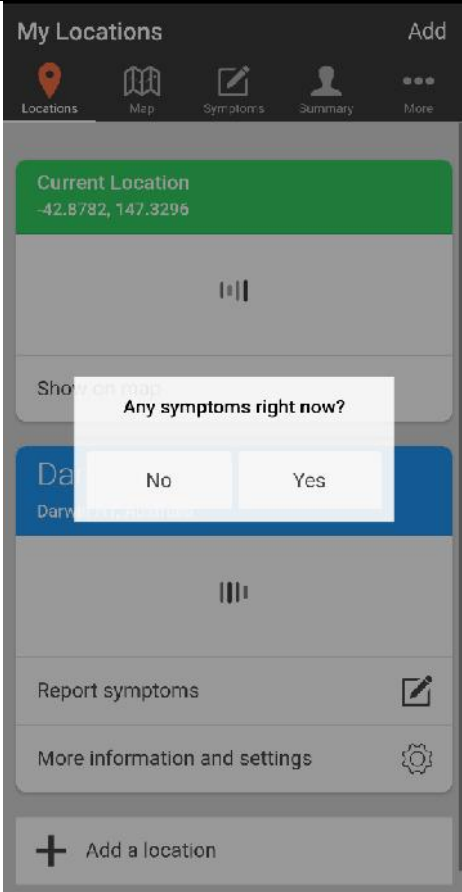
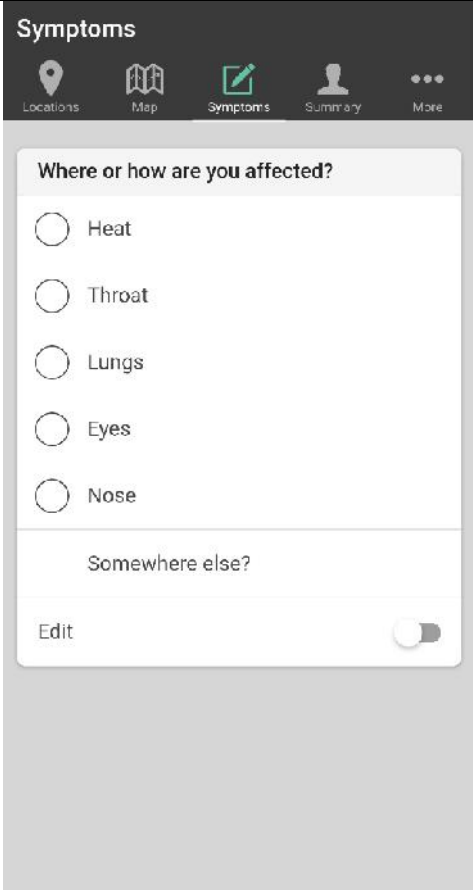
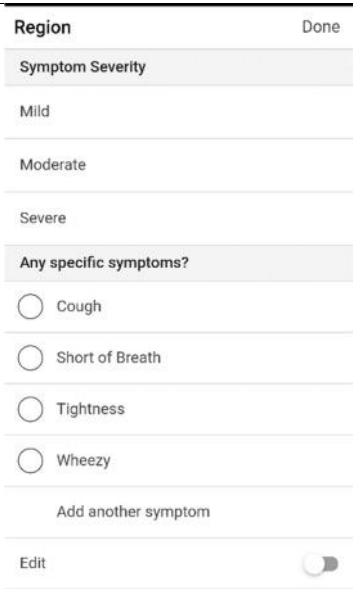
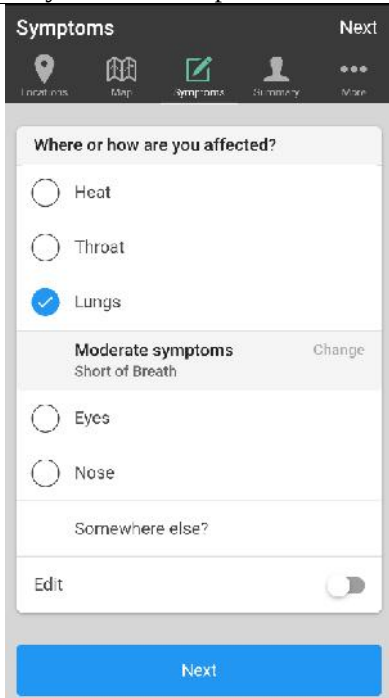
The symptom logging process is illustrated overleaf with screenshots.

Blinding to environmental conditions

AirRater can be used anonymously but all users are invited to register as study participants.

Study participants are blinded to the environmental conditions until they have logged a symptom, as shown in the first panel of the screenshot overleaf.

1. Any symptoms right now?
2. Where or how are you affected?
 - a. (heat/throat/lungs/eyes/nose/other)
3. What is the symptom severity? *(Optional)*
 - a. Mild
 - b. Moderate
 - c. Severe
4. Any specific symptoms? *(Optional)*
 - a. Irritable/lacking energy/light headed/other (for heat)
 - b. Self-described (for throat)
 - c. Cough/short of breath/tightness/other (for lungs)
 - d. Red/watery/itchy (for eyes)
 - e. Sneezing/runny/itchy (for nose)
5. Medication used?
 - a. Antihistamine
 - b. Asthma reliever
 - c. Other (self-described)
6. Triggers present?
 - a. Not sure/stress/cold air/food and/or drink/mould/animal contact/dust/exercise/other
7. Report created

	
1. User initiates a new symptom report	2. User asked to provide the location of symptoms. If they add their own region they are asked to provide a name.
	
