Reviewer #1

General comments: This manuscript describes the implementation of several different emissions parameterizations to prognostically simulate grass pollen in one region of Australia. The paper is relatively narrow in scope in that it is focused on one type of pollen (grass) in one small region of the globe. That said, it will be useful model for the region and has the potential to be applied to other regions for grass pollen. My comments are mostly minor and regarding changes for clarity and additional supporting information. I recommend the article for publication following these revisions.

We thank reviewer #1 for their helpful comments on our manuscript. This work is the inaugural version of VGPEM, which we hope can be expanded to cover other pollen taxa suited to all of Australia. The choice of ryegrass pollen in this initial version was because of its high human allergenic properties.

Line numbers review to the Discussions version of the manuscript.

Comments on the analysis

1. Regarding the statistical model functions shown in Figure 4: It is helpful to see what the dependencies look like, but it is unclear how these meteorological factors physically relate to what we know about pollen emissions. Can these observed dependencies be related to any physical processes?

As these statistical relationships are based on the pollen concentrations at the receptor sites (and therefore not the emissions), the relationships take into account transport and dilution effects.

We suggest that increased dilution due to an increased boundary layer height during warmer days might be responsible for the fall in the pollen response with temperature. The pollen response also decreases with increased relative humidity, as humid conditions would prevent pollen release from the plant.

Zink et al (2013) also show nonlinear temperature and RH functions describing pollen emission, which are similar to ours. They show an emission function for temperature peaking at 22°C then declining, and a relationship with relative humidity decreasing emissions between 50% and 90%. These relationships were achieved through minimization of errors between model and birch pollen measurements. Our relationships are similar, with temperature peaking at ~25°C and RH decreasing above 40% in V1 and 20% for V2. Sofiev et al (2013) suggest that pollen emission is neither inhibited nor promoted outside of 50-80% RH.

In terms of rainfall, Sofiev et al (2013) uses 0.5 mm hr-1 (the grid cell average rate) is taken as the threshold suppressing the pollen emission. Our rainfall term shows a sharp decline until about 2 mm day^{-1}, after which little additional pollen suppression occurs, although there is considerable uncertainty given the infrequent high-rainfall days.

Replace text on page 10 line 27. "The statistical parameterisations were based on ambient pollen concentrations rather than emissions, and thus the non-linear terms take into account transport and dilution processes. The temperature response in both models increased until 25 to 30°C. The decline in pollen response at higher temperatures is likely due to the dilution with a higher planetary boundary layer (associated with higher temperature); in this case, the assumption of declining emissions with increased temperature is likely incorrect. There is relatively little non-linearity with humidity, and the general trend is for increased concentrations (or emissions) in dryer conditions; this is explained by the drying required for anther dehiscence. The rainfall term shows a sharp decline until about 2 mm day^{-1}, after which little additional pollen suppression occurs, although there is considerable uncertainty given the relative paucity of high-rainfall days. The suppression of grass pollen concentrations (or emissions) is likely due to the low potential for anther dehiscence in moist conditions, and wet deposition of ambient pollen."

2. Risk category definitions: Page 4 – line 14 – Can you place these count categories (low, moderate, high, extreme) in context as compared to other counts in other regions (e.g., Europe, US)? This would give readers an idea of how high/low Australian counts are relative to other locations in the world. Additionally, for the evaluation based on risk categories on page 12, how do uncertainties in these thresholds influence the analysis?

Table of pollen count categories for grass where possible. P="pollen"

	Australia	MeteoSwiss (Zink et al 2013)	UK Met Office (Osborne et al 2017)[a]	US National Allergy Bureau[b]
Low	<19	<10	<29	1<P<4
Medium	20<P<49	10<P<70	30<P<49	5<P<19
High	50<P<99	70<P<300	50<P<149	20<P<199
Extreme	>100	>300	>150	>200

a Grass pollen. UK Met Office have 4 different grading systems dependent on taxa.
b https://www.aaaai.org/global/nab-pollen-counts/reading-the-charts

Text added to page 4 line 15. "The Australian grass count categories are similar to those used in the UK and Europe at the low and medium count categories, but the Australian extreme category is reached at pollen counts up to 3 times lower than Europe and the US (Zink et al., 2013; Osborne et al., 2017; US National Allergy Bureau)."

And correction at page 4 line 14 "...graded low if the count is 19 m^{-3} or less"

Figure 7 deals with the second point nicely, as modelled pollen concentrations falling just outside the defined risk category are defined as a 'miss', even though the modelled value may be just outside the category bin. In figure 7 we examine the Gerrity score, probability of detection, equitable threat score, and false alarm rate based on whether the model captures the high pollen risk category correctly. The r correlation and root mean squared error are only based on how close the modelled pollen is numerically to the observed pollen, and therefore 'decategorised'.

The categorised Gerrity score gives a worse result if the model misses by more than one category. The model/observed comparison is assessed using a weighted matrix. The further from the diagonal the model is, the weightings decrease (negative) producing a worse score. In this paper we present a range of statistics which assess different aspects of the model skill.

Add text to page 12 line 6. "Statistical evaluations using categorised and decategorised pollen counts will show how the Australian grass pollen thresholds impact our results."

We see that the best performing methods in each of the panels in figure 7 do not change much, with E8, E9 and E10 performing best in all cases. In terms of the uncertainty in the Australian grass pollen thresholds, the difference between the categorised and decategorised skill tests is small, ranging between 0.1 and 0.2 units.

		E8	E9	E10
Average r	Decat	0.54	0.47	0.65
Average RMSE/100	Decat	0.55	0.51	0.45
Average Gerrity	categorised	0.44	0.32	0.42
Average (r and RMSE)		0.545	0.49	0.55
Difference (above – Gerrity)		0.105	0.17	0.13

Add text to page 14 line 11. "Comparing the results of the decategorised Pearson correlation and RMSE against the categorised Gerrity score yields minor differences between 0.1 and 0.2 units, and suggests the Australian grass pollen thresholds influence the analysis by ~15%."

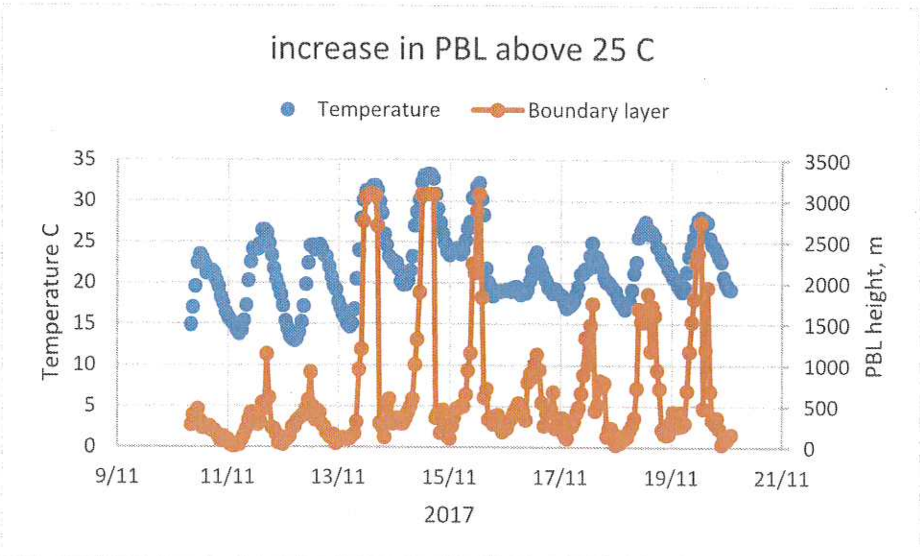
3. Page 6 line 24 – Any local evidence for why temperature would be increasing emissions? Because the temperature component seems to be driving the statistical models, it would be useful to understand why there is such a shift around 30oC.

Page 6 line 24 refers to the immediate timing function which is used for pollen emission methodologies and not the two statistical models. The temperature function applies a sliding scale between 6°C and 24°C, the function becoming 0.95 at temperatures higher than 24°C. These equations are not related to those from the statistical model on page 10.

Text changes concerning the pollen emission response to temperature above 30 °C are included in our answers to comment 1.

4. Page 10 – line 29 – The explanation of the sharp drop off with temperature and the growing BL height doesn't make very much sense. Can you verify if these changes with time/temperature relate to the simulated PBL height by the model?

We are not saying the boundary layer increases with dropping temperatures, rather higher temperatures increase the boundary layer and cause more dilution. Thus the pollen concentrations decrease.



There is a large increase in model boundary layer with higher temperatures, particularly above 30°C.

The average modelled boundary layer on November days below 25°C = 282 m, max =1742 m, and on days above 25°C =378 m, max=3083 m.

Add sentence on page 10 line 29. "On days in November where the temperature is above 25°C, the maximum modelled boundary layer height is nearly double the height modelled on days below 25°C."

5. Page 12, lines 25-30: What are the relative magnitudes of u and v winds in the region? E.g, If the u winds are higher than v (as they frequently are), would that explain the improved correlations? Additionally, how does this relate to the wind parameterization that is implemented? E.g., if the magnitude of v winds are always below the threshold, then this might explain the lack of correlation.

The observed (and modelled) average and maximum V winds are higher than the U winds for all the sites in west and central Victoria. The Max U winds are higher in the east of Victoria (Shepparton and Latrobe Valley, valley runs E-W so not surprising), but the difference is not as large as in the west.

AWS site	Average U obs (model)	Max U obs (model)	Average V obs (model)	Max V obs (model)
Hamilton airport	-0.07 (0.17)	8.7 (6.58)	-0.82 (-0.54)	13.53 (10.04)
Ballarat aerodrome	0.46 (0.10)	9.68 (6.20)	-0.86 (-0.55)	13.9 (10.13)
Bendigo airport	0.65 (0.23)	8.05 (4.61)	-1.35 (-1.05)	10.14 (7.36)
Geelong racecourse	-0.56 (-0.30)	5.83 (5.59)	-1.21 (-0.87)	10.15 (7.76)
Melbourne Olympic park	-0.24 (-0.43)	4.75 (5.50)	-0.63 (-0.73)	9.3 (8.51)
Scoresby	-0.06 (0.01)	4.75 (4.97)	-0.35 (-0.38)	15.48 (8.70)
Shepparton airport	-0.18 (0.01)	9.21 (6.51)	-0.92 (-0.74)	8.49 (6.20)
Latrobe valley airport	-1.00 (-0.12)	7.24 (5.29)	-0.35 (-0.12)	6.7 (5.29)

The emission parameterisation uses wind speed rather than the wind components U and V independently, therefore there are no U and V thresholds. There is no threshold minimum wind speed either, and the function yields 0.33 at a wind speed of 0 m/s. We do use a saturation wind speed of 5 m s^{-1} to scale the model wind speeds, which Sofiev et al (2013) describes as the maximum speed that wind actively helps the release of pollen.

Add text to page 7 line 1 to minimise confusion about there not being a lower wind threshold: " ...lower rate (0.33 for fstagnant) in still conditions..."

We add text to page 7 line 4: "... above which the wind speed does not promote the release of pollen."

Neither the above analysis of U and V nor this saturation wind speed explains the lack of correlation. Individual correlations for observed data are not strong (0 and 0.4) for U and V. average U correlation was 0.32 and average V is 0.22, which isn't a huge improvement.

I think the better U correlation is more a case of the geography of the pollen source regions being west of most of the pollen count sites, and thus the east-west wind component has a stronger relationship than north-south. We have also included wind roses for each AWS site in the supplementary material, together with a brief wind climatology of the 2017 season on page 12.

Include text on page 12 line 29. "We include a wind rose for each AWS site in the supplementary section to determine the strength of the winds. The roses show a strong southerly influence, corresponding with the afternoon sea breeze at most sites apart from Churchill, located within an east-west aligned valley. Sites further west in Victoria (Hamilton and Creswick) also show a northerly influence, generally with a greater percentage of wind speeds above 4 m s^{-1} than elsewhere."

6. Page 13 – line 10: Can you explain why the modeled RH correlation would be higher given that the model simulated observed RH with good fidelity?

Here we have difficulty in that the observations of pollen are not coincident with measured meteorological variables. However we are able to compare the observed meteorology with the model as we can extract model variables from any location in the grid. Thus the comparison of modelled RH with observed RH was at the same location. The comparison of observed RH at the AWS with observed pollen at the count sites was less strong, as the pollen count sites are some 10 – 29 km distant from the AWS sites.

The model is a simplification of reality, and modelled pollen has been coded to have a strong dependence on RH. Thus it is not surprising that the modelled correlations are stronger than those observed.

Added text to page 13 line 11. "The observed relationship may be weaker as the pollen measurements are not coincident with the AWS."

7. Page 13 (and conclusions, page 15 line 25)– It is unclear why wind speed is not a good predictor in your models. Can this be compared with other studies to place this finding in context.

Wind speed used alone in the intermediate timing is not a good predictor of pollen. Sofiev et al (2013) suggests wind promotes the pollen emission, but is not solely responsible. A plant needs to flower first before pollen is released, which tends to be controlled by temperature. After flowering, pollen that is ready to be released is easily picked up by the wind. However once this supply is exhausted, the strength of the wind does not matter (the saturation wind speed is 5 m s^{-1}). Sofiev et al (2013) also sees a low correlation with wind speed, suggesting that stronger wind speeds increase the emission rate but also increases ventilation and turbulent mixing.

Zink et al (2013) add "Theoretically, if unlimited amounts of pollen were available, higher wind speeds would yield stronger entrainment, and hence more airborne pollen. In reality, this is limited by the fact that at a certain point, the flowers will run out of pollen grains."

Viner et al (2010): "An unexpected result was the absence of a relationship between wind speed and pollen shed in our observations. However, we measured the same range of pollen shed rates at 1 m s–1, the lowest reliable measurement of wind speed by our anemometer, and 5 m s–1, indicating that only a light wind is necessary for pollen shed and stronger winds may not necessarily cause more pollen to be shed."

Add text to page 13 line 22. "...which provided poor prediction skill scores (average r=0.25, 0.18 and 0.17 respectively), similar to results by Viner et al (2010) and Zink et al. (2013). Wind promotes pollen emissions, but the plant must flower first - a process not controlled by wind speed (Sofiev et al., 2013)."

