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Evaluation of the performance of short-term curated daily airborne grass pollen forecasts in diverse biogeographical regions during the AusPollen Partnership project 2016–2020

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ABSTRACT

When providing pollen forecasts to the community, there is a need to verify the accuracy of curated forecasts, but evaluation is not routinely reported. This study of the AusPollen Partnership compared multi-category grass pollen forecasts for up to six days ahead with daily airborne grass pollen concentrations measured in Brisbane, Canberra, Melbourne, and Sydney, Australia during four pollen seasons from 2016 to 2020. The accuracy of categorical grass pollen forecasts predicting grass pollen concentrations in the high and greater, or moderate and greater categories, were assessed as often applied in meteorology using Gerrity scores, equitable threat scores, false alarm ratios, success ratios, and probability of detection of correct category. The skill of grass pollen forecasts curated by aerobiologists were compared with two retrospectively calculated naïve reference forecast methods; climatology and persistence. For Brisbane and Melbourne, high or greater grass pollen levels occurred on average 32% and 22% of days, whereas for Canberra and Sydney, there were few high days, but moderate or greater pollen levels occurred on average 26% and 19% of days, respectively. Average annual Gerrity scores for curated forecasts of high or greater improved with experience from 0.20 to 0.66 in Brisbane, and from 0.39 to 0.55 in Melbourne between 2016 and 2019. Average Gerrity Scores for moderate or greater categories in Sydney were 0.45 and 0.43 in 2016 and 2018 respectively, and in Canberra were 0.34 and 0.41, in the same years. The skill of curated forecasts was usually better than persistence forecasts, but the accuracy of the curated forecasts decreased with longer lead times. Although persistence grass pollen forecasts consistently performed better than climatologies, persistence depends on previous day pollen concentrations being available. Short-term curated daily grass pollen forecasts of the AusPollen Partnership offer useful information for people with allergic rhinitis and asthma, to help facilitate behavioural change and reduce the health burden. There is a need in Australia to extend local pollen records through sustained pollen monitoring to track climate-related changes as well as

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improve reliability of daily pollen forecasts. Globally, continued evaluation will enable reporting of accurate pollen forecasts to community, clinicians and government stakeholders.

1. Introduction

Grass pollen has been identified as a major outdoor allergen for human populations. In Australia, seasonal allergic rhinoconjunctivitis (AR) and asthma affect as many as 19% and 11% of the population, respectively (Australian Institute of Health and Welfare, 2019). Under circumstances of high to extreme grass pollen exposure in temperate biogeographical regions during spring-time thunderstorms with severe gust fronts, individuals with AR are at risk of asthma exacerbations which can be abrupt and severe requiring hospital admission and even for some intensive care (Davies et al., 2017). Grass pollen was identified as a key component cause of an epidemic of thunderstorm asthma affecting thousands of patients who presented to emergency departments and other health services with severe breathing difficulties after an event on November 21, 2016 in Melbourne, Australia (Thien et al., 2018). Ten patients died as a result of this thunderstorm asthma event (Victorian Coroner, 2018), and ryegrass pollen was indicated as the major allergen causing inflammation to airways (Lee et al., 2017; Sutherland et al., 2017). There have been other high incidences of asthma epidemics in temperate regions of Australia, where grass pollen has also been implicated (Davies et al., 2017; Girgis et al., 2000). As a vast island continent with diverse climatic zones, Australian grass pollen aerobiology shows marked spatial and temporal variation between states (Beggs et al., 2015; Haberle et al., 2014; Medek et al., 2016; Davies et al., 2021). Developing a capability for forecasting grass pollen exposure levels is therefore an important public environmental health priority. Early warnings for high pollen exposure would enable better preparedness for individuals with AR and result in a less likely burden on the hospital systems if asthma is to occur. Members of the public report validation of symptoms experienced to be one of the reasons why they seek local pollen information (Medek et al., 2019), therefore it is important to achieve accurate forecasts and give surety to the community.

Successful daily pollen forecasting must start with a network of standardised pollen monitoring observations. The US National Allergy Bureau maintains a network of 84 pollen counting stations managed by certified pollen counters across many, but not all states (National Allergy Bureau, 2021). Analysis of Australian airborne pollen records provide a historical lens to create pollen taxa calendars (Haberle et al., 2014; Ong et al., 1995), estimate the pollen season length and variability (Medek et al., 2016) and to provide the basis for forecast generation and evaluation. Whilst linear regression forecast models of grass pollen aerobiology in London have been developed based on pre-peak, peak and post-peak periods (Smith and Emberlin, 2005), in practice the UK Meteorology Office uses a combined persistence/expert judgement method to produce daily forecasts of tree, grass and nettle pollen and fungal spores (UK Seasonal Pollen Forecast Service,). The persistence method assumes today's pollen count will be the same as yesterday's pollen count. Expert judgement employs information on local vegetation types and flowering times together with knowledge of the preseason climate conditions. For example, more rainfall during the initial growing season increases biomass production and may lead to a higher than usual pollen production in the current season.

European countries, including Finland, France (Réseau National de Surveillance Aérobiologique, 2020) and Switzerland (MeteoSwiss), have employed three dimensional air dispersion models such as the System of Integrated modelling of atmospheric composition (SILAM, Sofiev et al. (2015)) and the Consortium for Small-scale Modeling (COSMO, Zink et al. (2013)). SILAM produces a 96 h ahead forecast Europewide for alder, birch, grass, olive, ragweed and mugwort pollen (System of integrated modelling of atmospheric composition), whilst COSMO predicts for alder, birch, grass and ragweed pollen (Consortium for Small-scale Modeling,). Some commercial outlets rely on weather parameters alone to issue pollen forecasts.

The AusPollen Partnership (Davies et al., 2016, 2022) was set up to establish the first coordinated initiative across four states to monitor pollen exposure, standardise pollen measurement processes (Beggs et al., 2018), evaluate how access to pollen information enables self-management of allergic disease (Medek et al., 2019), and to evaluate the components needed to build an innovative validated grass pollen forecast system. Forecasting methods require large sources of linked and standardized data, but prior to 2016 pollen monitoring in Australia was only undertaken by two groups. However, the 2016 Melbourne thunderstorm asthma event, and subsequent public health awareness, escalated the implementation of daily grass pollen forecasting, despite a lack of (standardized) historical pollen observations required for robust predictions outside of Melbourne and Canberra. Since the inception of the AusPollen Partnership in September 2016, four cities in the eastern states (from north to south: Brisbane, Sydney, Canberra and Melbourne) have monitored local daily grass pollen concentration and provided these data along with short-term categorical daily grass pollen forecasts to the community during their relevant grass pollen season (https://auspollen.edu.au/). Evaluation of the grass pollen forecasts provides assurance of the quality of aerobiological information disseminated to the community (Bastl et al., 2017). Statistical evaluation of pollen predicted by three dimensional atmospheric transport models has used common weather forecast evaluation techniques to determine accuracy over a particular time period (Siljamo et al., 2013; Emmerson et al., 2019). However, these techniques are not routinely applied to pollen forecasts disseminated to the community, and the quality of the AusPollen Partnership grass pollen forecasts has not previously been assessed.