3. On selecting a region the user is asked to select a severity (Mild, Moderate, or Severe) and any specific symptoms (itchy, watery, red etc).	4. The user has the option to edit or add to their symptom list.

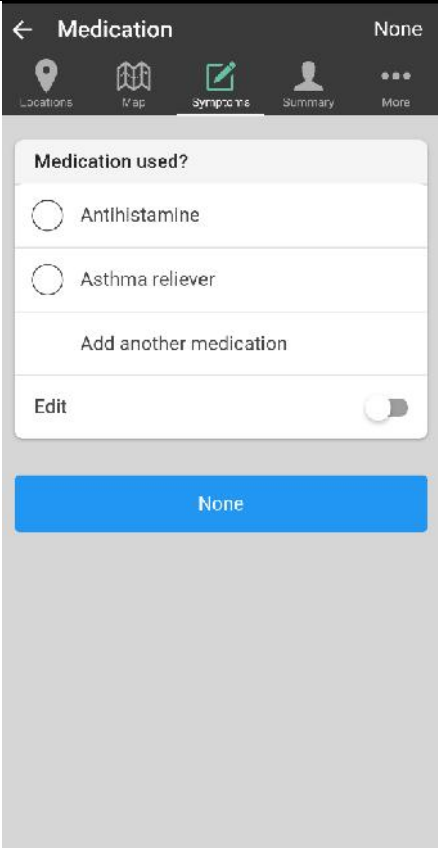
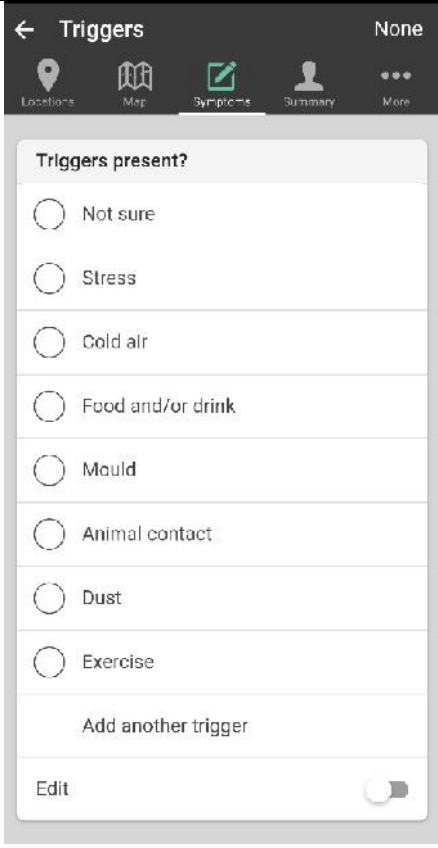
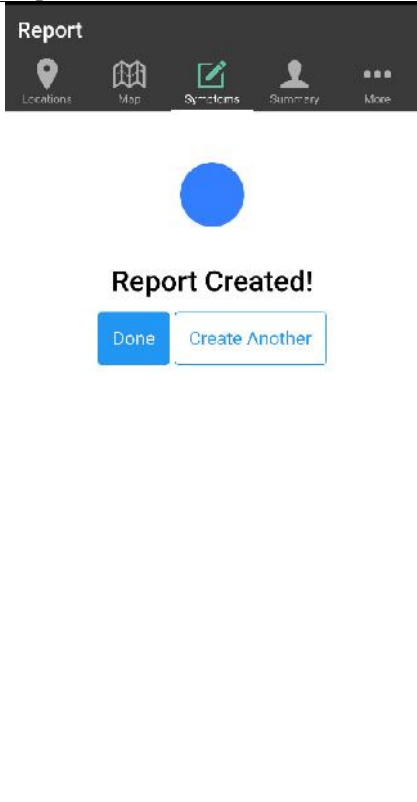
	
5. The user is asked if they have used medication. They are provided with the option to add their own medication.	6. User is asked if any triggers are present.
	
7. Report created	8. User is shown the current environmental conditions at their location and any other saved locations

Table A1: Summary of pollen data for Hobart over the study period (October 29, 2015 to October 29, 2018), showing all taxa contributing at least 1% or more of the total pollen load. Other taxa monitored include Arecaceae, *Coprosma*, Cyperaceae, *Nothofagus*, Platanaceae, *Populus*, and *Trifolium*; data not shown as these taxa contributed <1% of total pollen over the study period.