8. Section 4.3: There is little discussion of why performance is different at the eight different sites. This could be expanded in a revised manuscript.

The results section discusses how model performance tends to be better at sites outside of the city. In order for pollen to get to city locations there is more transport involved, and the pollen size is large and dense. Perhaps local sources are missing. There is also increased heat and turbulence in the city, and being relatively close to the coast introduces sea breezes. The strength and frequency of these southerly winds are shown in the supplementary for each site.

Most of the pollen emission methodologies rely on the distribution of pasture grass. We include satellite maps of each site and their surrounding fraction of pasture grass cover in the supplementary section. As the pollen has a relatively short lifetime, those sites located next to grass pixels tend to be modelled better than those which are not. The least well modelled site is Geelong, which has very strong southern ocean influences (approx. 15 km from the coast. There are limited grass pixels between the coast and the pollen count site.

Include sentence on page 8 line 33. "We include larger scale maps of the pasture grass coverage surrounding the pollen count sites in the supplementary material."

Add text to page 14 line 11. "The sites vary considerably in terms of surrounding land use, whereas all the pollen in the model comes from pasture grass. This impacts the individual site performance against the pollen observations. Hamilton, Dookie and Churchill are close to pollen source areas. Creswick is surrounded by forest. The Burwood and UoM sites are in heavily built up areas with green space, which is not included in the model pasture grass maps."

Include text on page 14 line 10. "The wind rose for Geelong shows the strong Southern Ocean influence, and there are few grass filled pixels between the coast and pollen count site which the model relies upon (supplementary)."

The model assumption is that all grass pollen comes from pasture grass. The meteorological parameters are all modelled very well, therefore individual site performance could come down to whether we have the correct spatial distribution of the pollen source regions. Inverse modelling could highlight discrepancies between our pasture grass emission source areas, and other grass land use categories contributing to grass pollen. However this is out of scope of the current paper.

Include text at page 15 line 18. "Inverse modelling could highlight where other grass land use categories contribute to grass pollen."

To test whether the pollen observations at all the count sites are related, we plot r^2 correlations. Observations in yellow, left, and modelled E10 scenario right.

	HAM	CWK	BGO	GEE	UOM	BUR	DOK	CHU
HAM		0.78	0.91	0.79	0.86	0.79	0.85	0.59
CWK	0.55		0.84	0.70	0.80	0.85	0.68	0.83
BGO	0.10	0.17		0.89	0.90	0.88	0.91	0.69
GEE	0.25	0.37	0.19		0.92	0.88	0.80	0.70
UOM	0.37	0.55	0.31	0.38		0.96	0.79	0.75
BUR	0.28	0.40	0.22	0.36	0.72		0.74	0.84
DOK	0.00	0.06	0.39	0.05	0.05	0.05		0.57
CHU	0.44	0.56	0.06	0.17	0.37	0.34	0.02	

Add text to page 15 line 16."Correlations between observed pollen at each site are not particularly strong (average r^2 = 0.28), suggesting that the pollen sources may not be related, or are highly localised. The modelled correlations between all sites are very strong because they share the same pollen source characteristics (average r^2=0.80)".

Editorial comments

1. Page 2 – line 1: Does this mean that throughout the world Melbourne has the highest population of allergy sufferers, or just in Australia? Does the reference support this? It appears to discuss the European community.

Table 1 (top line) of Bousquet et al (2008) shows Melbourne has the highest allergy rate in the world. Melbourne has the highest prevalence of nasal allergy (46), and the highest atopic nasal allergy (32) of any region studied. The title of the Bousquet paper is somewhat misleading as it refers to the European Community Respiratory Health Survey.

Alter text at page 2 line 1 to read "Melbourne, on the south east coast of Australia, has the highest prevalence of allergic rhinitis in the world (Bousquets et al 2008). Melbourne, in the State of Victoria, is a city of approximately 4.9 million inhabitants."

2. Page 2- lines 30-35: There are a few other dispersion model studies missing (e.g., oak study in CMAQ; Pasken and Pietrowitz, 2005)

Add text to page 2 line 32. "An understanding of pollen release biology together with accurate meteorological data is crucial for pollen forecasting (Pasken and Pietrowitz, 2005)."

Add text to page 2 line 33. "Indeed, climate induced spread of ragweed is predicted to double the number of Europeans suffering allergic responses by 2060 (Lake et al, 2017)."

3. Page 3 – line 10 – Does the lack of other wind-driven pollination species also apply to all other grasses? It is unclear if there are other Australian species that would be contributing to the grass pollen count outside of the ryegrass. My understanding is that different genuses of the Poaceae family are very hard to distinguish in daily counts.

Correct, grass pollen is counted, not ryegrass pollen. We use the physical properties of ryegrass to represent all grass pollen in the model, as it is the major allergen.

Other Melbourne researchers also comment on the dominance of ryegrass. Ong et al (1995) suggest that the Melbourne count, which is the most resolved for species, that it is all introduced species such as ryegrass and canary grass. The Medek et al (2016) paper talks about C3 grasses dominating in the temperate southern region of Australia (e.g. Victoria), mainly pasture grasses. And Schappi et al (1998) "In the cool temperate climate of this region, rye-grass (Lolium perenne) pollen is more abundant than pollen from other grass species (Smart and Knox, 1979), since rye-grass is grown extensively as pasture grass in this area and has a very high pollen output (Smart et al., 1979)"

Seminal work done by Smart et al (1979) counted anthers per flowering spike of grasses to the north of Melbourne. "Some grasses, for example brome and wild oat, have a low pollen output while others, particularly agricultural grasses, for example ryegrass, Yorkshire fog and canary grass, have a very high output. The high pollen producers are all introduced cool temperate pasture grasses. Native grasses, for example wallaby and kangaroo grass, are low pollen producers." Combined with the large areas of land given over to ryegrass production, ryegrass must be the dominant pollen producer in Victoria.

Alter text on page 3 line 10 "Native Australian grasses such as wallaby and kangaroo grass are generally not wind-pollinated and produce little pollen, whilst introduced agricultural pasture grasses such as ryegrass (Lolium perenne) and canary grass are high pollen emitters (Smart et al., 1979). Ryegrass is grown extensively in Victoria."

Change text at page 3 line 13 "attributed to ryegrass"

Add text to page 4 line 3. "DNA sequencing at UoM indicates ryegrass can contribute 60 to 90% of grass pollen counted over the 2016 pollen season (personal communication, E. Newbigin)."

4. Page 3 – line 30: Genus distinctions can be made based on volumetric sampling methods. Additionally, it would be helpful to note how many different pollen types (e.g, at the family or genus level) are counted at the Australian sites.

Grass pollen cannot be further categorized by microscopy (not to genus or species).

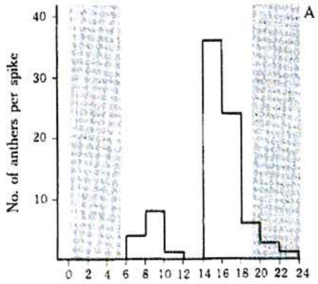
20 pollen taxa are listed in Haberle et al (2014) as species contributing more than 80% of annual pollen in Australia and New Zealand, of which 15 are found in Melbourne.

Add text page 4 line 1 "In Victoria, routine pollen counting since 2017 distinguishes between 15 pollen taxa, with Haberle et al. (2014) finding 70 % of the total pollen..., however we concentrate on....."

5. Page 6 – line 10 – Other studies (e.g., van Hout et al, 2008; Viner et al, 2010) have shown an early morning timing peak. Any ideas as to why ryegrass might be different?

The van Hout and Viner references refer to corn. I think the key here is that ryegrass and corn are entirely different plants. Ryegrass flowers in spring whereas corn flowers in summer. The time of pollen release also depends when pollen can get into the air (ie needs vertical uplift). If cool and damp (spring), the time of pollen release is likely to be later in the day.

Melbourne evidence for the later peak comes from Smart & Knox (1979) who measured rye-grass emissions with two daily peaks [early morning and late afternoon], the latter afternoon peak being 3.5 times higher than the morning. We have approximated this relationship by centring the release at noon, with a 4 hour standard deviation.



Pollen emission timing figure from Smart and Knox (1979)

Plants differ as to what conditions they need to dehisce: Zink et al (2013) "some grasses need high relative humidities for the opening of their anthers since they have to swell in order to crack." In Viner et al (2010) "Once an anther has lost sufficient moisture, the structure opens at its tip, releasing the mature pollen grains within."

Alcazar et al (2019) "Different grass species flower at different times of the year (Beddows 1931; Jones 1952) and day; this may affect the diurnal patterns in pollen from this family. As an example, Agrostis and Festuca flower at midday, whereas Anthoxanthum and Holcus flower in the morning or late afternoon (Hyde and Williams 1945; Peel et al. 2014)."

Peel et al (2014) "Vapour Pressure Deficit may be considered a proxy for the drying power of the air, and greater VPD earlier in the day may thus lead to earlier drying, emission and concentration peaks."

However I'm not sure any of the above is relevant to our study. Alter/add text to page 6 line 10. "...(measured as the number of exposed anthers) occurs in the early afternoon. As ryegrass flowers in spring when mornings are cool and damp, the anthers need to dry before pollen is released."

6. Figure 2- It's hard to see the correlation between the EVI and pollen count. A climatological average would show the timing better.

We present climatologies of the time series for figure 2 panels a and b.

Change figure 2 caption to read "(a) 16 year climatology in EVI from South West Victoria...."

7. Figure 4 – Can you put the V1 and V2 x axes on the same scale to improve visual comparisons?

Done.

8. Page 9 – I'm confused about the loss factor in Equation 11 – how were these set, and how are they different from a regular deposition rate?

Zink et al (2013) also propose a production and loss model, where the pollen reservoir is considered to be pollen available for release but has not left the plant. The pollen can rest on leaves etc. A loss can be incurred at this stage by animals brushing past or loss to the ground. Zink then suggest this 'random' loss process is similar to a half-life, such that after 12 hours, half the reservoir is lost. We extend this idea to provide a variable loss rate which is accelerated in wet conditions.

Rewrite page 9 line 7. "...and once exhausted by in-plant dry and wet deposition, or pollen release, the pollen reservoir is only replenished at a finite rate. Scenario E7 is a production-loss model for this pollen reservoir."

Rewrite section beneath equations on page 9. "where emissions, E are set to be the product of the available pollen reservoir, A and the instantaneous emission factor, I at grid-point (x,y) at time t. δt is the model time-step. The pollen produced, P is given by the product of the spatial and gross-timing terms, proportional to the fraction of the grass pollen season covered between t and t + δt, L is the amount lost between t and t + δt, T is the total length of the grass pollen season and λ is the loss rate due to direct deposition before the pollen leaves the plant. This loss can occur direct to the ground or via animals brushing past, and differs from the in-atmosphere wet and dry deposition rates. Zink et al

(2013) suggest this loss process is similar to a half-life, which we extend to provide a variable loss rate accelerated in wet conditions. The loss decay parameter (λ), is defined as a piece-wise polynomial function based on the rain rate such that pollen has a half-life on the plant of two days in dry conditions and 12 hours in wet conditions, with the latter corresponding to a rain rate of 2 mm h^{-1} .

9. Page 13 – lines 18-20: Move this text to the figure caption.

Already in figure caption so have removed from the main text.

References

Alcázar, P., Ørby, P.V., Oteros, J. et al. Cluster analysis of variations in the diurnal pattern of grass pollen concentrations in Northern Europe (Copenhagen) and Southern Europe (Cordoba). Aerobiologia (2019). https://doi.org/10.1007/s10453-019-09558-2

Bousquet, P. J., Leynaert, B., Neukirch, F., Sunyer, J., Janson, C. M., Anto, J., Jarvis, D., and Burney, P.: Geographical distribution of atopic rhinitis in the European Community Respiratory Health Survey I, Allergy, 63, https://doi.org/10.1111/j.1398-9995.2008.01824.x, 2008.

Erbas, B., Chang, J-H., Newbigin, E., Dhamarge, S. (2007) Modelling atmospheric concentrations of grass pollen using meteorological variables in Melbourne, Australia, International Journal of Environmental Health Research, 17:5, 361-368, DOI: 10.1080/09603120701628693

Haberle, S., Bowman, D., Newnham, R., Johnston, F., Beggs, P., Buters, J., Campbell, B., Erbas, B., Godwin, I., Green, B., Huete, A., Jaggard, A., Medek, D., Murray, F., Newbigin, E., Thibaudon, M., Vicendese, D., Williamson, G., and Davies, J.: The macroecology of airborne pollen in Australian and New Zealand urban areas, PLoS ONE, 9, e97 925, https://doi.org/10.1371/journal.pone.0097925, 2014.

Lake, IR, Jones, NR, Agnew, M, et al. Climate change and future pollen allergy in Europe. Environ Health Perspect. 2017; 125: 385- 391.

Medek, D. E., Beggs, P. J., Erbas, B., Jaggard, A. K., Campbell, B. C., Vicendese, D., Johnston, F. H., Godwin, I., Huete, A. R., Green, 30 B. J., Burton, P. K., Bowman, D. M. J. S., Newnham, R. M., Katelaris, C. H., Haberle, S. G., Newbigin, E., and Davies, J. M.: Regional and seasonal variation in airborne grass pollen levels between cities of Australia and New Zealand, Aerobiologia, 32, 289–302, https://doi.org/10.1007/s10453-015-9399-x, 2016.

National Allergy Bureau. https://www.aaaai.org/global/nab-pollen-counts/reading-the-charts. American Academy of Allergy, Asthma and Immunology.

Osborne, N.J., Alcock, I., Wheeler, B.W. et al. Pollen exposure and hospitalization due to asthma exacerbations: daily time series in a European city. Int J Biometeorol (2017) 61: 1837. https://doi.org/10.1007/s00484-017-1369-2

Pasken, R. and J.A. Pietrowiez (2005) Using dispersion and mesoscale meteorological models to forecast pollen concentrations, Atmos. Environ., 39, 2689-7701.