Forecast 'accuracy' measures the level of agreement with the observations, whereas the forecast 'skill' is the relative gain in accuracy compared to retrospectively calculated naïve forecast method like climatology or persistence. Therefore, the aims of this paper were 1) to determine the accuracy of aerobiologist curated pollen forecasting at four AusPollen sites during four pollen seasons spanning 2016 to 2020, and 2) to compare the curated forecast skill with grass pollen climatology and persistence forecast methods generated for the same time periods.

We anticipated that curated grass pollen forecasts would improve with experience and that some locations would be easier than others to forecast grass pollen levels, due to factors that influence forecasting accuracy (e.g., local seasonal weather patterns, local biogeography and the seasonal pollen index, length of historic pollen records and forecasts, and availability of models to support forecasting).

2. Materials and methods

We analysed daily airborne grass pollen concentration observations and forecasts from four cities in eastern Australia: Brisbane, Sydney, Canberra and Melbourne, over four consecutive pollen seasons of the AusPollen Partnership Project commencing in years 2016–2019.

2.1. Aerobiological data

Airborne pollen concentrations were monitored and daily grass pollen forecasts were disseminated for Brisbane, Sydney, Canberra and Melbourne (see Fig. 1 and Table S1 Supplementary for sampling details). These sites are part of the broader AusPollen Aerobiology Collaboration Network, now encompassing all Australian pollen monitoring sites and

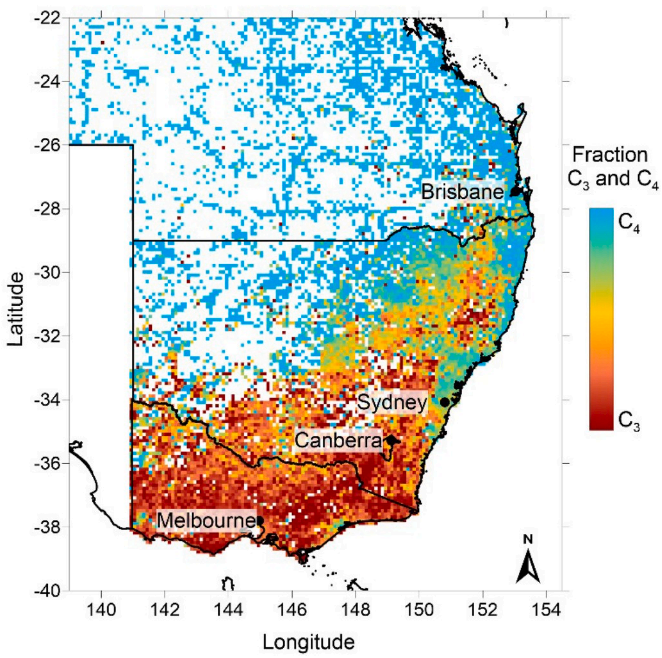

Fig. 1. Map of south eastern Australia to show locations of the four AusPollen sites and distribution of C3 (temperate) and C4 (subtropical) grasses (0.1° longitude x 0.1° latitude grid) within the states of Victoria (Melbourne), the Australian Capital Territory (Canberra), New South Wales (Sydney) and Queensland (Brisbane). Source: Atlas of Living Australia (http://www.ala.org.au).

projects (https://auspollen.edu.au/auspollensitesmap). The pollen monitoring processes; collection and counting, were standardised across the network (Beggs et al., 2018), but some characteristics of the monitoring sites (e.g. height of pollen trap, and sample collection time) and the pollen forecast techniques differed. Whilst the height of the pollen traps differed between sites, environmental pollen samples were collected daily on slides or Melinex tapes using Hirst-type volumetric pollen traps (Burkard Manufacturing, United Kingdom) and counted manually by light microscopy after staining with fuchsin dye as previously described (Davies et al., 2022).

The timing and length of the grass pollen season differs at each of the sites (Medek et al., 2016) due to the different dominant grass types present in local environments, e.g. prevalence of temperate C_3 grasses in the south (Fig. 1), and different climates. See supplementary section 1 for details on grass types. As the grass pollen forecasts are per AusPollen site and not for the entire region, these geographical differences do not impact the forecasting capability. To facilitate comparison of daily grass pollen forecast accuracy between years and locations, we included observations for the periods for which forecasts were disseminated from October 1 to December 31 for Sydney, Canberra and Melbourne, and November 1 to March 31 for Brisbane which approximately span the expected grass pollen seasons in those locations. While the Brisbane grass pollen season spans two calendar years, these seasons will be identified hereafter by their starting year (e.g., the 2016–2017 season will be identified as the 2016 season).

Grass pollen exposure levels in Australia are categorised 'low' if the airborne grass pollen concentration is less than 20 grains m^{-3}, 'moderate' from 20 to less than 50 grains m^{-3}, 'high' from 50 to less than 100 grains m^{-3} and 'extreme' at 100 grains m^{-3} and above (de Morton et al., 2011). These categories were used in the pollen forecasts made daily at each AusPollen site, for each of four consecutive pollen seasons. Each daily forecast consisted of six separate forecasts; one for the current day and one each for the five following days. Where possible, the previous day's pollen was counted before forecasting. To analyse the performance of the forecasts we used weather forecast verification measures and techniques, using Wilks (2019) as the basis.

2.2. The AusPollen grass pollen forecast methods

At the beginning of the AusPollen project in September 2016, standardized methods for monitoring pollen were established, and therefore robust grass pollen forecast methods had not been designed.

Forecasting daily pollen categories was introduced for the first time at all AusPollen sites in 2016, with only Melbourne having previously undertaken pollen forecasting. Methods for forecasting differed between the AusPollen locations, and are described below. The curated forecasts were based on expert local aerobiology knowledge, founded upon different levels of experience; all included the previous day pollen concentrations and current as well as predicted meteorological variables (maximum temperature, wind speed and precipitation).

The production of the curated forecasts by a human forecaster used expert judgement to decide on the category to forecast; low, moderate, high or extreme, given all the available data on the previous day pollen data, and weather forecasts; chance of rainfall, minimum and maximum temperature, wind speed and direction

Curated forecasts of daily grass pollen categories; low to extreme, were made for the current day and five following days, starting after the pollen was counted that morning. We refer to that morning forecast as the "day 0″ forecast, with the following 24h period as "day 1″, and so on. Additional details about pollen forecasting at each site given below.

2.2.1. Brisbane curated forecasts

The forecasting system in Brisbane predicted a pollen category using expert informed judgement in the 2016 and 2017 seasons. Starting in 2018, pollen forecast decision support was produced by unpublished regression and neural network models based on recent pollen concentrations, field observations, and predicted weather conditions. On Sundays in 2018, on Saturdays and Sundays in 2019, and public holidays, the curated pollen forecasts were made without the previous day's pollen concentration data, since those pollen samples were not collected or counted until after the weekend.

2.2.2. Sydney curated forecasts

The Sydney pollen forecasts used expert assessment informed by previous day pollen concentration (persistence) and adjusted to predict subsequent days pollen categories according to the forecasted weather variables; e.g. a very high temperature, high humidity or rain, will cause a downward adjustment in the forecasted pollen category.