Pollen type	% of total pollen	Days Present (%)	Pollen concentration distribution (days present only)					
			Min	Q1	Median	Q3	Max	IQR
Total Pollen	100	100	1	11	29	96	1799	85
<i>Acacia</i>	1	18	1	1	1	2	34	1
<i>Alnus</i>	3	26	1	1	2	6	104	5
Asteraceae	1	24	1	1	2	3	30	2
<i>Betula</i>	12	25	1	1	6	22	245	21
Brassicaceae	1	15	1	1	1	3	30	2
<i>Casuarina</i>	5	57	1	1	2	5	76	4
Chenopodiaceae	1	11	1	1	1	3	205	2
Cupressaceae	22	56	1	2	4	16	319	14
<i>Dodonaea</i>	13	32	1	2	4	13	349	11
Myrtaceae	10	71	1	2	3	8	173	6
Oleaceae	3	27	1	1	3	7	86	6
<i>Papaver</i>	1	5	1	1	2	5	100	4
Pinaceae	4	26	1	1	2	7	120	6
<i>Plantago</i>	1	19	1	1	2	3	63	2
Poaceae	10	53	1	2	3	9	174	7
Podocarpaceae	1	11	1	1	1	3	28	2
<i>Quercus</i>	1	13	1	1	2	4	35	3
<i>Rumex</i>	4	32	1	1	2	7	62	6
<i>Salix</i>	3	17	1	1	3	8	90	6
<i>Ulmus</i>	2	17	1	1	3	7	80	6

Table A2: Summary of meteorological and air quality data for Hobart over the study period (October 29, 2015 to October 29, 2018). The data derive from EPA Tasmania’s New Town BLANkET monitoring station. Q=Quartile, IQR = Interquartile Range.

Exposure	Days Present (%)	Distribution (days present only)					
		Min	Q1	Median	Q3	Max	IQR
Maximum temperature (°C)	100	8	15	19	23	37	8
Minimum temperature (°C)	100	0	7	10	13	26	6
Relative humidity (%)	100	19	55	64	72	96	17
Rainfall (mm)	45	0.2	0.4	1.4	3.9	81.4	3.5
PM _{2.5} (µg/m ³)	100	1	3	6	17	192	14

Sensitivity analysis - Definition of the active user base

Table A3 presents the results of a sensitivity analysis exploring the impact of the definition of the active user base as:

- 1) A 7-day average of active users, defined as any user who had interacted with the app in the preceding 7-days
- 2) A 14-day moving average of active users, defined as any user who had interacted with the app in the preceding 14-days.
- 3) A 28-day moving average of active users, defined as any who had interacted with the app in the preceding 28-days

The results are very similar, the principal difference being two more significant p-values with the longest time window: specifically, minimum temperature and *Dodonaea*. The main analysis used the 7-day moving average on the basis that it was (a) the most conservative and (b) best reflected the sometimes sharp short-term fluctuations in user numbers.

Table A3. Results of three negative binomial time-series models evaluating the associations between symptoms logged using the AirRater smartphone app and environmental covariates. The data-set covers all eye, nose and lung symptoms logged by AirRater users in Hobart between October 29, 2015 to October 29, 2018. The 7-day, 14-day and 28 day moving average refers to the time window used to define the active user base. Variables where the statistical significance (at 0.05) varies between models are highlighted in bold. All models were adjusted for public holiday and day of week. CI = confidence interval, IRR=Incidence Rate Ratio.

	7-day moving average		14-day moving average		28-day moving average	
	IRR (CI)	p	IRR (CI)	p	IRR (CI)	p
PM _{2.5}	1.057 (1.037-1.079)	<0.001	1.050 (1.026-1.074)	<0.001	1.051 (1.026-1.076)	<0.001
Max. Temp.	1.283 (1.125-1.444)	<0.001	1.258 (1.096-1.422)	0.001	1.257 (1.089-1.429)	0.002
Min.Temp.	0.854 (0.672-1.039)	0.112	0.844 (0.656-1.036)	0.1	0.818 (0.623-1.017)	0.066
Rel. Humidity	0.900 (0.853-0.947)	<0.001	0.906 (0.858-0.955)	<0.001	0.914 (0.863-0.965)	0.001
Rainfall	1.032 (0.951-1.118)	0.447	1.043 (0.959-1.132)	0.312	1.068 (0.980-1.164)	0.119
<i>Betula</i>	1.043 (1.022-1.066)	<0.001	1.044 (1.023-1.067)	<0.001	1.045 (1.022-1.069)	<0.001
<i>Casuarina</i>	0.929 (0.848-1.012)	0.091	0.928 (0.845-1.012)	0.09	0.939 (0.855-1.028)	0.17
Cupressaceae	1.022 (1.008-1.037)	0.002	1.025 (1.011-1.040)	<0.001	1.030 (1.015-1.045)	<0.001
<i>Dodonaea</i>	1.016 (0.996-1.037)	0.11	1.018 (0.998-1.039)	0.078	1.024 (1.002-1.046)	0.029
Myrtaceae	1.058 (1.020-1.100)	0.001	1.070 (1.031-1.112)	<0.001	1.070 (1.030-1.113)	<0.001
Poaceae	1.048 (1.005-1.094)	0.016	1.055 (1.011-1.101)	0.008	1.064 (1.019-1.114)	0.003

Sensitivity analysis – Registered vs anonymous users

Table A4 presents a sensitivity analysis exploring the impacts of including or excluding anonymous users.