Peel, R. G., Ørby, P. V., Skjøth, C. A., Kennedy, R., Schlünssen, V., Smith, M., Sommer, J., and Hertel, O.: Seasonal variation in diurnal atmospheric grass pollen concentration profiles, Biogeosciences, 11, 821-832, https://doi.org/10.5194/bg-11-821-2014, 2014.

Smart, I. J. and Knox, R. B.: Aerobiology of Grass-Pollen in the City Atmosphere of Melbourne - Quantitative-Analysis of Seasonal and Diurnal Changes, Aust J Bot, 27, 317–331, https://doi.org/10.1071/Bt9790317, 1979.

Smart, I. J., Tuddenham, W. G., and Knox, R. B.: Aerobiology of Grass-Pollen in the City Atmosphere of Melbourne - Effects of Weather Parameters and Pollen Sources, Aust J Bot, 27, 333–342, https://doi.org/10.1071/Bt9790333, 1979.

Sofiev, M., Siljamo, P., Ranta, H., Linkosalo, T., Jaeger, S., Rasmussen, A., Rantio-Lehtimäki, A., Severova, E., and Kukkonen, J.: A nu35 merical model of birch pollen emission and dispersion in the atmosphere. Description of the emission module, International Journal of Biometeorology, 57, 45–58, https://doi.org/10.1007/s00484-012-0532-z, 2013.

Van Hout et al., (2008) The influence of local meteorological conditions on the circadian rhythm of corn (Zea mays L.) pollen emission, agricultural and forest meteorology, 148, 1078-1092.

Viner, B.J., M.E. Westgate and R.W. Arritt, 2010: A model to predict diurnal pollen shed in maize. Crop Science 50, 235-245.

Zink, K., Pauling, A., Rotach, M. W., Vogel, H., Kaufmann, P., and Clot, B.: EMPOL 1.0: A new parameterization of pollen emission in numerical weather prediction models, Geosci Model Dev, 6, 1961–1975, https://doi.org/10.5194/gmd-6-1961-2013, 2013.

Interactive comment on "Development and evaluation of pollen source methodologies for the Victorian Grass Pollen Emissions Module VGPEM1.0" by Kathryn M. Emmerson et al.

Anonymous Referee #2

General comments: I would like to thank Ms Emmerson and colleagues for submitting an interesting and detailed manuscript which describes a thorough assessments of the different prognostic approaches used in the grass pollen emission-source methodologies in their model (VGPEM1.0), applicable to Victoria, Australia. The publication also includes an excellent review of most of the relevant material on pollen emission modelling approaches to date, nicely summarising the limitations of regression versus statistical approaches. Whilst focussed on specific pollen type as might be expected and germane to this study region (Poaceaea) this is justified due to the significant health impacts, as highlighted by the thunderstorm induced asthma dispersal incident referenced, and the results produced are useful. The link to EVI is also useful. As discussed in section 3 of their manuscript the modelling approach does not include some of the more detailed mechanisms associated with pollen emission, that may impact pollen production and re-suspension etc. which may influence the variances discussed, but this is justified due to the lack of quantitative observational as well as modelling information for these mechanisms. The POD, FAR and ETS approach is well described although some context would be helpful.

Pollen types and sources can of course vary enormously across the globe but this work provides much needed evidence with good statistical analysis for different approaches and their applications to other regions and pollen types.

There will be many in the community who welcome this work as highlighting a growing need for pollen and other allergen/pathogen consideration in pollution modelling. In my opinion the manuscript is worthy of publication. Only very small changes are needed in order to clarify certain areas (for the non-pollen experts) with answers to minor questions to help support one or two sections with occasional reflection in the conclusions.

We thank reviewer #2 for these helpful suggestions to improve the manuscript and make it clearer.

Comments

1. There a couple of other studies that might be worth referencing to place this work in a more global context, e.g. Lake et al. (2017),and Pasken and Pietrowitz.

Lake et al (2017) estimated the number of Europeans suffering allergic responses to ragweed by 2060 will more than double, due to climate change and the estimated spread of the plant. Climate change could prolong the pollen season, changing the pattern of exposure.

Pasken and Pietrowitz (2005) make short-term forecasts of oak pollen in Missouri, USA, finding that the accuracy of the meteorological data was crucial in tandem with an understanding of pollen release biology.

Add text to page 2 line 32. "An understanding of pollen release biology together with accurate meteorological data is crucial for pollen forecasting (Pasken and Pietrowitz, 2005)."

Add text to page 2 line 33. "Indeed, climate induced spread of ragweed is predicted to double the number of Europeans suffering allergic responses by 2060 (Lake et al, 2017)."

2. Section 2 Observations and characteristics of grass pollen. You list the pollen risk categories specific to Victoria/Australia. How do these factors relate to international risk factor league tables e.g. in the USA (where other factors such as Pollen and Overall national Capital Risk Factors for individual cities are produced or clinical risk factors in the EU usually in terms of grains per year, e.g. Agnew et al. 2018, Int J Environ Res Public Health).

This comment relates to analysis comment 2 reviewer #1 posed on international pollen classifications. In terms of pollen forecasting having a daily risk classification is crucial. Agnew et al (2018) look at allergic sensitization and disease in children, and relate the impacts to the number of ragweed pollen grains counted per year. Children living in high pollen areas (>5000 grains m^{-3} $year^{-1}$) were more at risk than those living in low pollen regions (<400 grains m^{-3} $year^{-1}$), though the study found that children brought up in rural areas had more resistance than city dwellers.

The Asthma Capital Risk Factors report lists cities in terms of eight contributing factors, pollen being one of them. It is not just about pollen (https://www.aafa.org/media/2119/aafa-2018-asthma-capitals-report.pdf).

Text added to page 4 line 15. "The Australian grass count categories are similar to those used in the UK and Europe at the low and medium count categories, but the Australian extreme category is reached at pollen counts up to 3 times lower than Europe and the US (Zink et al., 2013; Osborne et al., 2017; US National Allergy Bureau)."

Add text to page 4 line 15. "Whilst epidemiological studies commonly use annual pollen totals, we use a daily pollen risk classification system because we aim to predict daily pollen concentrations."

3. Section 3.1.6 Statistical Models. The limitation of the statistical models due to coarseness of the temporal training data (daily) is understood, however a sentence might be useful here explaining how this limitation is linked to the actual physical emission mechanism timescales via the gross timing function and day to day expected variation.

The statistical models are trained on daily data, and predict daily pollen concentrations when used at the BoM. However the C-CTM requires emissions at an hourly frequency and uses EVI data and hourly meteorological data to drive the emissions, therefore linking emissions to the day to day expected variation. The gross-timing function is meant to smooth out much of the day-to-day variation, and is modulated by the immediate-timing term when estimating variation in time in the emissions module.

Add text to page 9 line 27. "...thus cannot resolve higher-resolution temporal variation. The gross-timing function smooths out much of the day-to-day variation, and is modulated by the immediate-timing term when estimating temporal variability in the emissions module."

4. You show the non-linear relationships between VI, V2 model pollen responses and temperature, rainfall and relative humidity (Figure 4) – I assume the grayed areas represent the variances in each case? – So, can a brief sentence or two be included in this section to explain/summarise how these meteorological drivers actually physically relate to the pollen emission mechanisms please?

Add text to figure 4 caption. "The shaded regions correspond to ± twice the standard error of the GAM term."

Add text to page 10 line 25. "The shaded regions correspond to ± twice the standard error of the GAM term and are greater in regions of the distribution with fewer observations. For example, there were far fewer observations at the upper tail of the temperature range considered, and the standard errors are correspondingly larger."

The second part of the question relates to analysis comment 1 from reviewer #1.

Replace text on page 10 line 27. "The statistical parameterisations were based on ambient pollen concentrations rather than emissions, and thus the non-linear terms take into account transport and dilution processes. The temperature response in both models increased until 25 to 30 °C. The decline in pollen response at higher temperatures is likely due to the dilution with a higher planetary boundary layer. Thus the assumption of declining emissions with increased temperature is likely incorrect. There is relatively little non-linearity with humidity. The general trend is for increased concentrations (or emissions) in drier conditions, explained by the drying required before anther dehiscence. The rainfall response shows a sharp decline until about 2 mm day^{-1}, after which little additional pollen suppression occurs, although there is considerable uncertainty given the relative paucity of high-rainfall days. The suppression of grass pollen concentrations (or emissions) is likely due to the low potential for anther dehiscence in moist conditions, and wet deposition of ambient pollen."

5. How representative are these responses, especially temperature, for Australia generally and for this pollen type in particular? I am thinking of the study by Viner et al, 2010, as also pointed out by the Editor regarding the timing response.

Relates to editorial comment 5 of reviewer #1. Earlier Melbourne grass pollen GAM modelling by Erbas et al (2007) also found nonlinear terms for temperature, rainfall and RH.

Add text to page 10 line 29. "The shapes of these relationships are similar to those described by Erbas et al (2007) for grass pollen in Melbourne, and also by Zink et al (2013) for birch pollen in Europe."

6. Can this statistical approach be robust enough to respond to inter-annual variations?

The statistical approach accounts for inter-annual variation via the EVI time-series at each grid-cell. Higher winter-time peak EVI values are associated with higher cumulative grass pollen counts over the following season. The EVI approach factors in the recent growing conditions (accounting for both temperature and rainfall); this approach appears to be reasonably effective for grass pollen in the Mediterranean style climate of SE Australia.

Add text to page 11 line 10. "The statistical approach accounts for inter-annual variation via the EVI time-series at each grid-cell. Higher winter-time peak EVI values are associated with higher cumulative grass pollen counts over the following season."

7. How representative might these relationships shown in Figure 4 be with respect to interannual variation (will the EVI approach take this into account)?

We think the answer to this question relates to that given for the question 6.

The site at Melbourne is the longest running count site in Australia. Pollen data does extend back to the start of the 1990s but there are difficulties finding consistent satellite data at these earlier years to drive that component of the model.

We can see in figure 4 that the relationships for temperature and RH between V1 and V2 are similar. V2 is trained on one extra year at Melbourne and includes data from 7 additional sites than V1, yet the relationships do not change much – i.e., the peak in the temperature response for V1 and V2 are both ~0.5 and peak around 25-30°C, and there is a negative relationship with RH.

8. How do these dependencies, especially with temperature, compare to other pollen types described elsewhere in the literature as this obviously has implications for the risk factor analysis particularly if it is to be extended to other regions? A brief sentence on this might help with context.

At this stage we only propose to include grass pollen in an Australia wide model. It is expected that additional training data from other regions will be included at this stage. There are long time series of pollen counts in Sydney, Canberra, Brisbane and from sites in Tasmania. We know from these data that different seasonal timings will be introduced, as tropical grasses emit their pollen at different times of year (Beggs et al 2015).

Add text to conclusions, page 16 line 12 "Additional training data would be included to model pollen in other Australian regions, to account for the different seasonal flowering times of other grass species (e.g. C4 grasses) (Beggs et al. 2015)."

9. Page 13, line 6. You state that "Transport of pollen from the productive grasslands in the west of Victoria to Melbourne would rely on the U wind vector being modelled accurately, however the model lifetime of these pollen grains is 6 hours over a height of 1 km; too short for pollen emitted near Hamilton to reach Melbourne.' You pose the initial question suggesting you will justify this but then ignore the point by assuming it is modeled correctly in order to justify the conclusion that these grasslands were not the source. Perhaps you could rephrase this sentence to make it less confusing?

U and V are modelled well when compared to AWS data (fig 5). Investigation of the pollen transport distances are relatively short, due to pollen size and density. Generally the pollen counted locally is predominantly determined by local grass coverage.

Add text to page 13 line 6 instead of existing sentence. "The observed U and V correlations are not strong however, and do not point to particular locations being strong pollen sources. Inverse modelling may help pinpoint productive grass pollen regions for each site."

10. Page 13, line 8. You state "We extracted the boundary layer height from the model (unavailable in the observations), which showed that the modelled grass pollen is more strongly correlated to atmospheric dilution (average r=0.61) than it is to temperature (average r=0.44). The model RH is more negatively correlated with grass pollen levels (average r=- 0.52) than is observed." Now going back now to Page 10, where you state that, "This decline in concentrations may be due to increased boundary layer heights (and thus greater effective dilution) rather than a decrease in emissions."

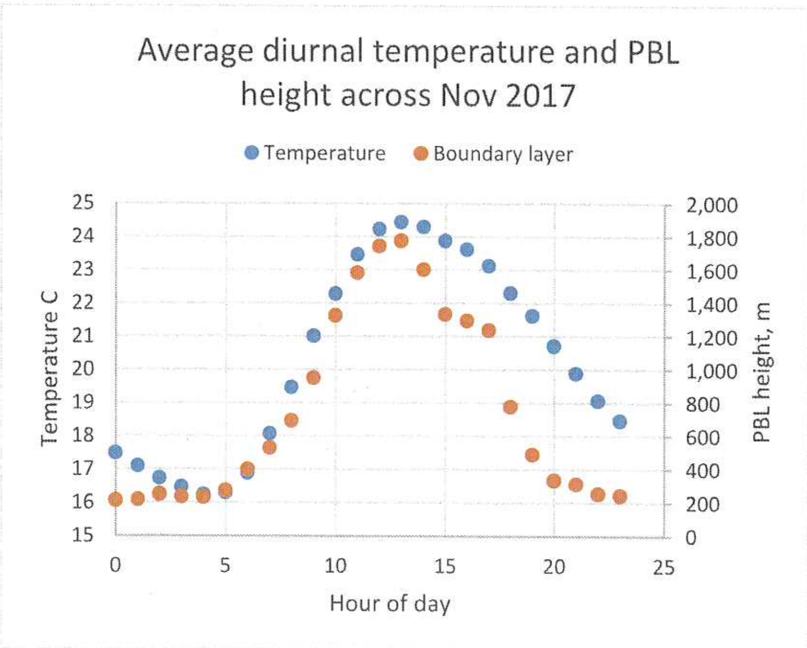
The latter statement I agree with but is this consistent with your statement about that a growing boundary layer depth is accompanied by a sharp drop in temperature – is this correct? Have I read this *correctly? One might expect that the concentrations are inversely related to the volume of air available for vertical mixing from the surface to the boundary layer top, or more precisely the mixed layer. So, increasing boundary layer height due to increasing convection during the day (and surface temperature)~ would lead to increased dilution due to turbulent mixing and dispersion in the lower boundary layer (unless in a zone impacted by strong recirculation from convective outflow or topographic influence). I believe this is generally observed in Melbourne. A drop in temperature response does not seem consistent?*

The statement on page 10 talks about non-linear pollen emissions with temperature, and that pollen emissions decrease at temperatures in excess of 30°C (not the temperatures themselves decreasing). We think this drop in pollen emissions at high temperature is because of an increase in boundary layer height causing dilution. We adjust the sentence on page 10 line 28 to make this point clearer:

"The temperature response in both models increased until 25 to 30°C. The decline in pollen concentration at higher temperatures is likely due to the dilution with a higher planetary boundary layer (associated with higher temperature)."