2.2.3. Canberra curated forecasts

The Canberra pollen forecast used expert assessment that considered a combination of the previous day pollen concentration and forecasted weather conditions, particularly wind strength and direction, and humidity to predict a pollen category. A number of factors affected the daily pollen concentration, including daily fluctuations in temperature, wind conditions, humidity and precipitation, and the biology of the grasses themselves. Most grasses flower in late spring and early summer in the Canberra region.

2.2.4. Melbourne curated forecasts

Daily grass pollen concentrations in 2016 were forecast using the meteorological typing method of Schäppi et al. (1998) and in 2017–2019 were produced using an automated statistical model that included gridded weather and environmental data, such as the seasonal record in pollen concentrations since 1991 as inputs (Emmerson et al., 2019; Bannister et al., 2021). Forecasters used the model output and their experience to produce a curated forecast category.

2.3. Forecast evaluation approach

The accuracy of the categorical pollen forecasts were evaluated against the observations using methods commonly used in the field of weather forecasting that answer specific questions about important aspects of forecast performance (Wilks, 2019).

The starting point was the categorical contingency table, sometimes called a confusion matrix, which counted the number of times forecasts and observations occurred together in each category (Table 1). Examination of the joint distribution showed the nature of the errors. For perfect forecasts only, the upper left to lower right diagonal elements of the table will be populated. A weighting of elements above or below the diagonal suggests high or low bias in the forecast and the worst errors were measured furthest from the diagonal. A variety of metrics were computed from the elements in the table describing how well the forecast predicted the correct category or, alternatively, a threshold of exceedance (for example, high and extreme together).

Most of the metrics used in this study were based on pollen category thresholds being met or exceeded, corresponding to a binary or dichotomous forecast. In this case Table 1 was collapsed into a 2 × 2 contingency table with well-known elements of hits, misses, false alarms and correct rejections as shown in Table 2. In pollen terms the event of interest ('Yes') is a day of significant pollen levels, so for instance a hit is the correct positive prediction of a relatively high pollen level and a correct negative the correct prediction of a relatively low level. Whilst a great number of metrics can be computed from the elements in Table 2 (see, for example, Wilks, 2019); below we describe the metrics used in this study.

The ability of the forecast to correctly predict observed occurrences is measured by the Probability of Detection, *POD* (also known as the sensitivity).

$$\mathrm{POD} = \mathrm{hits} / (\mathrm{hits} + \mathrm{misses}) \tag{1}$$

The fraction of "yes" forecasts that were correct is measured by the Success Ratio, *SR* (also known as the positive predictive value).

$$\mathrm{SR} = \mathrm{hits} / (\mathrm{hits} + \mathrm{false\ alarms}) \tag{2}$$

Both *SR* and *POD* inform the user on the trust that should be applied to the forecast with *SR* being conditional on a positive forecast and *POD* conditional on a positive observation. Both scores range from 0 to 1 where the latter reflects perfect performance.

The Frequency Bias, *FB*, measures the ratio of predicted to observed occurrences, with an ideal value being 1.

$$\mathrm{FB} = (\mathrm{hits} + \mathrm{false\ alarms}) / (\mathrm{hits} + \mathrm{misses}) \tag{3}$$

The Threat Score, *TS,* evaluates the number of correctly forecasted hits and will tend towards 1 for a perfect set of forecasts.

$$\mathrm{TS} = \mathrm{hits} / (\mathrm{hits} + \mathrm{misses} + \mathrm{false\ alarms}) \tag{4}$$

A variant on the *TS*, the Equitable Threat Score, *ETS*, measures the ability of the forecast to correctly capture predicted and observed occurrences, adjusted for expected hits due to random chance. This makes the *ETS* appropriate for comparing forecasts for different climatological regimes, for example, with different frequencies of high or extreme pollen concentrations. The *ETS* is given by

Table 1
Categorical contingency table for four-category pollen forecasts and observations. n_{ij} *refers to the number (or fraction) of times when a forecast for category* j *was made and category* i *was observed to occur.*

		Forecast			
		Low	Moderate	High	Extreme
Observed	Low	n_{11}	n_{12}	n_{13}	n_{14}
	Moderate	n_{21}	n_{22}	n_{23}	n_{24}
	High	n_{31}	n_{32}	n_{33}	n_{34}
	Extreme	n_{41}	n_{42}	n_{43}	n_{44}

Table 2
Categorical contingency table for binary forecasts. The convention is to present the "yes" (meeting or exceeding the threshold) values ahead of the "no" values.

		Forecast	
		Yes	No
Observed	Yes	*Hits*	*misses*
	No	*false alarms*	*correct rejections*

$$\mathrm{ETS} = (\mathrm{hits} - \mathrm{hits}_{\mathrm{random}}) / (\mathrm{hits} + \mathrm{misses} + \mathrm{false\ alarms} - \mathrm{hits}_{\mathrm{random}}) \tag{5}$$

where $hits_{random}$ = *(hits + misses)* × *(hits + false alarms)/# forecasts*. The *ETS* ranges from −1/3 to 1, with 1 representing perfect forecasts.

Some forecast users may take different actions dependent on the category that is predicted. To measure performance for multi-category forecasts, the Gerrity Score, *GS*, rewards correct forecasts of rare occurrences and differentiates between small and large category errors. The *GS* is the inner product of the contingency table (i.e. Table 1) and a scoring matrix based on the climatological frequencies of observations in each category. Details of the *GS* can be found in Wilks (2019). When the scoring matrix uses the sample climatology, *GS* yields values between −1 and 1, with a zero score indicating no predictive ability.

We applied these metrics to measure the accuracy of the pollen forecasts for day 0 to day 5 made at each AusPollen site from the start of the 2016 grass pollen season through to the end of the 2019 grass pollen season. We also presented the confidence intervals for each evaluation metric to determine the uncertainty in the results across years and sites.

2.3.1. Generation of pollen forecasts based climatology and persistence methods

To provide some context for the curated forecast performance we also evaluated values calculated retrospectively for two naïve forecast methods, namely persistence and a temporally varying seasonal climatology. Comparisons between the persistence/climatology forecasts and curated forecasts were made after amalgamating to a binary categorisation for values calculated for these naïve methods (e.g., Table 2).

For this additional analysis, the study accessed all four seasons of the AusPollen project, and previous airborne pollen data for each location. To define the pollen climatology for each site, pollen records for seasons commencing in the years indicated; Brisbane– 605 observations over 4 seasons (2016–2019), Sydney 430 observations over 5 seasons (2015–2019), Canberra 781 observations over 9 seasons (2008–2010 and 2014–2019), and Melbourne 1180 observations over 13 seasons (2007–2019). In this case, the *GS* can occasionally yield values outside [−1,1].

3. Results

Contingency tables for each site and year are shown in Fig. 2. To be of most protective use to allergy sufferers, we want to avoid incorrectly predicting low pollen when it was observed in the extreme pollen category (the bottom left box of each table). This occurred more frequently in 2016 for Brisbane (4 missed). Equally, avoiding extreme false alarms is important (the top right box of each table), where the forecast has predicted extreme pollen, but the observation was low.