As described in Section 2.1, in AirRater users may choose to use the app anonymously or to register as study participants. Study participants only are blinded to environmental conditions before symptom reporting: anonymous users are free to see the environmental conditions at any time, potentially introducing bias.

As shown in **Table A4**, the results of the model are very similar regardless of whether anonymous users are included or excluded. The key difference is that minimum temperature and *Dodonaea* become statistically significant (at 0.05) when anonymous users are excluded (ie. when the data-set is restricted to registered users only. This difference suggests that the model is slightly more sensitive when restricted to registered users, who provide approximately 80% of symptom reports. On this basis we conclude that any bias introduced by anonymous users viewing conditions has minimal impact and that registered users are likely a higher risk group. We opted to use the full data-set (anonymous users included) in our main analysis as part of our aim was to explore the utility of crowd sourced app data sourced from an uncontrolled study cohort.

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Table A4. Results of negative binomial time-series models evaluating the associations between environmental conditions and symptoms logged by (a) all users of the AirRater smartphone app and (b) registered users only. The data-set covers eye, nose and lung symptoms logged by AirRater users in Hobart between October 29, 2015 to October 29, 2018. Variables where the statistical significance (at 0.05) varies between models are highlighted in bold. CI = confidence interval, IRR=Incidence Rate Ratio.

	All users		Registered users only	
	IRR	p	IRR	p
PM _{2.5}	1.057 (1.037-1.079)	<0.001	1.059 (1.038-1.081)	<0.001
Max. Temp.	1.283 (1.125-1.444)	<0.001	1.235 (1.076-1.396)	0.003
Min. Temp.	0.854 (0.672-1.039)	0.112	0.816 (0.633-1.003)	0.049
Rel. Humidity	0.9 (0.853-0.947)	<0.001	0.898 (0.851-0.946)	<0.001
Rainfall	1.032 (0.951-1.118)	0.447	1.033 (0.952-1.119)	0.430
<i>Betula</i>	1.043 (1.022-1.066)	<0.001	1.047 (1.026-1.069)	<0.001
<i>Casuarina</i>	0.929 (0.848-1.012)	0.091	0.959 (0.877-1.043)	0.326
Cupressaceae	1.022 (1.008-1.037)	0.002	1.018 (1.003-1.033)	0.012
<i>Dodonaea</i>	1.016 (0.996-1.037)	0.11	1.024 (1.004-1.045)	0.018
Myrtaceae	1.058 (1.020-1.100)	0.001	1.049 (1.010-1.090)	0.008
Poaceae	1.048 (1.005-1.094)	0.016	1.028 (0.987-1.072)	0.165
Public Holiday	1.144 (0.148-2.255)	0.785	0.954 (-0.038-2.060)	0.931
Monday	1.969 (0.264-3.988)	0.282	1.847 (0.132-3.886)	0.352
Saturday	0.131 (-1.296-1.822)	0.294	0.471 (-1.032-2.257)	0.536
Sunday	1.617 (-0.044-3.586)	0.489	1.875 (0.149-3.929)	0.339
Thursday	2.443 (0.679-4.527)	0.112	2.654 (0.830-4.817)	0.076
Tuesday	2.449 (0.657-4.574)	0.117	2.78 (0.909-5.006)	0.061
Wednesday	3.414 (1.511-5.662)	0.011	3.63 (1.663-5.961)	0.007

Diagnostic plots – main analysis incorporating symptom reports from all users, all seasons