As I understand it the impacts of summer versus winter boundary layer height development can significantly influence pollutant concentrations in Melbourne whilst the wind direction, e.g. from the local hills and vegetation sources in summer, influences the background tracer concentrations (Coutts et al. 2007, Atmos.Env.)? In addition sea-breezes can also be important in Melbourne and I understand the wind rose for Melbourne displays a very strong annual N-S bimodality with higher frequencies of average winds from the N but of course higher frequencies of much stronger winds from the ocean, S (BoM)?

Perhaps a sentence or two describing the known evolution of the boundary layer height with time of day in the measurement period specific to Melbourne would help put this section in context. It would also be useful for the general readers (even if only by reference to previous work. I note you state there were no contemporaneous observations)?



There are no coincident observations of boundary layer height, and it is not routinely measured by the BoM. The Coutts et al (2007) paper only describes CO2 fluxes and not how the Melbourne boundary layer evolves. I have extracted the boundary layer height variable from the ACCESS model and plotted a diurnal average across November 2017.

Add text to page 13 line 10. "Average modelled diurnal boundary layer evolution during November 2017 in Melbourne is to increase after sunrise at 05:00 (AEST) to a peak of 1780 m at 13:00. The height begins to decline during the afternoon coincident with a southerly seabreeze, but is still above 1200 m at 17:00. The nocturnal boundary layer is around 200 m."

Although it is not necessary to reference this study the issue of significant variation of pollen concentrations with height may need to be discussed here, e.g. see Damialis, et al. (2017), Nature Scientific Reports. The latter compares surface, tower and aircraft measured pollen concentrations with altitude.

Given what we know about the short model lifetime of pollen, we see 1-2 orders of magnitude decrease in pollen concentrations between the surface and 250 m. Damialis et al (2017) found most of their grass pollen at the ground level rather than aloft, corroborating our finding.

Add text where the boundary layer is discussed, "Over 77% of grass pollen is found at ground level (Damialis et al 2017) due to its size and density. The lifetime of our model pollen over 1 km is 6 hours."

11. Perhaps you could include a brief summary of the wind climatology (your U and V components) as this is central to predicting wind pollinated species. This would also be helpful to place your wind thresholds in context, especially in terms of how these contribute to emission mechanisms and the correlation (or lack thereof`) you observe with these thresholds.

Include text on page 12 line 29. "We include a wind rose for each AWS site in the supplementary section to determine the strength of the U winds. The roses show a strong southerly influence, corresponding with the afternoon sea breeze at most sites apart from Churchill, located within an east-west aligned valley. Sites further west in Victoria (Hamilton and Creswick) also show a strong northerly influence, generally with a greater percentage of wind speeds above 4 m s^{-1} than elsewhere."

12. Section 5 Conclusions. How do your conclusions regarding the wind and RH correlations in particular compare with European and US studies?

Sofiev et al (2013, fig 4) also show observed pollen being negatively correlated with RH, and has very little correlation with observed wind speed. The reason for the low correlation with wind speed is "the result of two competitive effects. The stronger wind speed increases the emission rate but also improves ventilation and promotes turbulent mixing".

Would be better placed in the results discussion. Page 13 line 24. "Sofiev et al (2013) also show observed birch pollen in Europe being negatively correlated with RH, and has very little correlation with observed wind speed, due to the competing effects of strength versus increased ventilation and mixing."

13. Would it be helpful to include a statement concerning how much variation the smoothed statistical approach potentially might miss over and above the seasonal maxima?

Move text from page 14 lines 4-7 to bottom of page 13 (keeps E10 discussion together). Include the following text: "Both the statistical emission parameterisations assume an underlying Cauchy distribution, which is modulated by the effects of wind, temperature, humidity and rainfall. At each model grid-cell, the peak and magnitude of this bell curve is calculated from statistics inferred from the EVI gradient."

Rewrite text on page 16 line 9. "The smoothed statistics for E10 used 16 years of observational data from the UoM and one year from the seven other Victorian sites. The smoothed statistical approach is modulated by the hourly effects of wind, temperature, RH and rainfall, which introduces temporal variation. The EVI also varies spatially and temporally, meaning that this method is suitable for future years and for other regions of Australia."

References

Asthma and Allergy Foundation of America. Asthma Capitals Risk Factors 2018. https://www.aafa.org/media/2119/aafa-2018-asthma-capitals-report.pdf

Beggs, P. J., Katelaris, C. H., Medek, D., Johnston, F. H., Burton, P. K., Campbell, B., Jaggard, A. K., Vicendese, D., Bowman, D. M. J. S., Godwin, I., Huete, A. R., Erbas, B., Green, B. J., Newnham, R. M., Newbigin, E., Haberle, S. G., and Davies, J. M.: Differences in grass pollen allergen exposure across Australia, Aust. NZ J. Publ. Heal., 39, 51–55, https://doi.org/10.1111/1753-6405.12325, 2015.

Coutts, A. M., Beringer, J., & Tapper, N. J. (2007). Characteristics influencing the variability of urban CO2 fluxes in Melbourne, Australia. *Atmospheric Environment*, *41*(1), 51 - 62.

Damialis, et al. (2017), Estimating the abundance of airborne pollen and fungal spores at variable elevations using an aircraft: how high can they fly? Nature Scientific Reports, 7, Article number: 44535.

Erbas, B., Chang, J-H., Newbigin, E., Dhamarge, S. (2007) Modelling atmospheric concentrations of grass pollen using meteorological variables in Melbourne, Australia, International Journal of Environmental Health Research, 17:5, 361-368, DOI: 10.1080/09603120701628693

Haberle, S., Bowman, D., Newnham, R., Johnston, F., Beggs, P., Buters, J., Campbell, B., Erbas, B., Godwin, I., Green, B., Huete, A., Jaggard, A., Medek, D., Murray, F., Newbigin, E., Thibaudon, M., Vicendese, D., Williamson, G., and Davies, J.: The macroecology of airborne pollen in Australian and New Zealand urban areas, PLoS ONE, 9, e97 925, https://doi.org/10.1371/journal.pone.0097925, 2014.

Lake, IR, Jones, NR, Agnew, M, et al. Climate change and future pollen allergy in Europe. Environ Health Perspect. 2017; 125: 385- 391.

Osborne, N.J., Alcock, I., Wheeler, B.W. et al. Pollen exposure and hospitalization due to asthma exacerbations: daily time series in a European city. Int J Biometeorol (2017) 61: 1837. https://doi.org/10.1007/s00484-017-1369-2

Pasken, R. and J.A. Pietrowiez (2005) Using dispersion and mesoscale meteorological models to forecast pollen concentrations, Atmos. Environ., 39, 2689-7701.

Schäppi, G. F., Taylor, P. E., Kenrick, J., Staff, I. A., and Suphioglu, C.: Predicting the grass pollen count from meteorological data with regard to estimating the severity of hayfever symptoms in Melbourne (Australia), Aerobiologia, 14, 14–29, https://doi.org/10.1007/BF02694592, 1998.

Sofiev, M., Siljamo, P., Ranta, H., Linkosalo, T., Jaeger, S., Rasmussen, A., Rantio-Lehtimäki, A., Severova, E., and Kukkonen, J.: A nu35 merical model of birch pollen emission and dispersion in the atmosphere. Description of the emission module, International Journal of Biometeorology, 57, 45–58, https://doi.org/10.1007/s00484-012-0532-z, 2013.

US National Allergy Bureau. https://www.aaaai.org/global/nab-pollen-counts/reading-the-charts. American Academy of Allergy, Asthma and Immunology.

Van Hout et al., (2008) The influence of local meteorological conditions on the circadian rhythm of corn (Zea mays L.) pollen emission, agricultural and forest meteorology, 148, 1078-1092.

Viner, B.J., M.E. Westgate and R.W. Arritt, 2010: A model to predict diurnal pollen shed in maize. Crop Science 50, 235-245.

Zink, K., Pauling, A., Rotach, M. W., Vogel, H., Kaufmann, P., and Clot, B.: EMPOL 1.0: A new parameterization of pollen emission in numerical weather prediction models, Geosci Model Dev, 6, 1961–1975, https://doi.org/10.5194/gmd-6-1961-2013, 2013.

Development and evaluation of pollen source methodologies for the Victorian Grass Pollen Emissions Module VGPEM1.0

Kathryn M. Emmerson[1], Jeremy D. Silver[2], Edward Newbigin[3], Edwin R. Lampugnani[3], Cenk Suphioglu[4], Alan Wain[5], and Elizabeth Ebert[5]

[1]Climate Science Centre, CSIRO Oceans & Atmosphere, Aspendale. VIC 3195, Australia
[2]School of Earth Sciences, University of Melbourne, VIC 3010, Australia.
[3]School of BioSciences, University of Melbourne, VIC 3010, Australia.
[4]School of Life and Environmental Sciences, Deakin University, Waurn Ponds, VIC 3216, Australia
[5]Bureau of Meteorology, Docklands, VIC 3008, Australia

Correspondence: K.M. Emmerson (kathryn.emmerson@csiro.au)

Abstract. We present the first representation of grass pollen in a 3D dispersion model anywhere in Australia, tested using observations from eight counting sites in Victoria. The region's population has high rates of allergic rhinitis and asthma, and this has been linked to the high incidence of grass pollen allergy. Despite this, grass pollen dispersion in the Australian atmosphere has not been studied previously, and its source strength is untested. We describe ten pollen emission source methodologies examining the strengths of different immediate and seasonal timing functions, and spatial distribution of the sources. The timing function assumes a smooth seasonal term, modulated by an hourly meteorological function. A simple Gaussian representation of the pollen season worked well (average r=0.54), but lacks the spatial and temporal variation that the satellite-derived Enhanced Vegetation Index (EVI) data can provide. However poor results were obtained using the EVI gradient (average r=0.35), which gives the timing when grass turns from maximum greenness to a drying and flowering period; this is due to the greater spatial and temporal variability from this combined spatial and seasonal term. Better results were obtained using statistical methods that combine elements of the EVI dataset, a smooth seasonal term and instantaneous variation based on historical grass pollen observations (average r=0.69). The seasonal magnitude is inferred from the maximum winter-time EVI, while the timing of the peak of the season was based on the day of the year when the EVI falls to 0.05 below its winter maximum. Measurements are vital to monitor changes in the pollen season, and the new pollen measurement sites in the Victorian network should be maintained.

1 Introduction

Pollen is a biological particle, produced by plants to transfer haploid genetic material during reproduction. With allergenic properties pollen can be a human irritant, and is strongly linked to seasonal allergic rhinitis and asthma. ~~Whilst allergic effects~~

~~are experienced worldwide, the highest concentrations of allergic rhinitis sufferers live in Melbourne, Victoria,~~ Melbourne, on the south east coast of Australia, has the highest prevalence of allergic rhinitis in the world (?). Melbourne, in the State of Victoria, is a city of approximately 4.9 million inhabitants (?). Prior to 2017 pollen forecasts in Melbourne were generated manually by aeroallergen scientists, relying on persisting the previous day's pollen count and an interpretation of forecasted weather (?). Yet despite the availability of a simple pollen forecast, they were not connected to the likelihood of thunderstorms, which proved fatal on the afternoon of ~~November 21st~~ 21 November 2016 (?). During rush hour, a north-south line of thunderstorms developed west of Melbourne, and swept eastwards across the city. In the following hours, 9900 people visited hospitals with breathing difficulties, overwhelming the emergency services. It is possible that strong winds collected large quantities of grass pollen from north western pasture regions, which were concentrated along the edge of the gust front. Victoria had experienced the world's largest epidemic thunderstorm asthma event. In the aftermath, the State government funded better planning of health-care resources to improve preparedness and response arrangements for similar events in future (??). This plan included development of a pilot thunderstorm asthma early warning service using statistical pollen forecasts (?), operated by the Bureau of Meteorology (BoM) and concurrent development of a pollen forecasting system, built around pollen emission and transport modelling. The pollen emissions component is called the Victorian Grass Pollen Emissions Module version 1.0 (VGPEM1.0).

Pollen is generally not included in air quality models because its atmospheric lifetime is usually too short to be of interest. Recently human exposure to pollen has become a focus, particularly in the northern hemisphere (e.g. ??) and urban areas (?), such that detailed vegetation taxa maps are being produced for pollen forecasting (?).

Techniques to model atmospheric concentrations of pollen have included statistical techniques and dispersion models. Statistical techniques using standard multiple regression analyses have predicted whether airborne pollen concentrations will be higher or lower than a long term mean with > 87 % accuracy (?), but require decade-long datasets (?), and are improved by the availability of multiple sampling sites. Statistical models require a representation of the flowering season, but perform poorly if the timing of the flowering season changes ~~in different seasons~~ (?), or in urban areas subject to local scale turbulence and heat island effects (?). Meteorological dispersion models can capture these effects, but are more computationally demanding to run. Physical dispersion of pollen includes 1) emission from the pollen source regions, 2) atmospheric transport and 3) deposition, using measurements to validate the predictions.