For Brisbane and Melbourne, high or extreme pollen (hereafter referred to as 'high+') occurred on an average of 32% and 27%, respectively of days in the 2016–2019 pollen season (Fig. 2). However, the success in predicting the extreme category was variable at both these two sites, with missed extreme days mostly forecast as moderate or high in most years. This could be due to potential biases of human forecasters (Roberts and Wernstedt, 2019). The Brisbane forecasters seemed to prefer to forecast 'safely' and overpredict the categories, reasoning that the loss (ill health, lost work, hospitalisation) was weighted heavier than the cost of preparedness. Additionally, there were few, if any, repercussions of a false positive high pollen forecast, but individuals may

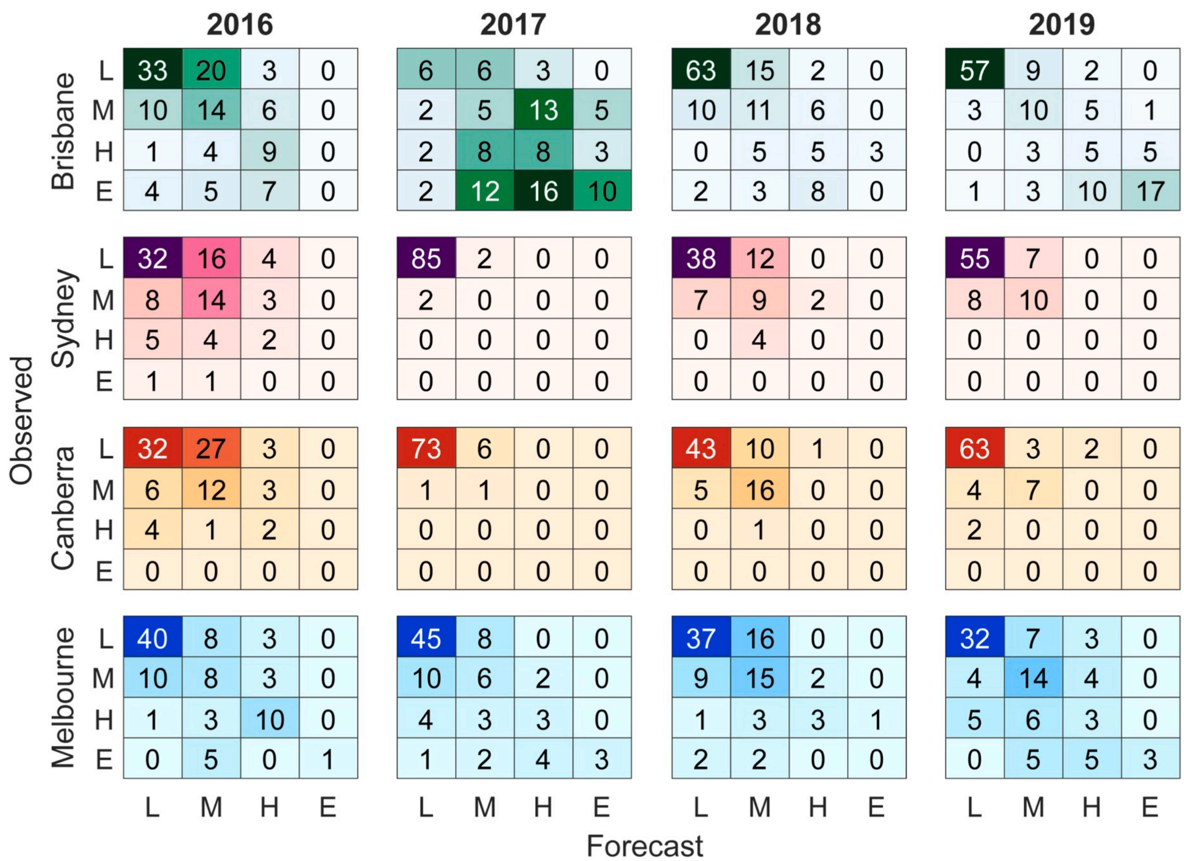

Fig. 2. Contingency tables for day 0 curated pollen forecasts. To highlight the relative weighting of each cell in each year, the colours are mapped linearly from 0 to the maximum matrix entry (darker). The colours green (Brisbane), pink-purple (Sydney), orange-red (Canberra) and blue (Melbourne) are used throughout the manuscript. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

lose trust in the information provided.

Over the 4 years at each site, there was a reduction in numbers of forecasts featuring outcomes in two opposite cross-diagonal boxes. On most days, it was the low pollen category that is most often observed and correctly predicted by the curated forecasts. Brisbane in 2017 is the exception with most observations being extreme and most curated forecasts being in the high pollen category that year. While Canberra and Sydney have had few incorrectly predicted high and extreme pollen forecasts since 2016, these sites also experienced very low pollen during that time with less than 1.5% of grass pollen observations in the high+ categories.

Canberra and Sydney rarely observed grass pollen levels in the high+ categories for all pollen seasons data (Fig. 3a), and during this AusPollen project period (Fig. 3b), due to drought conditions. Originally, we intended to assess the accuracy of forecasts of grass pollen in the high+ category, but this would remove Canberra and Sydney from the analysis as having too few samples for robust statistical analysis. A more useful assessment of annual forecast performance would judge the accuracy of Canberra and Sydney forecasts on the ability to correctly predict ‘moderate’ or above (hereafter referred to as ‘moderate+’) grass pollen. Fig. 3a considers all the grass pollen observations at each site and shows the average frequency of each category. The distribution of categories in the 2016–2019 seasons (Fig. 3b) did not differ much from the distribution of data from when all seasons were used. The similarities between the Canberra and Melbourne category distribution when comparing 9–13 seasons to just 2016-19 provides some confidence that the distribution of the Brisbane and Sydney data are representative even though there are fewer seasons of available data.

Categorical performance diagrams were used to plot four metrics of the day 0 curated forecast accuracy; the probability of detection, the success ratio, the frequency bias and threat score (Roebber, 2009). These metrics are based on the 2 × 2 contingency table where a category threshold is used to delineate ‘hits’, ‘misses’ and ‘false alarms’. The best forecasts lie in the top right region of the plots where POD, SR, FB and TS approach 1 in the two diagrams in Fig. 4 using two different thresholds for comparison: ‘high+’ threshold (Fig. 4a) and ‘moderate+’ thresholds

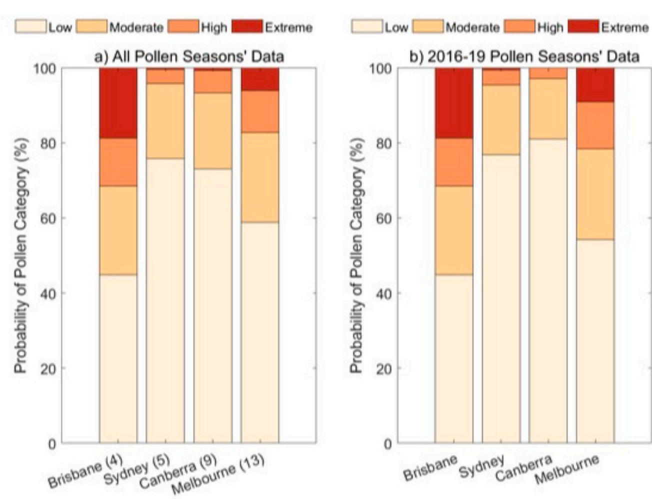

Fig. 3. Frequency of each pollen category measured at each location, a) using all seasons of available data including earlier data prior to standardization with number of available previous seasons indicated in brackets on x labels) and b) for the four years of forecast analysis for the AusPollen project.