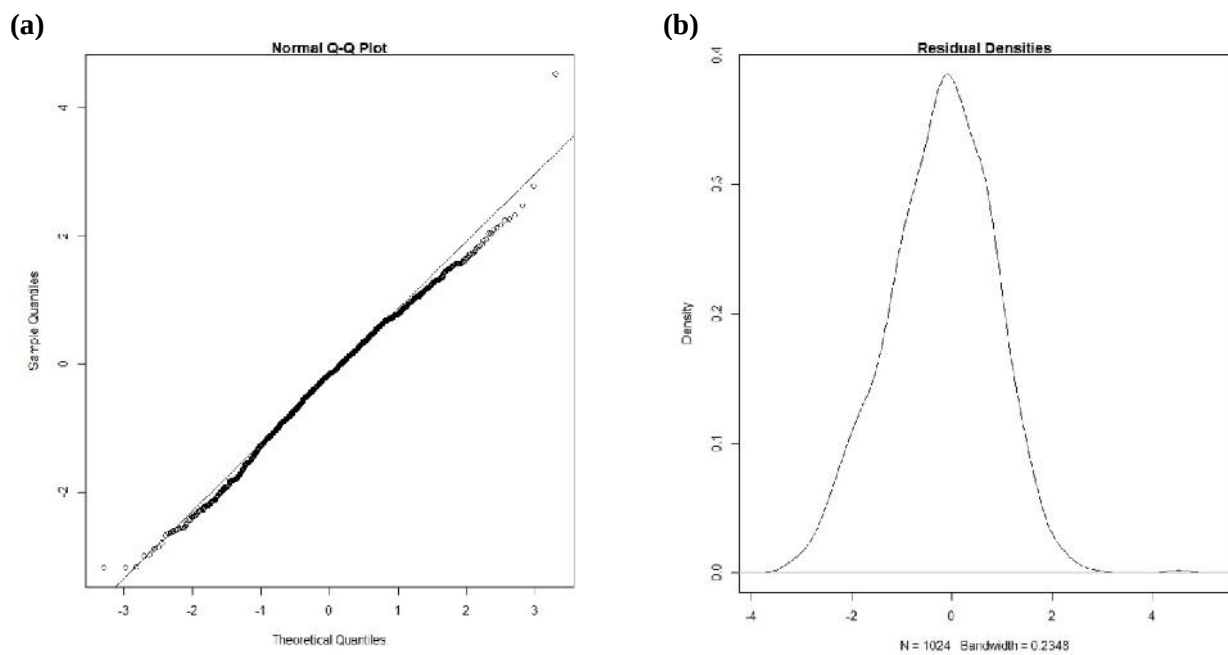


Figure A1: Diagnostic quantile-quantile (QQ) (left) and residual (right) density plots for a negative binomial time-series model evaluating the associations between symptoms logged using the AirRater smartphone app and environmental covariates. The data-set covers all eye, nose and lung symptoms logged by AirRater users in Hobart between October 29, 2015 to October 29, 2018.