? were amongst the first to develop a numerical description of pollen within a dispersion model, using a flowering map to simulate the cedar pollen season in the Tohoku district of Japan. In the USA, the Biogenic Emission Inventory System was adapted to emit birch and ragweed pollen and predicted the timing of the birch pollen peak to within two days (?). An understanding of pollen release biology together with accurate meteorological data is crucial for pollen forecasting (?). ? modelled pollen from 13 different taxa based on plant functional type mapping for the USA, which could be used on climatic timescales. ~~In Europe~~Indeed, climate induced spread of ragweed is predicted to double the number of Europeans suffering allergic responses by 2060 (?). In Germany, ? simulated hazel and alder pollen emissions and transport~~across Germany~~, but did not verify their predictions as no pollen measurements were available. ? simulated oak pollen emission in northern Germany by incorporation of landscape structural mapping, finding oak pollen plumes transported up to 100 km away. The EMPOL1.0 model for birch pollen across all of Europe was comprehensively evaluated by ?. The Finnish Meteorological Institute has developed the System for Integrated modeLling of Atmospheric coMposition (SILAM; ?, and references therein), to calculate concentrations of six pollen species at 10 km resolution on an hourly basis for all of Europe. This group have found the most important input parameter is temperature (?).

Studies of pollen have focused on those taxa having a high allergenic burden which differs depending on region. In Europe, birch tree pollen is the major allergen and has been the focus of intense research activity (????). However birch is not common to Australia. Ragweed pollen, which is a common allergic trigger in the northern hemisphere, grows in the northeast and east of Australia but not elsewhere (?). ~~The native Australian vegetation produces little pollen(?), and there are no large forests of introduced allergenic tree species. European settlers introduced ryegrass (*Lolium perenne*) to southern Australia as they thought it superior for agricultural pasture~~Native Australian grasses such as wallaby and kangaroo grass are generally not wind-pollinated and produce little pollen, whilst introduced agricultural pasture grasses such as ryegrass (*Lolium perenne*) and canary grass are high pollen emitters (?). Ryegrass is ~~wind-pollinated (i.e. not self- or vector-pollinated)~~ grown extensively in Victoria and produces large volumes of pollen in spring. In Southern Australia most of the allergenic burden has been attributed to ~~these pasture grasses~~ ryegrass via skin prick tests (??). Further, the rupturing of ryegrass pollen grains releases much smaller starch particles capable of causing asthma (??). VGPEM1.0 therefore focuses on pasture grass and has the following goals. The first is to improve public health emergency planning and response arrangements around thunderstorm asthma, by providing a tool for appropriate information providers (i.e. Melbourne Pollen Count and Victorian Department of Health and Human Services). VGPEM will also feed into other forecasting models like BoM's thunderstorm asthma forecast.

This paper documents the first representation of grass pollen in a 3D dispersion model anywhere in Australia. As the greatest uncertainty is the pollen emission characteristics, we develop and evaluate 10 methodologies, using observations from eight counting sites in Victoria. First we describe these grass pollen observations, and determine their correlations with observed meteorological variables. Second, the grass pollen emission methodologies are described and tested at a spatial resolution of 3 km. The best performing method is recommended for VGPEM1.0.

2 Observations and characteristics of grass pollen

Despite Australians having high rates of asthma and allergy compared to other Western nations (?), there were few Australian pollen observation sites for routine monitoring or research in 2016 (?). In Australia, all pollen sampling is performed using Burkard volumetric pollen traps (?). Samples are histologically stained and counted manually under a microscope by trained personnel who reference the samples to pollen taxonomic standards. One limitation of this method is that pollen cannot be classified into particular species, or even genus, based on visual examination alone.

The University of Melbourne (UoM) operated a pollen count site in Victoria sporadically from the late 1970s to 1990, but since 1991 has counted annually over the three-month period of October, November and December, coinciding with the grass pollen season (?). ~~Whilst about~~ In Victoria, routine pollen counting since 2017 distinguishes between 15 pollen taxa, with ? finding 70% of the total pollen measured at the UoM site is *Cupressaceae* from a nearby cemetery~~(?),~~. However we concentrate on the *Poaceaea* (grass) pollen, as it is the dominant outdoor human allergen in Australia. DNA sequencing at UoM indicates ryegrass can contribute 60 to 90% of grass pollen counted over the 2016 pollen season (personal communication, E. Newbigin). The amount of grass pollen season in any particular year in Melbourne is strongly related to the amount of spring rainfall, which promotes grass growth and flowering (?). The cumulative grass pollen count over the Oct-Dec season in Melbourne ranges between ~~1500-5000~~ 1500 and 5000 grains m^{-3}, with daily maximums reaching 400 grains m^{-3} (?). In Melbourne, the highest pollen counts are usually associated with northerly continental air masses (?), with an evening peak coinciding with the onset of the stable nocturnal boundary layer and descending air (?).

Two other pollen counting sites close to Melbourne at Burwood and Geelong have been in operation since 2012 by Deakin University. Five new sites were introduced in 2017 around Victoria situated within university or hospital grounds (Figure 1a,b and Table 1). Pollen sampling occurred daily during the 2017 grass pollen season at 9am, representing the mean daily pollen concentration from 09:00h the previous day to 08:59h on the day of collection. Pollen observations from these eight sites are used to assess the accuracy of pollen predictions in this study.

In Australia, grass pollen counts are graded 'low' if the count is ~~less than 20 m^{-3}~~ 19 m^{-3} or less, 'moderate' if between ~~20-49~~ 20 and 49 m^{-3}, 'high' if between ~~50-99~~ 50 and 99 m^{-3} and 'extreme' if above 100 m^{-3}. Whilst epidemiological studies commonly use annual pollen totals, we use a daily pollen risk classification system because we aim to predict daily pollen concentrations. The Australian grass count categories are similar to those used in the UK and Europe at the low and medium count categories, but the Australian extreme category is reached at pollen counts up to 3 times lower than Europe and the US (???). Between 20 and 60 days in each Melbourne season are observed in the moderate or above category, and up to 37 days in the high or above category (?). However it is clear climate change is impacting the timing and strength of the grass pollen season (?), as are changes to agricultural practices and the expanding boundary of the city. These changes highlight the importance of long term observations and the need to sustain the new pollen observation sites in Victoria.

3 Treatment of pollen in VGPEM1.0

Pollen is set-up in VGPEM1.0 as an inert particle tracer. The pollen source methodologies are tested using the CSIRO Chemical Transport Model (C-CTM), a framework of modules designed to calculate concentrations of gases and aerosol which are subjected to emission, dispersion and deposition within the atmosphere (?). The C-CTM has been used to model impacts of anthropogenic emissions on urban air sheds (??), volatile organic compounds from vegetation ~~(??)~~ (???) and also used to investigate health impacts by reducing the sulfur content in shipping fuels (?). The C-CTM is driven by meteorology from the Australian Community Climate and Earth System Simulator model (ACCESS, ?), run at 3 km resolution using boundary conditions from ERA-Interim for a domain covering Victoria (Figure 1a). ACCESS provides the meteorological parameters necessary for pollen emission and transport, namely wind speed and direction, temperature, relative humidity (RH) and rainfall.

Particles are output as μg m^{-3} in the C-CTM, and require unit conversion to calculate grains m^{-3} (consistent with the pollen observations), using the mass of 1 pollen grain. Grass pollen diameters are found in the range $30-40$ μm (?). Early calculations by ? estimated the mass of one ryegrass pollen grain in Melbourne to be 1×10^{-9} g, which converts to a very low density of 44.5 kg m^{-3} using a 35 μm diameter. The grass pollen density is a large source of uncertainty. Whilst Smart's study is local to our work, studies of pollen from other grass taxa yield much higher densities, for example 980 kg m^{-3} for *Secale* (rye) (?) and *Dactylis glomerata* (?).

The pollen density also impacts on the dry deposition velocity, which controls the length of time the pollen grain is airborne. The C-CTM dry deposition parameter follows Stoke's law. ? measured *Gramineae* (grass) pollen with a fall speed of 3.5 cm s^{-1}. ? suggest the deposition of grass pollen is four times larger than the 1 cm s^{-1} estimated for birch pollen, and consistent with the 4.3 cm s^{-1} measured by ? on *Secale* (rye). We will assume each pollen particle is 35 μm in diameter, is spherical and has a density of 1000 kg m^{-3}, consistent with values used by Melbourne based researchers (??), and similar to the grass pollen density used in ?. A 35 μm particle with a density of 1000 kg m^{-3} yields a deposition velocity of 4.6 cm s^{-1} which is similar to ?. Using these values, the estimated mass of each pollen grain is 22.4×10^{-9} g.

This work relates exclusively to forecasting the presence of intact grass pollen grains in the air, within Victoria, Australia and does not consider thunderstorm cells nor the interactions of grass pollen grains within them. The process of re-entrainment of pollen grains once they are deposited to the ground is not considered, nor is the rupturing process that releases the allergenic contents of the grains - present on small starch particles. Whilst the impacts of pollen rupturing on numbers of cloud condensation nuclei has been investigated by ?, ruptured pollen grains are not routinely monitored in Victoria. Future development of VGPEM may incorporate some of these processes.

3.1 Pollen emissions framework

Pollen emission and transport has never been modelled in Australia, therefore we trial three different emission frameworks and vary their inputs. In some instances we test parameters proven not to work elsewhere and for other pollen taxa, to investigate whether Australian ryegrass pollen characteristics are different. The first framework is a spatio-temporal decomposition of factors, the second is a pollen production-loss model and the third is a derivative of the statistical model for daily grass pollen concentrations used in the BoM's pilot forecasting system (?). The pollen emission rate E at grid-point (x,y) and time t is expressed as:

$$E(x,y,t) = I(x,y,t) \times G(x,y,t) \times S(x,y) \qquad (1)$$

where I is the immediate timing (hour-by-hour variation due to changes in prevailing meteorology), G describes the gross seasonal timing (also termed the 'phenology factor') and S provides the spatial source distribution for a given season. The functions I, G and S are each dependent on other factors, which may include modelled meteorology, land-use data or satellite data; these details are discussed in subsequent sections.

Table 2 gives the combinations of options for calculating $E(x,y,t)$ that are tested in this study. Each emission methodology is run for three months between October and December 2017 to cover the period of the pollen measurements. The modelled pollen is also averaged on a 24 hourly basis (to 09:00h each day) to be consistent with the 2017 pollen observations.

3.1.1 Immediate timing, I

We consider two representations of the immediate timing function (I). The first, and simplest assumes that emissions are related to transport and therefore are proportional to the surface wind speeds, used in scenarios E1, E2 and E3. The second method, used in scenarios E4, E5, E6, E7 and E8 accounts for several meteorological factors, treating them as having independent effects.

$$I(x,y,t) = f_h \cdot f_{\mathrm{RH}} \cdot f_{\mathrm{PR}} \cdot f_{\mathrm{WS}} \cdot f_{\mathrm{TM}} \tag{2}$$

where the terms f_h, f_{RH}, f_{PR}, f_{WS} and f_{TM} represent, respectively, the response to hour-of-day, RH, precipitation, wind speed and temperature. This approach is similar to ?, eq. 12, representing pollen emissions from birch trees. The assumption is that grass pollen emissions are greatest when conditions are hotter, windier, drier, with less rain, and around midday. The midday assumption stems from an observational study conducted near Melbourne showing the peak timing of ryegrass pollen release (measured as the number of exposed anthers) occurs ~~during daylight hours and~~ in the early afternoon (?, fig. 6). As ryegrass flowers in spring when mornings are cool and damp, the anthers need to dry before pollen is released. This timing is represented as a Gaussian distribution with a mean at the local solar noon (12:00 h) and a standard deviation σ_{h}, of either 2 or 4 hours (?). The larger σ_{h} parameter allows for a wider peak in pollen around noon-time in later scenarios E6, E7 and E8.

For RH we adapt the approach of ?, who used a piece-wise linear relationship scaled from 1 (RH of 50% or less) to 0 (RH of 80% or above). For wind speed, ? assumed a smaller emission rate ($f_{\mathrm{stagnant}} = 0.33$) in stagnant conditions and scaled smoothly to a saturation value (1.0) for higher wind speeds. We adapt this approach to the case of RH, but use a logistic function ($f_l(y;\alpha,c) = \frac{1}{1+e^{-\alpha(y-c)}}$, for location parameter c and rate parameter α), where the rate and location parameters are set to yield $f_l(50;\alpha_{\mathrm{RH}},c_{\mathrm{RH}}) = 0.95$ and $f_l(80;\alpha_{\mathrm{RH}},c_{\mathrm{RH}}) = 0.05$, with α_{RH} being negative, meaning that the assumed emissions rate decreases with increasing humidity. The final f_{RH} is then:

$$f_{\mathrm{RH}} = f_{\mathrm{stagnant}} + (1 - f_{\mathrm{stagnant}}) \cdot f_l(\mathrm{RH};\alpha_{\mathrm{RH}},c_{\mathrm{RH}}) \tag{3}$$

The equation for the temperature term (f_{TM}) is identical to the RH term (Eq. 3), but taking temperature (° C) as the argument and with different rate and location parameters. These are defined such that $f_l(6;\alpha_{\mathrm{TM}},c_{\mathrm{TM}}) = 0.05$ and $f_l(24;\alpha_{\mathrm{TM}},c_{\mathrm{TM}}) = 0.95$. The implied rate parameter (α_{TM}) is positive, meaning that grass pollen emissions are assumed to increase with increasing temperature.

A similar approach is taken for precipitation (f_{PR}), with the logistic rate and location parameters constrained to satisfy $f_l(0;\alpha_{\mathrm{PR}},c_{\mathrm{PR}}) = 0.95$ and $f_l(0.5;\alpha_{\mathrm{PR}},c_{\mathrm{PR}}) = 0.05$, where the precipitation is given in units of mm hr^{-1} and α_{PR} is negative. We cannot impose a constraint of the function being 1.0 for zero precipitation, as the logistic function approaches 1.0 asymptotically. Instead, we scale the result based on the function's value for zero humidity (defined above as 0.95), resulting in:

$$f_{\mathrm{PR}} = f_{\mathrm{stagnant}} + (1 - f_{\mathrm{stagnant}}) \cdot f_l(\mathrm{PR};\alpha_{\mathrm{PR}},c_{\mathrm{PR}})/f_l(0;\alpha_{\mathrm{PR}},c_{\mathrm{PR}}) \tag{4}$$

As noted above, the effect from wind speed (f_{WS}) is assumed to scale smoothly from a lower rate of 0.33 for f_{stagnant} in still conditions. We follow the parameterisation of ?, equation 11:

$$f_{\mathrm{WS}} = f_{\mathrm{stagnant}} + (1 - f_{\mathrm{stagnant}}) \cdot (1 - \exp(-\mathrm{WS}/U_{\mathrm{satur}})) \tag{5}$$

where wind speeds (m s^{-1}) are scaled by a saturation wind speed ($U_{\mathrm{satur}} = 5$ m s^{-1}), above which the wind speed does not promote the release of pollen.