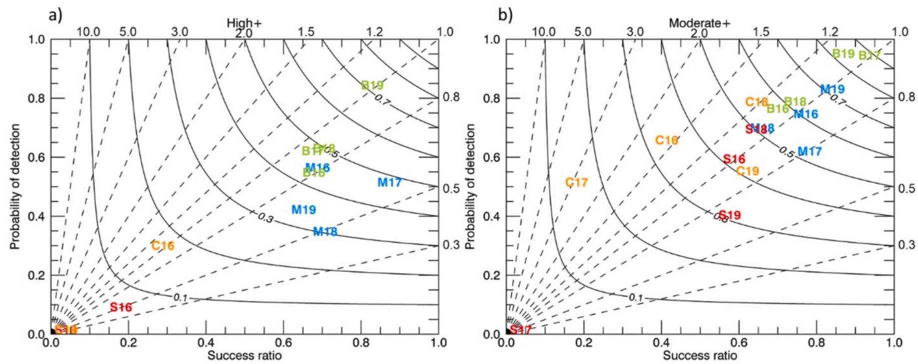

Fig. 4. Categorical performance diagram for forecasts meeting or exceeding a) 'high+' and b) 'moderate+' thresholds. Dashed lines emanating from 0,0 are lines of constant frequency bias. Black curved lines show the threat score. The first letter refers to city, (B= Brisbane, C= Canberra, M = Melbourne and S= Sydney) and is followed by a number representing the year (2016, 2017, 2018 and 2019).

(Fig. 4b). In low pollen years (Canberra and Sydney 2017–2019) there were insufficient data to quantify forecast performance using a high threshold, and so no points were plotted for these sites/years in Fig. 4a.

The best curated forecasts of moderate+ pollen in each location occurred in 2017 for Brisbane, 2018 in Canberra, 2019 in Melbourne, and 2018 in Sydney. Canberra forecasts tended to be biased high (Fig. 4b). For the high+ curated forecasts the best performance occurred in 2019 for Brisbane and 2017 for Melbourne; Melbourne forecasts tended to be biased low (Fig. 4a). Ideally, as forecasting experience increased from 2016 to 2019, the curated forecasts would feature more prominently towards the upper right-hand corner of the performance diagrams.

The accuracy of the Brisbane high+ curated forecasts had improved the most over time, with a nearly perfect score for the 2019–2020 grass pollen season. The Brisbane curated forecast ability to correctly predict moderate+ observations was also excellent in 2017 and 2019. For all locations, forecasts of high+ pollen were less accurate than forecasts of moderate+ pollen. Rare extreme events by definition, are more difficult to characterize and therefore predict.

A challenge in analysing all sites using the same mapping of four levels to binary categories (i.e. Table 1 to Table 2) is the significantly differing distributions of observed pollen levels. Using the high+ cut-off was reasonable for Brisbane and Melbourne, but not for Canberra and Sydney where high+ observations make up less than 5% of the total. Therefore, the rest of this study were assessed on high+ grass pollen for Brisbane and Melbourne, and moderate+ grass pollen for Canberra and Sydney. For these results then, direct comparisons between the two groups could not be made, however, we could still assess at each location whether grass pollen forecast performance improved from the 2016 to 2019 seasons, and whether the performance of the day 1–5 forecasts declined with increasing lead time. We considered the results insignificant where there were fewer than 20 observed days counted in the chosen evaluation category (Supplementary Table S2), thus discounting Sydney and Canberra in 2017 and 2019, and Melbourne in 2018.

3.1. Accuracy in the curated forecasts: Equitable threat score and Gerrity skill score

We used the *ETS* to answer the question "do the curated forecasts capture the high+ (or moderate+) observed pollen values well, taking into account correct forecasts due to random chance?" (We assessed the *POD* of the curated forecast in Supplementary Fig. S1). The *ETS* for the curated forecasts were generally better for the day 0 forecasts than later days for each location and generally degraded as the number of days

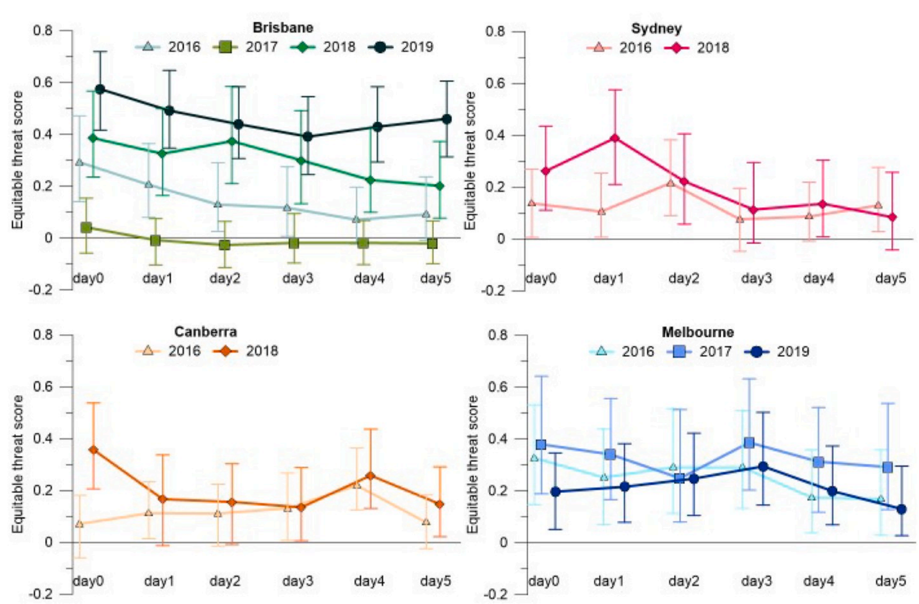

Fig. 5. Equitable threat scores for the curated forecast at each location across the 2016 to 2019 grass pollen seasons. The error bars represent the 95% confidence intervals. Scores are based on 'high+' pollen for Brisbane and Melbourne and 'moderate+' pollen for Sydney and Canberra. Years where there were no or few 'moderate+' days have been omitted for Sydney and Canberra.

ahead increased (Fig. 5). The 95% confidence intervals, calculated using a bootstrap approach (supplementary section 2), showed that there was substantial uncertainty in the *ETS* values related to small sample sizes. This implies many of our comparative results are indicative and were not statistically significant when the mean result of a particular year was within the confidence intervals of other years.