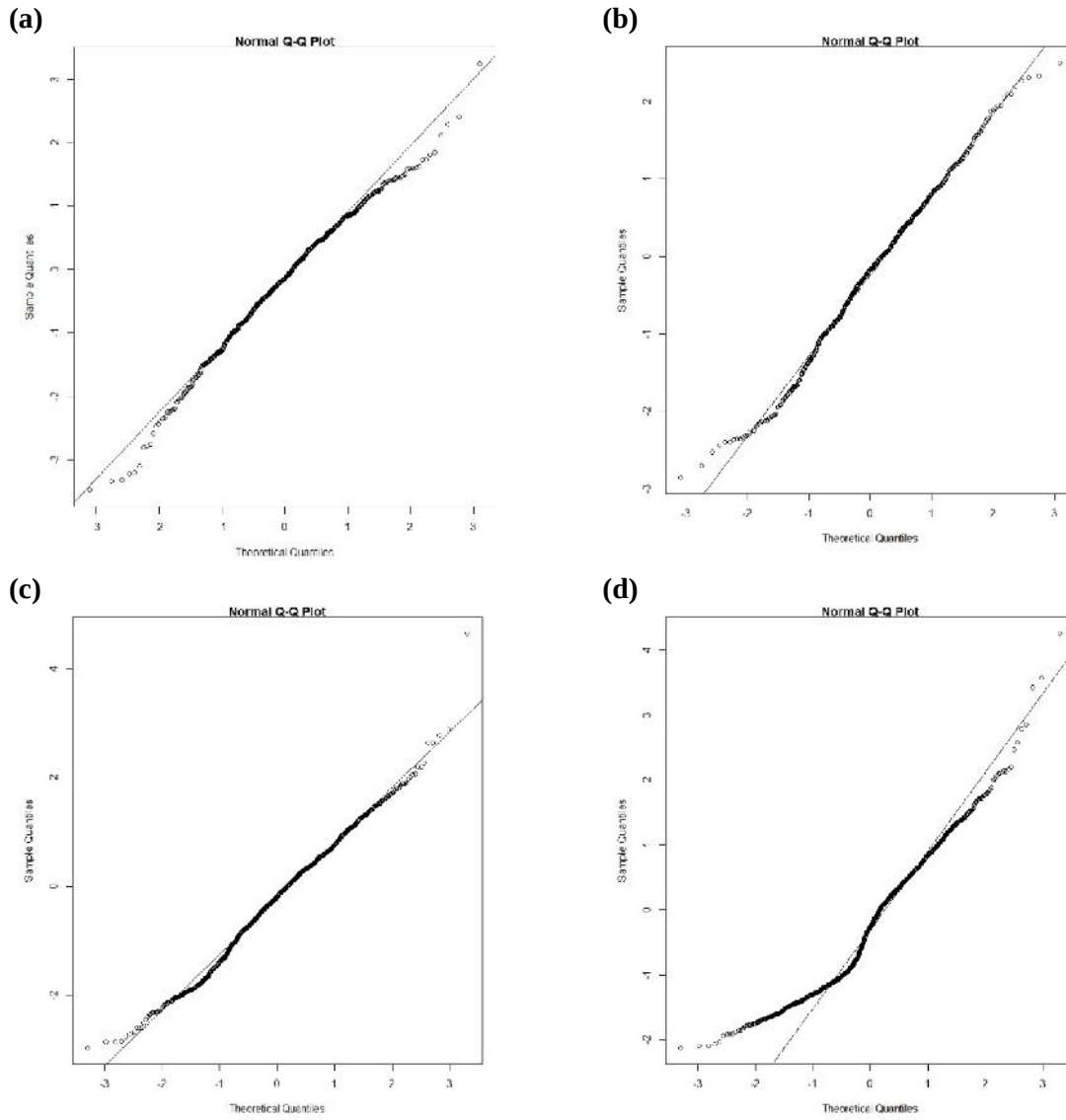


Figure A2: Diagnostic quantile-quantile (QQ) plots for negative binomial time-series models evaluating associations between symptoms logged using the AirRater smartphone app and environmental covariates. The data-set covers eyes, nose and lung symptoms logged by AirRater users in Hobart between October 29, 2015 to October 29,^h 2018, stratified in two ways: (i) spring/summer (September-February) versus autumn/winter (March-August); and (ii) eyes/nose versus lung symptoms. Panels (a) and (b) show the results for the spring/summer and autumn/winter analyses respectively; panels (c) and (d) show the eyes/nose and lung model results respectively.

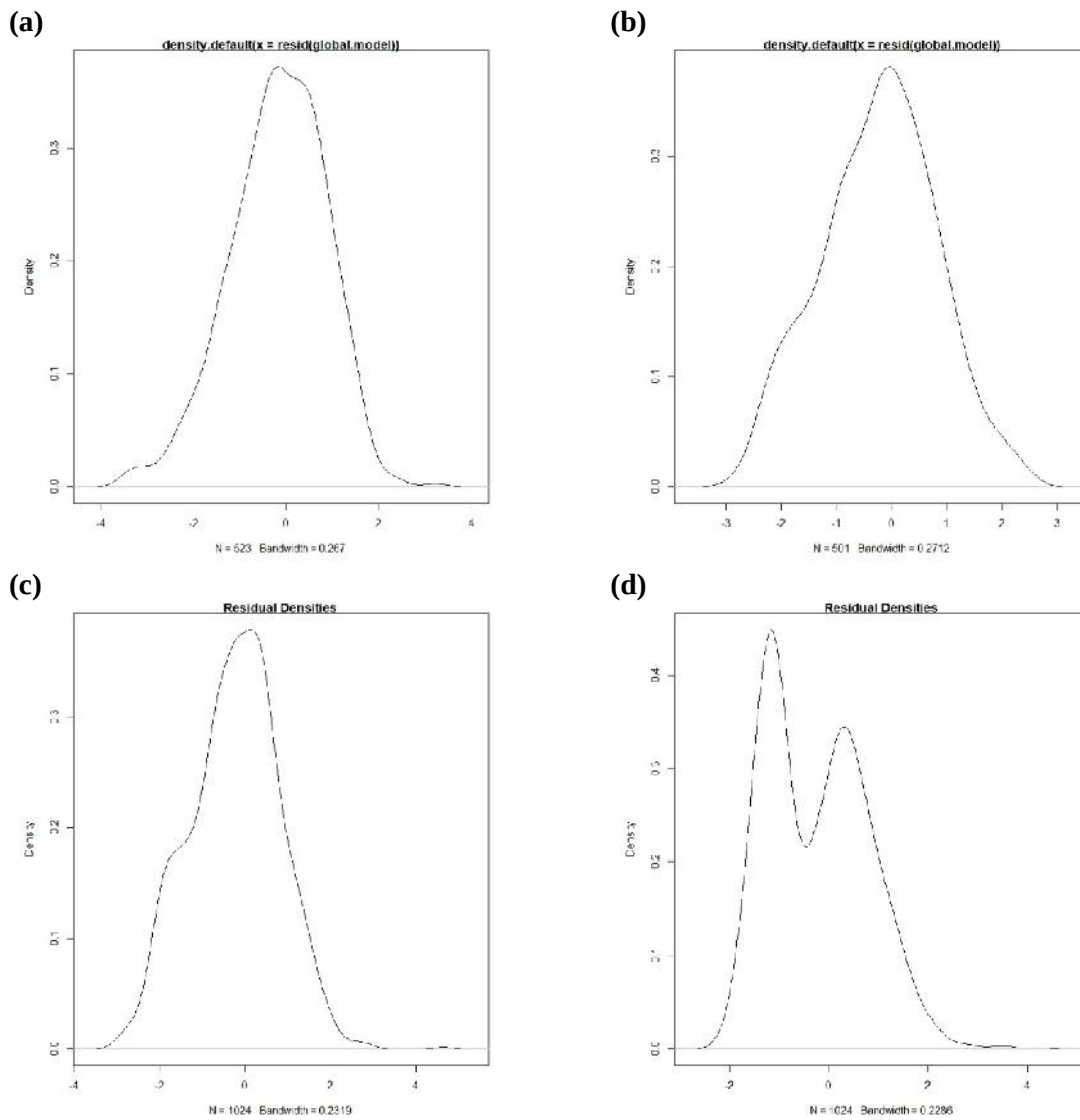


Figure A3: Diagnostic residual density plots for negative binomial time-series models evaluating associations between symptoms logged using the AirRater smartphone app and environmental covariates. The data-set covers eyes, nose and lung symptoms logged by AirRater users in Hobart between October 29, 2015 to October 29, 2018, stratified in two ways: (i) spring/summer (September-February) versus autumn/winter (March-August); and (ii) eyes/nose versus lung symptoms. Panels (a) and (b) show the results for the spring/summer and autumn/winter analyses respectively; panels (c) and (d) show the eyes/nose and lung model results respectively.