3.1.2 The gross timing, G

We consider two representations of the gross timing, a Gaussian distribution to represent the growth and decline of the spring-time pollen season, and the Enhanced Vegetation Index (EVI). The Gaussian distribution (Eq. 6) is normalised to integrate to the theoretical maximum spatial production of ryegrass pollen over the season, estimated by ? as 464 kg ryegrass pollen hectare^{-1} in grasslands to the north of Melbourne.

$$G(x,y,t) = \frac{F}{\sqrt{2\pi\sigma^2}} \exp\left[-\frac{(d-n)^2}{2\sigma^2}\right] \tag{6}$$

where d is the day number (from Oct 1$^{\mathrm{st}}$ to Dec 31$^{\mathrm{st}}$ = 92 days) within the season, n is the mean day number of that season (46.5), σ is the standard deviation (26.7), and F is a normalisation factor of 9.53×10^{-8}, so that seasonal emissions integrate to 464 kg ha^{-1}. This Gaussian representation is used in scenarios E1, E5, E6 and E7.

We apply a second Gaussian representation in scenario E8 which uses the shapes of the 2017 observed pollen time-series to 'shift' the distribution by either moving the mean earlier or later in the grass season, and/or adjusting the standard deviation to be tighter or wider. The curves are fitted by optimising the root mean squared error (RMSE) between the pollen counts and the original Gaussian distribution (shown in the supplementary material). The peak of the grass pollen season is earlier in Bendigo and Dookie than day 46.5, thus all grassland north of 37 °S replaces n with 34.7 and σ reduces to 15.5 (F remains the same as above). The peaks in observed pollen at Creswick and Churchill are later in the season and count more pollen than other sites, thus at locations south of 37 °S and east of 143.5 °E, n is replaced with 50.5, σ is narrowed to 19.3 and F increased to 1.2×10^{-7}. At sites west of 143.5 °E (i.e. Hamilton), the peak of the pollen observations are greater and distributed more tightly, thus n reverts to 48.1, σ is narrowed to 7.7 and F is increased further to 1.56×10^{-7}.

3.1.3 Enhanced Vegetation Index, EVI

? developed a non-linear statistical model for pollen concentrations using satellite greenness indices across areas surrounding a receptor point. The EVI is a measure of landscape greenness, which is less affected by saturation in higher biomass regions than the widely used Normalised Difference Vegetation Index (?). The EVI value typically increases rapidly with time during spring due to foliage growth in deciduous trees or grass growth. In the Victorian temperate climate, fresh grass rapidly dries (or 'cures') in late spring and early summer, causing a fall in EVI. Given the absence of deciduous forests in Australia, most of the temporal variation in EVI is due to grass growth and curing. Here we investigate a relationship between the timing of the pollen season and the gradient in EVI over a region in the South West of Victoria, spanning 37.3-38.3 °S and 142-143.3 °E (appearing as dashed lines in Figure 3). This region is upwind of Melbourne, in terms of the prevailing climatological wind, and has high agricultural activity.

Using the Moderate Resolution Imaging Spectroradiometer (MODIS) MOD13C1 data (from the Terra satellite and at 0.05° resolution), Figure 2a shows the gradient in averaged EVI drops off rapidly, around the same time as the pollen season peaks. Figure 2b shows the first derivative of EVI is anti-correlated with the grass pollen time-series at UoM. If we examine interannual variation, assessing the day-of-year when the EVI falls most rapidly (represented as the middle of the 16-day EVI compositing window) and the day-of-year when the grass pollen peaks (having first applied a smoothing spline to the pollen time-series), a relationship between these two quantities is observed: the Pearson correlation is 0.4, the slope of the linear regression is 1.006 and the means of the two Julian dates differs by only 2.7 days (Figure 2c). This agreement is especially notable given the uncertainty induced by the wide EVI compositing window.

Taking this one step further, we apply a similar analysis to each individual $0.05 \times 0.05°$ MODIS pixel (Figure 3). Given the high deposition velocity of grass pollen grains (4.6 cm s^{-1}, as discussed above), the contribution of pollen emitted from the productive grassland areas in western Victoria to observations recorded in Melbourne is likely to be minimal. However, this analysis may help inform our understanding about the relationship between the remotely-sensed vegetation index and broad-scale features of the pollen season. The timing of the fall in EVI in South West Victoria not only correlates well with the timing of the grass pollen season experienced in Melbourne (Figure 3a), but also the differences in timing are relatively small (Figure 3b). The north-west of the state is generally much drier than in the south-east (Figure 1c), and the north-west area dries out earlier in the year (Figure 3c). Areas identified as crops or pasture (Figure 1d) demonstrate a more rapid fall in EVI (Figure 3d).

This exploratory analysis suggests that in this bioclimate the broad parameters of the pollen season can be diagnosed from the EVI fields. On a broad temporal scale, a fall in EVI over pollen source regions is associated with increasing pollen emissions. In light of this, we consider an EVI-based representation of the gross timing (G).

$$G(x,y,t) = \max\left(0, -\frac{\partial \mathrm{EVI}(x,y,t)}{\partial t}\right) \tag{7}$$

The $\max(\cdot)$ function ensures that the emissions are strictly positive. We note that Eq. 7 incorporates both temporal and spatial information, and can thus be used to represent the spatial distribution (S), in which case we can set $S(x,y) = 1.0$ for all grid-points (x,y) (scenario E3). Alternatively, we can use the same spatial forcing (based on an assumed land-use classification) to provide an extra spatial constraint. ∂EVI is used in scenarios E2 and E4.

3.1.4 The spatial function, S

Mapped grass and pasture for Victoria were extracted from the Australian Land Use and Management (ALUM) Classification (?) and were re-gridded from 50 m resolution to the 3 km grid used by the C-CTM. ALUM includes 193 categories of which only three are assumed to overlap with grazing pastures ('Grazing modified pastures', 'Native/exotic pasture mosaic' and 'Grazing irrigated modified pastures'); the fractional coverage of these three classes together is shown in Figure 1d. We include larger scale maps of the pasture grass coverage surrounding the pollen count sites in the supplementary material. While many cultivated cropping cereals grown in the region are also grasses (e.g. wheat, barley), they are mostly self-pollinating and thus produce very little pollen compared to wind-pollinated grass species such as ryegrass. The area to the east of Melbourne is mountainous and therefore not arable (Figure 1e), whilst the region to the northwest is arid (Figure 1c). The most productive areas of pasture grass in Victoria are found in the west of the region near Hamilton and south west of Churchill. The ALUM grass map is used in scenarios E1, E2, E4, E5, E6, E7 and E8.

3.1.5 Pollen production and loss model

In reality, there is a finite amount of grass pollen available for release at a given time, and once exhausted ~~(by dry or wet depositionor advection) pollen~~ by in-plant dry and wet deposition, or pollen release, the pollen reservoir is only replenished at a finite rate. ~~We develop a 'production-loss' model for scenario~~ Scenario E7 is a production-loss model for this pollen reservoir.

$$
\begin{aligned}
E(x,y,t) &= A(x,y,t)\cdot I(x,y,t) &\quad (8)\\
A(x,y,t) &= A(x,y,t-\delta t)+P(x,y,t-\delta t)-L(x,y,t-\delta t) &\quad (9)\\
P(x,y,t) &= S(x,y,t)\cdot G(x,y,t)\cdot\left(\frac{\delta t}{T}\right) &\quad (10)\\
L(x,y,t) &= A(x,y,t)\cdot\exp(-\lambda\cdot\delta t) &\quad (11)
\end{aligned}
$$

where emissions, ~~A~~E ~~is the amount of pollen available for release on the grass~~ are set to be the product of the available pollen reservoir, A and the instantaneous emission factor, I at grid-point (x,y) ~~at~~ and time t~~,~~. δt is the model time-step. The pollen produced, P is ~~the amount produced on the plant~~ given by the product of the spatial and gross-timing terms, proportional to the fraction of the grass pollen season covered between t and $t+\delta t$~~,~~. L is the amount lost between t and $t+\delta t$, T is the total length of the grass pollen season and λ is the loss rate ~~(~~due to direct ~~dry or wet deposition). We can interpret the above as follows; emissions are set to be the product of the available pollen load and the instantaneous emission factor (Eq. 8). The available pollen load is the sum of available pollen at the last time-step and pollen produced since then, less any loss since the last time-step (Eq. 9). The pollen produced is given by the product of the spatial and gross-timing terms, proportional to the fraction of the grass pollen season covered during the time-step (Eq. 10). The pollen lost is based on an exponential decay (Eq. 11), assumed to incorporate direct wet and dry deposition before the pollen leaves the grid-cell~~deposition before the pollen leaves the plant. This loss can occur direct to the ground or via animals brushing past, and differs from the in-atmosphere wet and dry deposition rates. ? suggest this loss process is similar to a half-life, which we extend to provide a variable loss rate accelerated in wet conditions. The loss decay parameter (λ), is defined as a piece-wise polynomial function based on the rain rate ~~,~~such that pollen has a half-life on the plant of two days in dry conditions and 12 hours in wet conditions, with the latter corresponding to a rain rate of 2 mm h^{-1}.

3.1.6 Statistical Models

In parallel to the emission-dispersion modelling presented here, statistical forecasting methods have been trialled for use in Victoria. These models are non-linear regression equations that use weather model data, derived parameters from the MODIS

EVI, and land-use maps as predictors. These data can be decomposed into a slow-moving seasonal component (similar to gross-timing term described above) and a second component that accounts for day-to-day variation. The models were trained on daily pollen count data, and thus cannot resolve higher-resolution temporal variation. The gross-timing function smooths out much of the day-to-day variation, and is modulated by the immediate-timing term when estimating temporal variability in the emissions module. The two statistical models are described in detail in ?, and summarised here. 'V1' used data from Melbourne spanning ~~2000-2016~~ 2000 to 2016 (scenario E9) while 'V2' also used the 2017 data from the eight Victorian sites (scenario E10). The V1 model was developed ahead of the 2017 pollen season before counts were available at the new pollen sites, as the BoM required input for their pilot thunderstorm asthma service. The seasonal component was represented as a Cauchy distribution (which decays more slowly than a Gaussian distribution), with a fixed scale parameter ($k = 19$ days). The magnitude of the pollen season (corresponding to the maximum of the seasonal term) was estimated by univariate linear regression on the winter-time maximum EVI. The timing of the seasonal maximum was estimated by the day-of-year when the EVI falls to 0.05 below its winter-time maximum. The magnitude and timing were smoothed spatially using an inverse cubed distance weighting.

Both V1 and V2 were constructed as Generalised Additive Models (**?**), a form of multivariate regression that allows for a non-linear influence of the predictor variable on the response variable. The response variable used was the $\log(x + 1)$-transformed pollen count. The log of the Cauchy term and a number of derived weather parameters were considered for inclusion in the model. Each model was built up via forward step-wise variable-selection: starting with a "null model" (predicting nothing but the mean), terms were considered for inclusion. Each predictor was trialled as having a linear or alternatively non-linear effect on the response variable, and the out-of-sample prediction skill was tested. The combination of predictor and form (i.e., linear or non-linear) that yielded the biggest gain in predictive skill was retained. This procedure was repeated until the incremental impact on predictive skill of additional terms was negligible. The model skill was tested by leaving out entire pollen seasons, fitting the model without these data, then assessing on the out-of-sample subset. Model skill was quantified using the Pearson correlation between predicted and observed pollen.

The statistical models were adapted for 3D dispersion modelling to use hourly meteorological inputs (or daily, in the case of precipitation). The adapted forms of the two models are:

$$\begin{aligned}
\log(1+\mathrm{P}_1(x,y,t)) &= -0.290 + 0.970\cdot\mathrm{R}_1(x,y,d) - 0.183\cdot\log(\mathrm{PR}(x,y,d)+1) - 0.117\cdot\log(\mathrm{PR}(x,y,d)) \\
&+ f_{\mathrm{TM1}}(x,y,t) + f_{\mathrm{RH1}}(x,y,t) \qquad (12) \\
\log(1+\mathrm{P}_2(x,y,t)) &= 1.225 + 0.770\cdot\mathrm{R}_2(x,y,d) - 0.033\cdot\mathrm{WS}(x,y,t) + f_{\mathrm{RH2}}(x,y,h) \\
&+ f_{\mathrm{TM2}}(x,y,t) + f_{\mathrm{PR}}(x,y,d) \qquad (13)
\end{aligned}$$

where *P* is the predicted pollen emission for version i on at grid-point (x, y) and time t, R_i is the seasonal term based on the EVI parameters at grid-point (x, y) and for day d (outlined below) and *WS* is the wind-speed ($\mathrm{m\,s^{-1}}$). In both versions of the statistical model, the variable-selection process assigned a non-linear response to the temperature, f_{TMi} (° C), and RH f_{RHi} (%). Only V2 uses a non linear term for daily precipitation, f_{PR} (mm). The non-linear relationships between pollen emission and increasing temperature, RH and precipitation are shown in Figure 4. The shaded regions correspond to ± twice the standard error of the GAM term, and are greater in regions of the distribution with fewer observations. For example, there were far fewer observations at the upper tail of the temperature range considered, and the standard errors are correspondingly larger.