Brisbane showed improvements in *ETS* for the 2018 and 2019 curated forecast, but scored more poorly in 2017 when the total pollen count for the season, or seasonal pollen index (SPI), was the highest (Supplementary Table S3) as compared to 2016 (Fig. 5). The *ETS* in Melbourne was highest in 2017 when there were more high or extreme pollen observations. Sydney's highest average *ETS* occurred in 2018, with a slightly better forecast accuracy on day 1 in that year. The accuracy of the Canberra forecast was also better in 2018 but for day 0. To put these values in context, the daily rainfall forecasts from the Bureau of Meteorology have *ETS* values of about 0.3 (Dare and Ebert, 2017). Each site had good and bad forecast years during the period of this project. Whilst there was a positive relationship between the SPI and rainfall over the 100 km radii from each pollen monitoring site (Davies et al., 2021), 2017 was not a high pollen year in Melbourne (Supplementary Table S3) despite spring rainfall being average or above average in Victorian districts that year (Supplementary Table S4). The impact of drought years on the SPI, particularly for Canberra and Sydney (Davies et al., 2021), consequently affected grass pollen forecasting and our study of the forecast accuracy for these sites.

The *GS* was assessed using three categories for Melbourne and Brisbane (low, moderate and high+), but using only two categories (low and moderate+) for Sydney and Canberra because these sites had insufficient data for three category analysis, whilst Melbourne and Brisbane's distributions were better represented by three rather than two categories. The *GS* rewards correct prediction of rare events with a higher score (Fig. 6) and answered the question, "does the curated forecast predict the observed pollen categories well?". The results were similar to the *ETS* scores in that the accuracy of the curated forecast degrades for predictions further from the current day. This may be due to higher uncertainty in the meteorological forecasts further forward, or that there is more of a tendency for the forecaster to play it safe at longer lead times due to the higher uncertainty. Human judgement could also introduce bias in the following ways:

- Tendency to forecast 'safely' – i.e. given a close choice between categories, the forecaster may tend to choose the higher, preferring a false alarm over a false negative on the theory that it is 'better to be safe than sorry'.
- Tendency to prefer a mid-range forecast (moderate/high) over an end-of-range forecast (low/extreme), or 'hedging your bets' as extreme pollen observations occur rarely.

There was significant variation in forecast accuracy between years. There was strong evidence of improvement in Brisbane with average three-way *GS* improving from 0.20 in 2016 to 0.66 in 2019, and very little overlap of the 2019 confidence intervals with those of other years. Melbourne's average three-way *GS* also increased: 0.39, 0.47, 0.55 for 2016, 2017, 2019 respectively (noting the overlap in confidence intervals). Using the two-way *GS* at the other sites, an average *GS* of 0.45 and 0.43 was recorded for Sydney in 2016 and 2018 respectively, with 0.34 and 0.41 for Canberra in the same years. Confidence intervals for Canberra and Sydney are large due to small samples of moderate+ forecasts and observations.

What is a good *GS*? Tam and Wong (2017) calculated scores of 0.27–0.56 when forecasting cloud cover in Hong Kong. Model hindcast prediction of the 2017 'high' pollen category at eight sites within Victoria, including the Melbourne AusPollen site included here, generated *GS* with a wide range between −0.2 and 0.7 (Emmerson et al., 2019). The *GS* achieved in this work were mostly in the upper half of these ranges, especially in Melbourne, for Sydney up to day three days ahead, and with experience for Brisbane.

3.2. Skill in the curated forecasts: comparison with generated climatology and persistence forecasts

A "climatology" pollen forecast describes a mean value or an expected temporal evolution across the timespan of a year or season, ideally summarised from many years of pollen monitoring. In the absence of a forecasting system it provides a plausible forecast. Smoothing curves (splines and summed Gaussians) were used

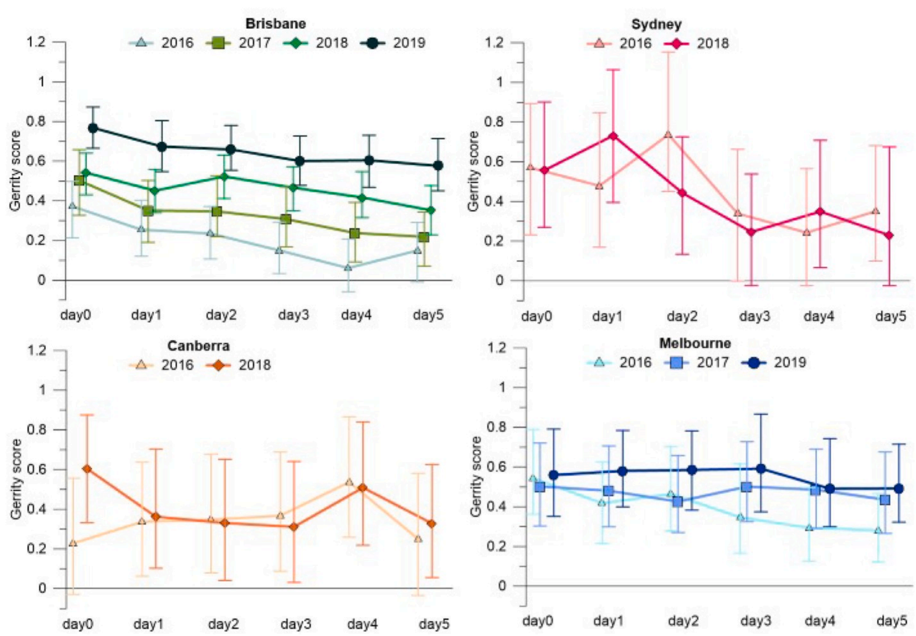

Fig. 6. Gerrity scores for the curated forecasts at each location across the 2016 to 2019 grass pollen seasons. The error bars represent the 95% confidence intervals. Scores are based on 'high+' pollen for Brisbane and Melbourne and 'moderate+' pollen for Sydney and Canberra. Years where there were no or few 'moderate+' days have been omitted for Sydney and Canberra.

retrospectively to construct airborne grass pollen climatologies for each site, using all available years of data, including those generated prior to the AusPollen project in which counting processes were standardised. Curve fitting parameters (spline smoothness and the number of summed Gaussians respectively) were adjusted to avoid overfitting the climatologies, i.e. to avoid including short-period peaks or troughs. Gaussian curves fitted better in most cases (Fig. 7). Melbourne fitted similarly with either single or double Gaussian curve, having a short single-peaked pollen distribution, whilst the other sites fitted better to two summed Gaussian curves, either because of asymmetry in the pollen build-up and decline, or because of a tendency to have two pollen peaks per season. Supplementary Table S5 provides statistical details on how the climatologies are significantly different to the curated and persistence forecasts at each site.