Supplementary figures and tables from analyses presented in the main text

Table A5: Results of a negative binomial time-series model evaluating the associations between symptoms logged using the AirRater smartphone app and environmental covariates. The data-set covers all eye, nose and lung symptoms logged by AirRater users in Hobart between October 29 2015 to October 29 2018. The model was adjusted for public holiday and day of week. CI = confidence interval, IRR=Incidence Rate Ratio.

	IRR	SE	CI 2.5	CI 97.5	P-value ¹	
PM _{2.5}	1.057	1.011	1.037	1.079	<0.001	***
Max Temp	1.283	1.077	1.125	1.444	<0.001	***
Min Temp	0.854	1.093	0.672	1.039	0.112	
Rel. Humidity	0.900	1.025	0.853	0.947	<0.001	***
Rainfall	1.032	1.042	0.951	1.118	0.447	
<i>Betula</i>	1.043	1.010	1.022	1.066	<0.001	***
<i>Casuarina</i>	0.929	1.042	0.848	1.012	0.091	.
Cupressaceae	1.022	1.007	1.008	1.037	0.002	**
<i>Dodonaea</i>	1.016	1.010	0.996	1.037	0.110	
Myrtaceae	1.058	1.018	1.020	1.100	<0.001	***
Poaceae	1.048	1.020	1.005	1.094	0.016	*