~~For both V1 and V2, the seasonal term contributes the most variance to the modelled emissionsfollowed by the temperature term~~The statistical parameterisations were based on ambient pollen concentrations rather than emissions, and thus the non-linear terms take into account transport and dilution processes. The shapes of these relationships are similar to those described by ? for grass pollen in Melbourne, and also by ? for birch pollen in Europe. The temperature ~~term~~ response in both models ~~was associated with a strong (near-linear increase) until a value of 25-30~~increased until 25 to 30° C ~~, after which there is a rapid decline~~ (Figure 4a,c). ~~This decline in concentrations may be due to increased boundary layer heights (and thus greater effective dilution) rather than a decrease in emissions~~The decline in pollen response at higher temperatures is likely due to dilution with higher planetary boundary layers. On days in November where the temperature is above 25° C, the maximum modelled boundary layer height is nearly double the height modelled on days below 25° C. Thus the assumption of declining emissions with increased temperature is likely incorrect. There is relatively little non-linearity with humidity. The general trend is for increased concentrations (or emissions) in drier conditions, explained by the drying required before anther dehiscence. The rainfall term shows a sharp decline until about 2 mm day^{-1}, after which little additional pollen suppression occurs, although there is considerable uncertainty given the relative paucity of high-rainfall days. The suppression of grass pollen concentrations (or emissions) is likely due to the low potential for anther dehiscence in moist conditions, and wet deposition of ambient pollen.

The seasonal term based on the EVI parameters is given as:

$$\mathrm{R}_i(x,y,d) = \log(SF_i(x,y)\cdot f_C(d,\mu_i(x,y),k)), \text{ where} \tag{14}$$

$$f_C(d,\mu,k) = \left(\pi\cdot k\cdot\left[1+\left(\frac{d-\mu}{k}\right)^2\right]\right)^{-1} \tag{15}$$

$$SF_1(x,y) = \max(-4355.913+21490.343\cdot E_{\mathrm{max,smoothed}}(x,y),10^{-10}) \tag{16}$$

$$\mu_1(x,y) = E_{\mathrm{drop,smoothed}}(x,y) \tag{17}$$

$$SF_2(x,y) = 267.627+8853.990\cdot E_{\mathrm{max,smoothed}}(x,y) \tag{18}$$

$$\mu_2(x,y) = 202.478+0.385\cdot E_{\mathrm{drop,smoothed}}(x,y) \tag{19}$$

where the scale factor parameter $SF_i(x,y)$ is based on the smoothed value of the winter-time maximum EVI ($E_{\mathrm{max,smoothed}}(x,y)$), while the timing of the peak of the pollen season ($\mu_i(x,y)$) was assumed to scale linearly with smoothed field of the day-of-year when the EVI drops 0.05 below its winter-time maximum (see ?, for further details). The statistical approach accounts for inter-annual variation via the EVI time-series at each grid-cell. Higher winter-time peak EVI values are associated with higher cumulative grass pollen counts over the following season.

3.2 Statistical evaluation

The skill of the pollen forecasts depends in part on how well the meteorology is predicted. The Pearson correlation indicates the strength of the correspondence without consideration of differences in magnitude, whist the index of agreement (IOA, described in the supplementary material) is a good indicator of model performance. The normalised mean bias (NMB) gives the relative difference between the model and observations.

To determine the best pollen emission methodology, we look for skill in the ability of VGPEM to forecast the possibility of the pollen being classed as high or extreme (> 50 grains m^{-3}), which is a level that health impacts may be felt more strongly. The number and timing of predicted high pollen days is evaluated quantitatively for consistency and accuracy, by calculating the probability of detection (POD), the false alarm ratio (FAR), and the equitable threat score (ETS) from a simple table of model outcomes (Table 3). The POD is the fraction of correctly identified high model forecasts compared to the observations, between 0 and 1.

$$POD = \frac{a}{a+c} \quad (20)$$

The FAR puts a value between 0 and 1 on how many of the predicted high pollen days did not correspond with an observed high pollen day.

$$FAR = \frac{b}{a+b} \quad (21)$$

The ETS is the fraction of modelled high pollen days that were correctly predicted, and adjusted for correctly modelled days occurring with random chance. The ETS value is between -1/3 and 1, with a score of 0 indicating no skill; this is defined as

$$ETS = \frac{a - a_{\text{random}}}{a+b+c-a_{\text{random}}}, \quad (22)$$

where

$$a_{\text{random}} = \frac{(a+c)\times(a+b)}{a+b} \quad (23)$$

As **?** point out, low skill scores are given to models whose pollen concentrations are close to observed concentrations yet fall into separate 'risk' categories. For example the model predicts 48 grains m^{-3} and classed as 'moderate' whilst the observations are 52 grains m^{-3} and are 'high'. Therefore we also evaluate the modelled pollen against the observations in terms of their Pearson correlation, RMSE and Gerrity score. Statistical evaluations using categorised and decategorised pollen counts will show how the Australian grass pollen thresholds impact our results. The Gerrity score puts a value on the accuracy of VGPEM in predicting all the observed pollen categories, relative to that of random chance (**?**). Gerrity scores range between -1 and 1, with 0 indicating no skill and 1 being a perfect model. Calculation of Gerrity scores is complex and is described fully in the supplementary material.

The best forecasting methodology will have a high Pearson correlation, Gerrity score, POD and ETS and a low FAR and small RMSE.

4 Results and discussion

4.1 Verification of meteorology

Meteorological variables are extracted from the ACCESS runs at the locations of the AWS closest to the pollen observation sites (Table 1). At some pollen observation sites the AWS are located more than 10 km away, and nearly 30 km away in the case of Dookie. A direct comparison is made of hourly temperature, wind speed, wind vectors, precipitation and RH between ACCESS and the AWS observations, using the Pearson correlation, IOA and NMB. (Figure 5). Here the NMB is normalised by the mean of the absolute value of the observations (as opposed to the mean of the observations) because wind vectors contain negative values. Temperature and RH are both modelled with a high degree of accuracy at all sites, demonstrating a high Pearson correlation (average r=0.9), almost no bias, and high IOA (average IOA=0.8). Predicted wind speeds are biased slightly low (average NMB=-0.2). The V (north–south) component is similarly well modelled as the U (east-west) component (average V r=0.80 compared to average U r=0.77). Precipitation has a low degree of bias (average NMB=0.17) but not particularly well correlated with observations (average r=0.21), and has a lower overall IOA (average IOA=0.55).

4.2 Observed and modelled pollen correlations with meteorology

We assess which measured AWS meteorological variables are most strongly related to the observed pollen. Figure 6a shows observed grass pollen is most strongly correlated with temperature at the majority of sites (average r=0.44), and most negatively correlated with RH (average r=-0.34).

Observed wind speed is not strongly related to observed grass pollen, except when combined with direction, specifically the U wind vector is generally a stronger predictor of pollen (average r=0.32) than the V wind vector (average r=0.22). We include a wind rose for each AWS site in the supplementary section to determine the strength of the winds. The roses show a strong southerly influence, corresponding with an afternoon sea breeze at most sites apart from Churchill, located within an east-west aligned valley. Sites further west in Victoria (Hamilton and Creswick) also show a northerly influence, generally with a greater percentage of wind speeds above 4 m s^{-1} than elsewhere. Precipitation washes pollen from the air, but shows no correlation here as rain during the 2017 season was infrequent (average r=0). Pollen observations at Dookie are the least correlated with any of the meteorological variables, perhaps because the closest AWS is 29 km away.

Figure 6b shows Pearson correlations for the modelled pollen against ACCESS meteorology, using scenario E8 as an example that uses the meteorological timing function. The strengths of the modelled correlations are broadly similar to those observed in Figure 6a, but the model is more strongly coupled to wind speed (average r=0.25) and less correlated to the U wind vector than is observed (average r=-0.07). ~~Transport of pollen from the productive grasslands in the west of Victoria to Melbourne would rely on the U wind vector being modelled accurately, however the model lifetime of these pollen grains is 6 hours over a height of 1 km; too short for pollen emitted near Hamilton to reach Melbourne~~The observed U and V correlations are not strong however, and do not point to particular locations being strong pollen sources. Inverse modelling may help pinpoint productive grass pollen regions for each site. We extracted the boundary layer height from the model (unavailable in the observations), which showed that the modelled grass pollen is more strongly correlated to atmospheric dilution (average r=0.61) than it is to temperature (average r=0.44). Average modelled diurnal boundary layer evolution during November 2017 in Melbourne increases after sunrise at 05:00 (AEST) to a peak of 1780 m at 13:00. The height declines during the afternoon coincident with a southerly sea breeze, but is still above 1200 m at 17:00. The nocturnal boundary layer is around 200 m. Over 77% of grass pollen is found at ground level (?) due to its size and density. The lifetime of our model pollen over 1 km is 6 hours. The model RH is more negatively correlated with grass pollen levels (average r=-0.52) than is observed. The observed relationship may be weaker as the pollen measurements are not coincident with the AWS.

4.3 Verification of pollen source methodologies

The modelled pollen concentrations are first normalised by the observed seasonal mean across all observation sites, equal to 47 grains m^{-3}. This normalisation allows the evaluation of trends in the daily grass pollen concentrations without considering their magnitude, as this can be corrected later. For 2017, observed individual site means range from 31 grains m^{-3} at Melbourne to 60 grains m^{-3} at Creswick. The lowest means are found in the densely populated regions of Geelong, Melbourne and Burwood (see figure 1f). Figure 7 shows correlations and statistical results for each pollen observation site. Numbers of observed days in the lumped high and extreme category (> 50 grains m^{-3}) are above 20 days for all sites. ~~The points are coloured red for Gaussian emissions methodologies, yellow for ∂EVI, green for the production and loss model and blue for statistical methodologies describing the pollen season.~~

E1, E2 and E3 used wind speed as the immediate timing function, which ~~did not provide good~~ provided poor prediction skill scores (average r=0.25, 0.18 and 0.17 respectively)~~. Observed wind speed was not strongly correlated to observed pollen , but it was useful to test this parameter in Victoria~~, similar to results by ? and ?. Wind promotes pollen emissions, but the plant must flower first - a process not controlled by wind speed. Wind also correlates poorly with pollen observations due to the competing effects of strength versus increased ventilation and mixing (?). Subsequent method E5 used the meteorological timing function that included temperature and RH and performed better (average r=0.43). ? also show observed birch pollen in Europe being negatively correlated with RH. Widening the timing of the peak pollen emission from 2 to 4 hours, as included in E6, improved results further over E5 (average r=0.44).

At most sites the Gaussian description of the season performed better than the ∂EVI, shown by improvements in FAR of E1 over E2 both of which used wind speed as the immediate timing descriptor (average FAR=0.57 and 0.61 respectively), and E5 over E4 both of which used the meteorological timing function (average FAR=0.48 and 0.52 respectively). These results point to using ∂EVI data as a descriptor of the pollen season as providing poor skill at most of the sites. The ∂EVI data is very noisy. However E4 using the ∂EVI data and a meteorological timing function gives a good Gerrity score (0.54) and high POD (0.92) and ETS (0.40) at Dookie. When other elements of the EVI data are used in the statistical models (E9 and E10), such as the winter maximum and the day on which the EVI falls below 0.05 of the winter maximum, the pollen prediction is much improved at most sites (average POD E9=0.67 and E10=0.69). The performance of E10 indicated improvements in forecasting skill at all sites with the exceptions of Dookie and perhaps Bendigo. E10 predicted the lowest FAR of high pollen predictions at five of the eight observation sites (average FAR=0.37). The ETS adjusts the model score for achieving high pollen predictions at random. E10 achieves higher ETS scores at four of the eight sites (average ETS=0.35). Both the statistical emission parameterisations assume an underlying Cauchy distribution, which is modulated by the effects of wind, temperature, RH and rainfall. At each model grid-cell, the peak and magnitude of this bell curve is calculated from statistics inferred from the EVI gradient.

The pollen production and loss model E7 had a very high POD (0.96) at Hamilton, but the method was less effective elsewhere with high FAR and RMSE scores at the other observation sites (average FAR=0.55 and RMSE=63). E7 used the Gaussian distribution for the seasonal term which could be improved upon, but the method was superseded by the good performance of the statistical models (with the exception of E9 in Hamilton and Geelong). ~~The performance of E10 indicated improvements in forecasting skill at all sites with the exceptions of Dookie and perhaps Bendigo. E10 predicted the lowest FAR of high pollen predictions at five of the eight observation sites (average FAR=0.37). The ETS adjusts the model score for achieving high pollen predictions at random. E10 achieves higher ETS scores at four of the eight sites (average ETS=0.35).~~

The Geelong pollen observations are not well modelled by most of the emission methodologies with Gerrity scores mainly in the negative region and high FAR greater than 0.8. E10 provides the best scores by far at Geelong with a 0.62 Pearson correlation and 0.3 Gerrity score, though overall, results are poorer for Geelong than any other site. The wind rose for Geelong shows the strong Southern Ocean influence, and there are few grass filled pixels between the coast and pollen count site which the model relies upon (supplementary).

The sites vary considerably in terms of surrounding land use, whereas all the pollen in the model comes from pasture grass. This impacts the individual site performance against the pollen observations. Hamilton, Dookie and Churchill are close to pollen source areas. Creswick is surrounded by forest. The Burwood and UoM sites are in heavily built up areas with green space, which is not included in the model pasture grass maps.

Comparing the results of the decategorised Pearson correlation and RMSE against the categorised Gerrity score yields minor differences between 0.1 and 0.2 units, and suggests the Australian grass pollen thresholds influence the analysis by about 15%. If the best performing scenario for each observation site and under all scoring methods is counted from Figure 7, shifted Gaussian methodology E8 is best 12 times, statistical representation E9 is best 4 times and E10 25 times. E9, built using data prior to the 2017 season, has a stronger dependence on precipitation than E10, which is not supported by the correlation of 2017 pollen with meteorology. This suggests that the V2 statistical approach to the immediate timing combined with an EVI-based approach to the gross timing and a spatial source, is likely to produce the most accurate pollen forecasts.

It is useful to plot the observed and modelled pollen as a cumulative time series, as this indicates the timing of increased and decreased pollen counts (Figure 8). Here we focus on the best performing scenarios from each of the seasonal emission methods, capturing the range in descriptions of the pollen season. The observations show an "S" shaped profile, with increased pollen gradients in November. By the end of the 2017 season, all modelled profiles reach a cumulative total of 4200 grains m^{-3} due to normalisation to the same observed mean value.