We compared the site average day 0 to day 5 curated forecast *GS* with the calculated persistence and climatology forecasts developed above to assess where they showed skill over those naïve forecasts (Fig. 8). For most sites, there was a general decline in the curated forecast *GS* with increasing number of days forecast ahead. This may be because curated forecasts employed the latest meteorological forecasts, which were usually reliable for short lead times of 1–3 days. However, at longer lead times the weather forecast, and the "memory" of persistence both decline and the advantage of an experienced forecaster is largely lost. Thus a useful question we can consider from Fig. 8 is "does the curated skill in forecasting support the current six day forecast practice"? Melbourne and Canberra, with the longest pollen records, showed better performance of curated forecast over persistence, and a tendency to less degeneration of curated forecast score with lead time. In general, though, poorer accuracy of the curated grass pollen forecasts at the longer lead times for most sites indicates a higher risk that false positives or 'missed' pollen categories might be predicted. With a four day or longer lead time the skill of curated forecasts generally remained above the persistence forecast, but the advantage narrowed suggesting that sites might consider discontinuing the daily forecast service at day 3. Other national services do not provide pollen forecasts beyond day four (e.g. SILAM, 2020).

It was also noted, that overall for most sites the accuracy of the curated forecasts was better than retrospectively calculated persistent forecast (i.e. the curated forecast showed skill). This was not evident in the representation of the overall average *GS* for the four seasons for Brisbane. We note however, that Brisbane improved the skill of the curated forecast with experience to an annual average *GS* of 0.66 in 2019 (Fig. 6). Also, in Brisbane, the level of grass pollen in the atmosphere exceeded the definition of a 'high' category (50 grains m^{-3}) early in the season and often remained or fluctuated above this threshold for some time, giving apparent weight to the persistence method. However, persistence does break down if pollen observations are not available for any reason, such as on weekends when pollen samples may be collected and counted at a later date (as was the case for Brisbane in the two later years of the project), or during times of power interruptions, damage to the pollen collection equipment, or failure of the Melinex tape or staining. By contrast, the persistence method did not work well at Melbourne, because the observed levels of grass pollen in the atmosphere fluctuated between categories from day to day (see Supplementary Fig. S2 for persistence *GS* for each site, year and forecast lead time).

The simple climatology "forecasts", calculated after completion of the project monitoring and forecasting period, performed poorly in almost all cases, except Canberra (lower than curated but higher than persistence), with large confidence intervals. The Sydney climatology forecast performed particularly badly, because 2016 and 2018 had few observations above the 'low' category and the climatology forecast didn't predict these occasions correctly. There is a heavy negative penalty for a 'miss' (see Table 2) in the *GS* matrix.

4. Discussion

There were marked differences in the curated forecast accuracy amongst sites and between years. There are also substantial uncertainties in the values of the verification metrics due to small samples and due to variability in counting of pollen (Milic et al., 2021). In the first instance, we used categorical performance diagrams to compare the forecast accuracy at the high+ and moderate+ pollen thresholds, finding too little data at Sydney and Canberra in the high+ pollen category. The Brisbane curated forecasts were the most accurate across all four forecast years in the high+ and moderate+ pollen categories. All sites performed better in the moderate+ pollen category, where the threshold for a correct 'hit' was 20 grains m-3. The reduction in missed high+ predictions and false positives over the four years indicates improvement in the curated forecasts with experience.

We also examined whether the performance of the curated forecast degraded with increasing lead time. The AusPollen project provided grass pollen forecasts for the current day and up to five days ahead. Our

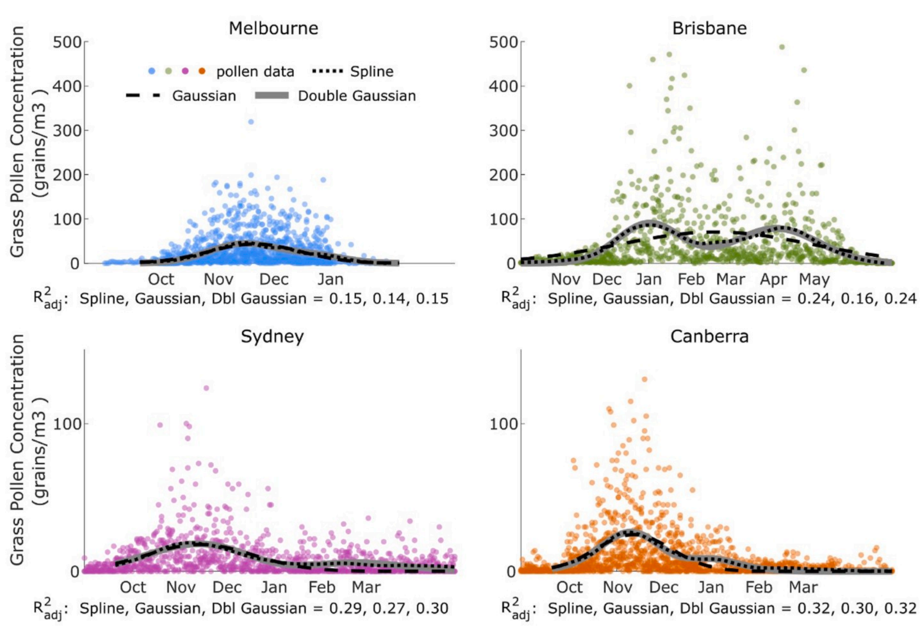

Fig. 7. Idealised climatological fits calculated retrospectively for all current standardized and historical available seasonal pollen observations.

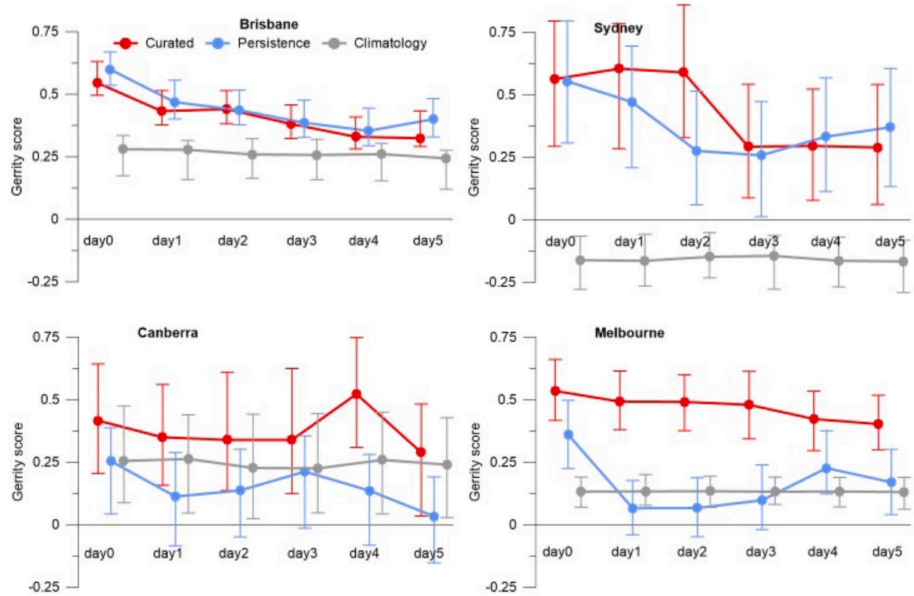

Fig. 8. Project overall average Gerrity scores from day 0 (d0) to day 5 (d5), comparing the curated forecast to retrospectively calculated persistence and climatology based pollen categories, across all sites and years with more than 20 observations in an evaluation category. Note that Brisbane and Melbourne data was analysed using a three-way GS while Canberra and Sydney data used a two-way GS.

results have determined that the forecast accuracy at day 5 is poorer than days 0–3 at all sites, and the point at which accuracy really starts to decrease varies between day 2 and day 4 at different locations.