Signif codes: '***' = <0.001, '**' = 0.001-0.01; '*' = 0.01-0.05, '.' = 0.05-0.1

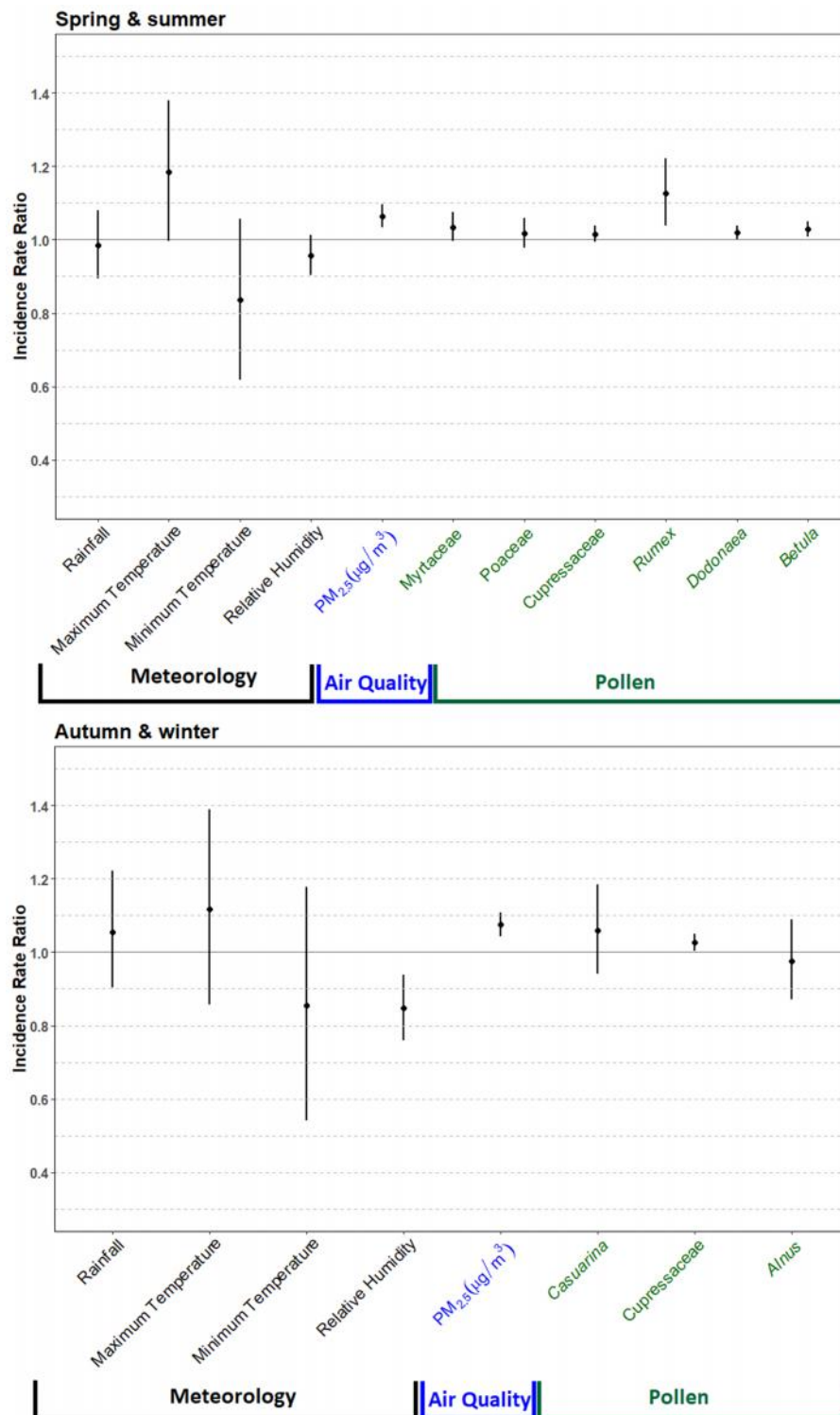


Figure A4: Results of negative binomial time-series models evaluating associations between symptoms logged using the AirRater smartphone app and environmental covariates. The data-set covers eyes, nose and lung symptoms logged by AirRater users in Hobart between October 29 2015 and October 29 2018, stratified into two groups: spring/summer (Sep-Feb) and autumn/winter (Mar-Aug). Only pollen taxa contributing at least 5% of the pollen load in the relevant period were included. Bars show the 95% confidence interval.

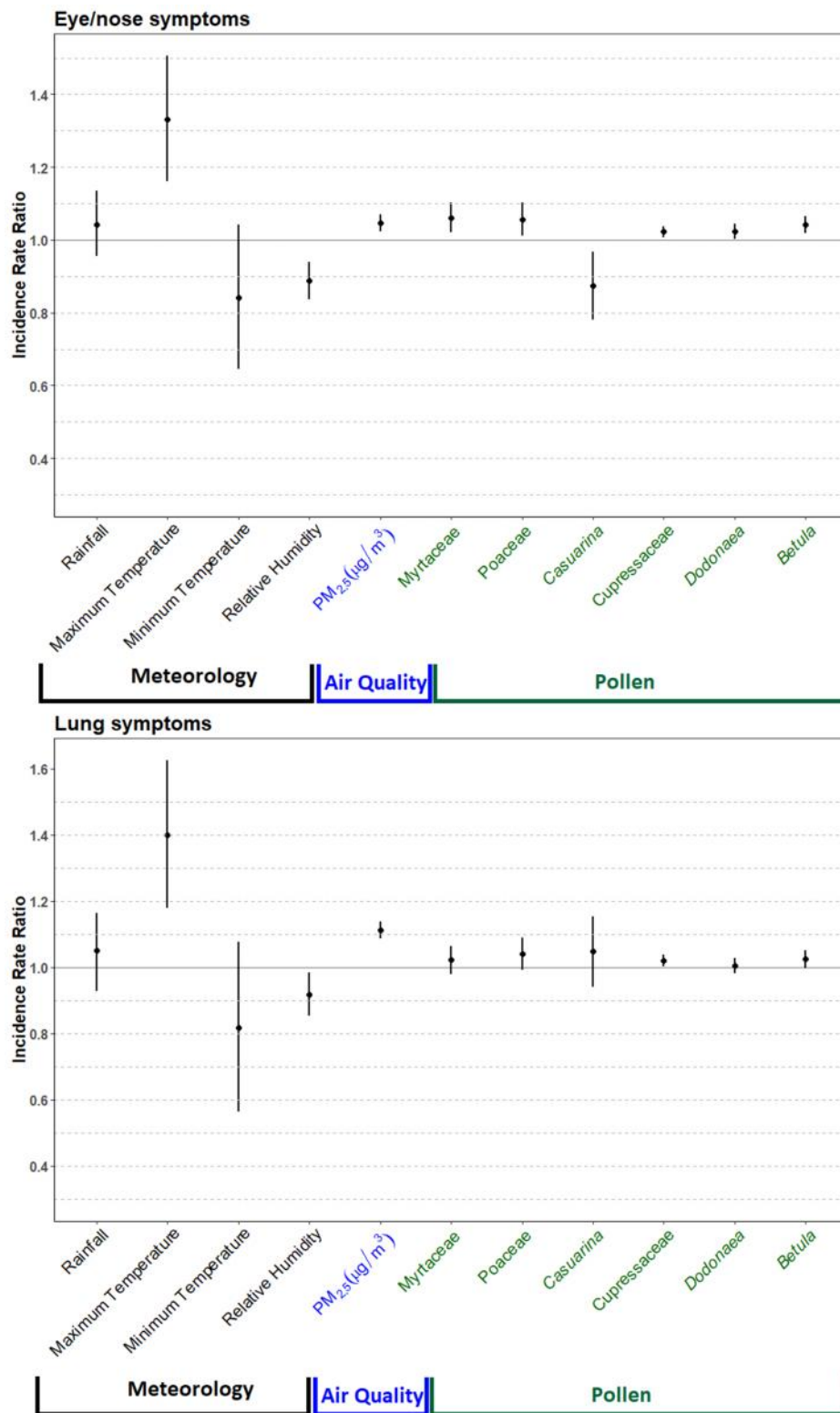


Figure A5: Results of negative binomial time-series models evaluating associations between symptoms logged using the AirRater smartphone app and environmental covariates. The data-set covers eyes, nose and lung symptoms logged by AirRater users in Hobart between October 29, 2015 and October 29, 2018, stratified into two groups: eyes/nose and lungs. Only pollen taxa contributing at least 5% of the pollen load were included. Bars show the 95% confidence interval.