There is evidence that the accuracy of the curated forecast at Brisbane has improved with time. The accuracy of the curated forecast tended to improve at Sydney, Canberra and Melbourne after 2016, noting the large range in the confidence interval bars. Despite persistence often providing reasonable forecast skill, particularly for Brisbane based on higher or greater categories, it relies on pollen observations being available. If there is a break for any reason, then the persistence method breaks down. Moreover inherently, persistence forecasting will always fail to predict changes in pollen level, and these points of change may be crucial to allergy sufferers. Furthermore, the persistence forecast is not mechanistic and so offers no path for forecast improvement through better representing pollen production release, transport and deposition.

The curated forecasts always outperformed the climatology forecasts. In some cases the climatologies produced very poor GS. Daily pollen levels can fluctuate significantly, but climatology only represents an average season at each site, and will fail to predict short but potentially dangerous daily peaks (as well as failing to predict temporary lows or respites from high pollen loads). A climatology forecast does not consider the large interannual swings between dry and wet seasons which produce much less or more pollen, respectively, nor importantly the influence of gradual medium-term shifts due to climate change, or the effect of medium scale weather patterns such as the Southern Oscillation index. Moreover, reliance on historical data or climatology to predict current daily pollen levels may fail to identify changes in pollen seasonality such as advance in season start (Anderegg et al., 2021) or magnitude (Addison-Smith et al., 2021). Nevertheless, more representative climatologies, or seasonal pollen forecasts e.g. Tseng et al. (2020), could be developed as longer pollen records become available at these sites. There is a need, particularly in Australia and other Southern Hemisphere sites where there are relatively few sites (Davies et al., 2021), to sustain pollen monitoring, track the influence of weather and climate-related changes, and to improve the reliability of pollen forecast models.

There are opportunities to improve the curated pollen forecast capabilities:

- accumulating more years of standardized pollen monitoring data (models supporting the current Brisbane curated forecasts were constructed using only two years of data),
- better understanding the factors driving grass flowering and pollen production e.g. seasonal climate effects (e.g. dry years versus wet years), and pollen dispersion,
- improving the definition of grass pollen sources, and climate or species-specific behaviour in pollen production and release,
- improving the spatial and temporal accuracy of weather forecasts as input to pollen forecasts,
- improved access and availability to new technologies such as automated real-time pollen monitoring, real-time grass phenology, and by high resolution near real-time satellite imagery. Grass pollen measurements are currently subject to a significant amount of uncertainty both due to quantification methods (Addison-Smith et al., 2020) and human factors (Milic et al., 2020) and automated pollen monitoring may help minimise some of these sources of error,
- machine learning, statistical prediction, and emission/dispersion modelling (e.g. Emmerson et al., 2019, 2021) approaches for forecasting grass pollen in Australia. Potentially, a well-designed (and evaluated) three-dimensional dispersion model could provide important pollen forecasts for locations which don't have pollen monitoring, and where there are gaps in the observations.

5. Conclusions

This is the first time that curated pollen forecast accuracy has been evaluated in Australia, and it was done applying methods used in weather forecast evaluation, with pollen concentrations determined using standardised pollen counting methods (Beggs et al., 2018). Differences were noted in forecast accuracy between sites and years, possibly relating to forecasting experience, depth of historic pollen data records, and complexity of the pollen season.

Considering forecast accuracy for these sites beyond the immediate day, this study suggests that the network should provide daily grass pollen forecasts up to three days ahead. Such forecasting has implications for members of the community with pollen allergy who make decisions on behaviour; allergen avoidance, medication use, based on knowledge of local pollen information (Medek et al., 2019). Thus there is a responsibility for networks such as the newly established AusPollen Aerobiology Collaboration to evaluate the accuracy and reliability of pollen forecasts provided to community users. Pollen forecast accuracy depends on local pollen aerobiological knowledge and information derived from meteorological and other environmental factors that influence grass phenology and pollen production, release, transport and deposition. With climate change and more frequent extreme weather events, including drought, bushfires or thunderstorms, grass pollen aerobiology will become more variable (Katelaris and Beggs, 2018), and may be more difficult to forecast. There is a need for further research and development of locally applicable pollen forecast methods, and therefore a real need to keep funding the pollen monitoring network. The pollen forecast evaluation method we have described here might be applied by other aerobiological monitoring networks to aid model development and increase confidence in the value of pollen forecasts distributed to the community.

Data availability

AURIN data repository:

https://data.aurin.org.au/dataset/auspollen-rocklea-qld-6168c420545c70ad5962f414-na

https://data.aurin.org.au/dataset/auspollen-campbelltown-nsw-6168c4200e772c4de5849e89-na

https://data.aurin.org.au/dataset/auspollen-parkville-vic-6168c42016eb4e98d9b8cb28-na

https://data.aurin.org.au/dataset/auspollen-canberra-act-6168c4209b7c5111055ffa84-na.

CRediT authorship contribution statement

K.M. Emmerson: Conceptualization, Data curation, Writing – original draft, Formal analysis, Visualization. **E. Addison-Smith:** Conceptualization, Data curation, Writing – original draft, Conceptualization, Visualization. **E. Ebert:** Conceptualization, Data curation, Writing – original draft. **A. Milic:** Data curation. **D. Vicendese:** Data curation, Formal analysis. **E.R. Lampugnani:** Data curation. **C.H. Katelaris:** Data curation. **S.G. Haberle:** Data curation. **E. Newbigin:** Data curation. **J. M. Davies:** Conceptualization, Data curation, Funding acquisition, Resources, Writing – review & editing.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: JMD, BE, EE, CHK, EN, AH, SH, DM, and PJB report the grant from the Australian National Health and Medical Research Council GNT1116107, with financial co-contribution from Asthma Australia and Stallergenes Greer Australia Pty Ltd, as well as in kind non-financial support from Australasian Society for Clinical Immunology and Allergy, Asthma Australia, Bureau of Meteorology, Commonwealth Scientific and Industrial Research Organisation, Stallergenes Greer Australia Pty Ltd, and Federal Office of Meteorology and Climatology (MeteoSwiss), for the conduct of this AusPollen Partnership project. JMD, PB and AH report grants from Australian Research Council (DP210100347; DP170101630) for related research. JMD reports grants from the Australian Research Council (DP190100376; LP190100216), National Foundation of Medical Research Innovation, Abionic SA, The Emergency Medicine Foundation, and Queensland Chief Scientist Citizen Science Grant, outside the scope of submitted work. JMD reports QUT has patents broadly relevant US PTO 14/311944 and AU2008/316301 issued. ERL reports grants and non-financial support from Bureau of Meteorology outside the conduct of the study. PJB and JMD report grants from Bureau of Meteorology outside the submitted work. KME, BAS, AM, and DV have nothing to declare.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.aeaoa.2022.100183.

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