The ∂EVI method E4 tends to emit grass pollen too early in the season compared with observations at most sites. However at Dookie the shape of the season in E4 and E8 compares better to the observations and E4 captures the mid November change when pollen counts decrease, better than E10, The observed pollen at Dookie experienced a much larger grass pollen input from the middle of October to early November than E10 (but is represented well by E8). There is little additional observed pollen at Dookie after early November, which is at least 20 days earlier than at the other sites. At Melbourne, Bendigo and Burwood, both E8 and E10 predict the early part of the grass pollen season very well, but emitted too much modelled pollen towards the end of the season. The steeper gradient in E8 and E10 at Melbourne between the middle to the end of November shows that too much pollen was being emitted then. In contrast, observed pollen at Churchill, Creswick, and Hamilton show a rapid increase in emissions at the end of November which is not matched by either E8 or E10. However the observations suggest that additional pollen continues to be emitted towards the end of December at Creswick and Churchill, prolonging the season. Scenario E8 captures the steep November gradient at Hamilton very well.

The observed and modelled pollen cumulative profiles in Melbourne, Geelong and Burwood are less smooth than the other regional sites, perhaps indicating more atmospheric variability near the coasts. It might also indicate the larger distances between the urban sites and the grass pollen production regions (more transport, less local production), as compared to the monitoring sites within grass pollen production areas (less transport, more local production). Here we also note the apparent lack of an 'S' shape in the modelled profiles at Geelong, which may account for the poor model performance at this site.

Table 4 splits the best model predictions from E8 and E10 into low, moderate, high and extreme categories to directly compare with observed categories. Here data from all counting sites are combined to ensure a large sample size. The diagonal in each table highlights the number of days the model has correctly predicted the observed category. Values far from the diagonal indicate the model has under or over-predicted the observed pollen. We want to avoid occasions where the observed pollen is extreme, but the model predicts low pollen. Table 4 shows that both E8 and E10 have good skill in predicting low observed pollen days. Both models also show high occurrences of predicting moderate pollen when the observed category is low. **?** found difficulties in modelling moderate category days, which is not the case here. Both models are equally good at predicting the high and extreme observed categories. E10 has less occurrences than E8 of predicting extreme pollen on days when observations were low. However there are six cases in E8 and one in E10 that predict low pollen when the observations were extreme. These cases occur around the 10-11th November within the city at Geelong, Melbourne and Burwood. Examining the meteorology from this period (pollen counts are date-stamped at 9am, but represent the preceding 24 hours), shows the model has captured the observed temperature, wind speed, direction and zero rainfall. The observed wind direction is from the south and south east, bringing mainly clean, marine air. However observed pollen is extreme on these days, suggesting a highly localised source. One explanation is that only pasture grass is considered in the model, whereas grass is usually present in most other land-use categories. There is green space within most cities on both public and private land, and grass plants are efficient at colonising disturbed areas such as road verges. Correlations between observed pollen at each site are not particularly strong (average r^2=0.28), suggesting that the pollen sources may not be related, or are highly localised. The modelled correlations between all sites are very strong because they share the same pollen source characteristics (average r^2=0.80). Inverse modelling could highlight where other grass land use categories contribute to grass pollen. Future development of VGPEM could consider the sub-gridscale grass fraction using high-resolution satellite data sources.

5 Conclusions

The aim of this work was to develop and assess the utility of a grass pollen emission methodology for use in a pollen forecasting tool for Victoria in Australia. Our work is the first of its kind for Australia, and whilst initially based in the State of Victoria, future work will see the methodology applied nationally.

Grass pollen was observed during 2017 at eight sites in Victoria, showing strongest correlations with temperature (positive) and RH (negative). Correlations of grass pollen with wind speed and precipitation were not strong.

Ten grass pollen emission source methodologies were presented in this work. Most used the locations of pasture grass in Victoria in combination with meteorological parameters and a seasonal pollen emission parameter. The seasonal parameter was either based on a simple Gaussian representation of time variation, or on the Enhanced Vegetation Index which measures greening from satellite. Each source methodology was run using a host transport model driven by ACCESS numerical weather predictions, at a spatial resolution of 3 km. The pollen was treated as an inert particle of diameter 35 μm and 1000 kg m^{-3} density, however these parameters are uncertain and impact the aerodynamic properties of the pollen.

Comparison of predicted meteorology with observations showed that ACCESS is very good at predicting temperature but less so for precipitation, compared to other meteorological parameters. Wind speeds are biased a little low, but are not the strongest correlating meteorological parameter for observed pollen. Use of wind speed as the immediate timing function in the pollen emissions framework also performed poorly. The key to predictive skill in immediate timing was to use a meteorological timing function that incorporates the parameters most correlated with observed pollen, namely temperature and RH.

Grass pollen source terms using the ∂EVI data did not perform particularly well, the Victorian grass pollen season perhaps better described by a simple Gaussian variation. Whilst emission method E8 worked well, the method is limited by fixed timings for the start and end of the pollen season, and the distributions were only trained on the 2017 Victorian observation data. These data may not account for regional variation nor inter-annual variability.

Implementing the maximum EVI value together with the date on which the EVI falls to 0.05 below this maximum, within a statistical methodology predicted pollen concentrations with much better skill. The ~~statistical model~~ smoothed statistics for E10 ~~uses these EVI data together with 25~~ used 16 years of observational data from the UoM ~~,~~ and one year from the seven other Victorian sites. ~~As the EVI comes from satellite data and~~ The smoothed statistical approach is modulated by the hourly effects of wind, temperature, RH and rainfall, which introduces temporal variation. The EVI also varies spatially and temporally, ~~these methods are more~~ meaning that this method is suitable for future years ~~, and have potential to work well outside of Victoria~~ and for other regions of Australia. Additional training data would be included to model pollen in other Australian regions, to account for the different seasonal flowering times of other grass species (e.g. C4 grasses) (?). The E10 methodology will be implemented in VGPEM1.0.

Long term observations are vital to record the grass pollen emission strength across Victoria in future years, particularly tracking changes brought about by climate change, changes to agricultural practices and the growth of cities into rural areas. The new Victorian pollen observation stations established after the thunderstorm asthma event in November 2016 should be maintained to aid forecasting of potential threats in future. Advances in technology may provide automated pollen counting in future which would improve the temporal resolution, and the possibility of recognising ruptured pollen grains. These technologies are required to support pollen forecasting, and to constrain future modelling of the pollen rupturing process.

Code availability. The pollen emissions code is available as a text file in the supplementary section.

Data availability. The Victorian pollen counts and forecasts from all eight sites are disseminated to the public via the web, a smartphone app (named "Melbourne Pollen Count" for iOS and Android) and an automated Facebook and Twitter account (@MelbournePollen).

Author contributions. KME and JDS devised the experiments, wrote the VGPEM code and most of the manuscript. KME ran the C-CTM. EN and ERL oversee six of the Victorian pollen count sites. CS oversees the two Deakin pollen count sites. AW provided the ACCESS meteorology. EE is the project manager. All authors edited the manuscript.

Competing interests. The authors declare that they have no conflicts of interest.

Acknowledgements. This work was funded by the Victorian Department of Health and Human Services. We are grateful to the pollen counters at each of the sites. Dr Penelope Jones at the University of Tasmania performed an external audit of the count data examined here. We acknowledge the valuable and ongoing technical support from the University of Melbourne Science IT Team, especially Ms Usha Nattala and Dr Uli Felzmann as well as the team at Infrastructure Services. J. Silver's work on the initial development of the emission module code was funded by a McKenzie Fellowship from the University of Melbourne.

Table 1. Locations of Burkard pollen sampling network in Victoria arranged west to east, and their nearest Automatic Weather Station (AWS). Code refers to site names within figures of this paper. UoM = University of Melbourne.

Site	Code	Lon °E	Lat °N	Location	Closest AWS (distance, km)
Hamilton	H	142.03	-37.74	Hamilton hospital grounds	Hamilton airport (10.4 km)
Creswick	Cw	143.90	-37.42	UoM satellite campus	Ballarat aerodrome (15.3 km)
Bendigo	Bg	144.30	-36.78	Latrobe University satellite campus	Bendigo airport (5.5 km)
Geelong	G	144.36	-38.14	Deakin University Waurn Ponds campus	Geelong racecourse (7.0 km)
Melbourne	M	144.96	-37.80	UoM city campus	Melbourne Olympic park (3.3 km)
Burwood	Bu	145.12	-37.85	Deakin University Burwood campus	Scoresby (11.4 km)
Dookie	D	145.71	-36.38	UoM satellite campus	Shepparton airport (29.3 km)
Churchill	Ch	146.43	-38.31	Federation University campus	Latrobe Valley airport (11.6 km)

Table 2. Options tested for pollen emission in this study. EVI = Enhanced Vegetation Index.

Scenario	Immediate timing, I	Gross timing, G	Spatial function, S
E1	Wind speed	Gaussian	Grass map
E2	Wind speed	∂EVI	Grass map
E3	Wind speed	∂EVI	1.0 (embodied in ∂EVI value)
E4	Meteorological function, $\sigma_h = 2$	∂EVI	Grass map
E5	Meteorological function, $\sigma_h = 2$	Gaussian	Grass map
E6	Meteorological function, $\sigma_h = 4$	Gaussian	Grass map
E7	Meteorological function, $\sigma_h = 4$	Gaussian	Production/Loss model
E8	Meteorological function, $\sigma_h = 4$	Shifted Gaussian	Grass map
E9	Statistical model V1	EVI based	EVI based
E10	Statistical model V2	EVI based	EVI based

Table 3. The 2×2 contingency table describing each model outcome.

	Observation	
Model	Yes	No
Yes	(*a*) Hit	(*b*) False alarm
No	(*c*) Miss	(*d*) Correct negative

Table 4. The number of days the model predicts a particular observed pollen category for E8 (left) and E10 (right). Data from all Victorian sites are combined. ~~Coloured~~ Bold text highlights where the model captures the correct observed category

E8	Observation				E10	Observation			
Model	Low	Moderate	High	Extreme	Model	Low	Moderate	High	Extreme
Low	**229**	49	18	6	Low	**116**	15	4	1
Moderate	69	**33**	29	13	Moderate	189	**72**	40	17
High	34	32	**35**	35	High	33	30	**46**	39
Extreme	14	15	21	**55**	Extreme	1	11	10	**50**

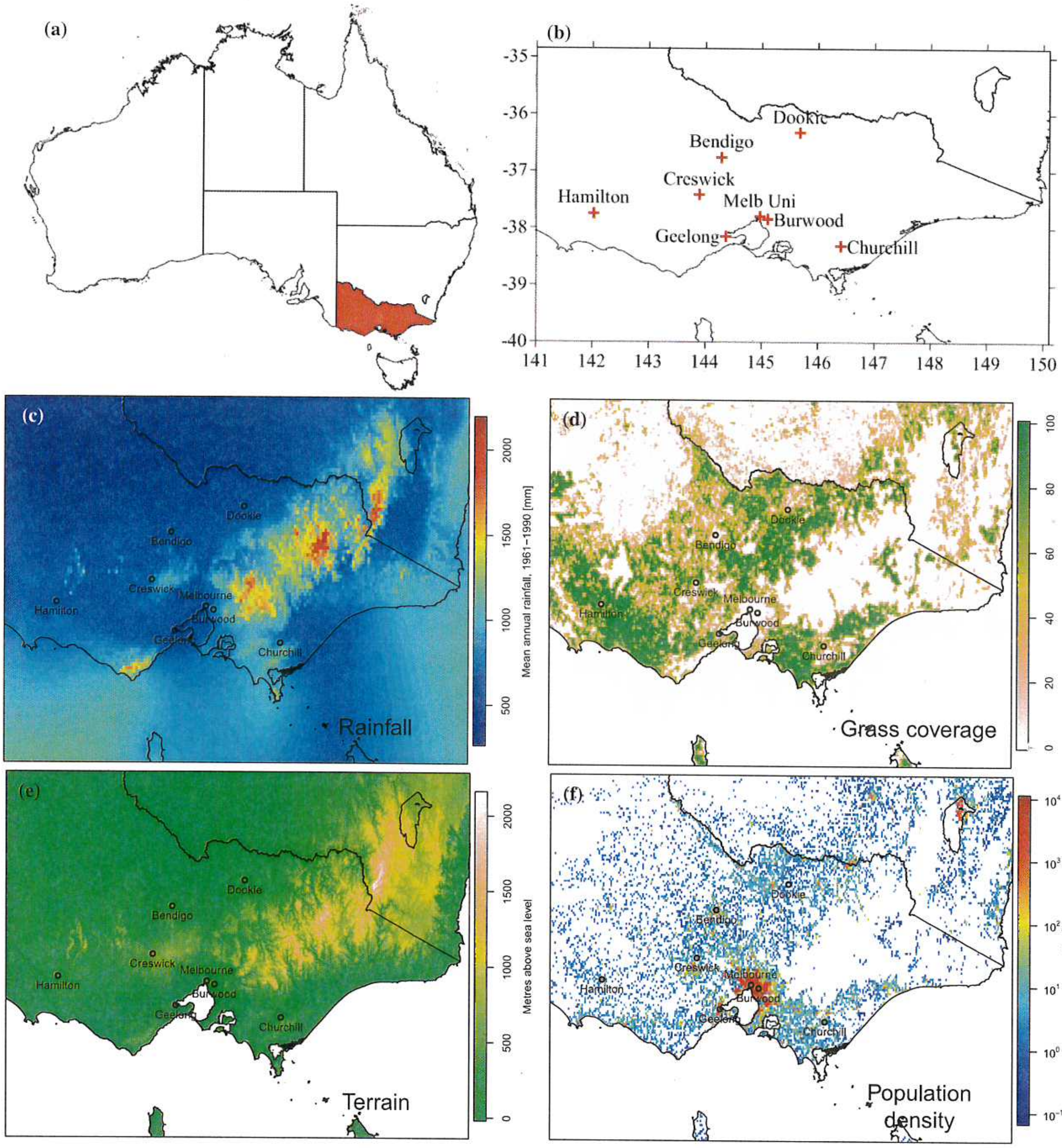


Figure 1. Maps of (a) Victoria within Australia, (b) pollen observing sites in the domain, (c) mean annual rainfall, (d) pasture grass coverage, (e) terrain, (f) population density. Data sources: (c) BoM, (d) ABARES, (e) Geoscience Australia, (f) Bureau of Statistics. The pollen counting site locations are shown.

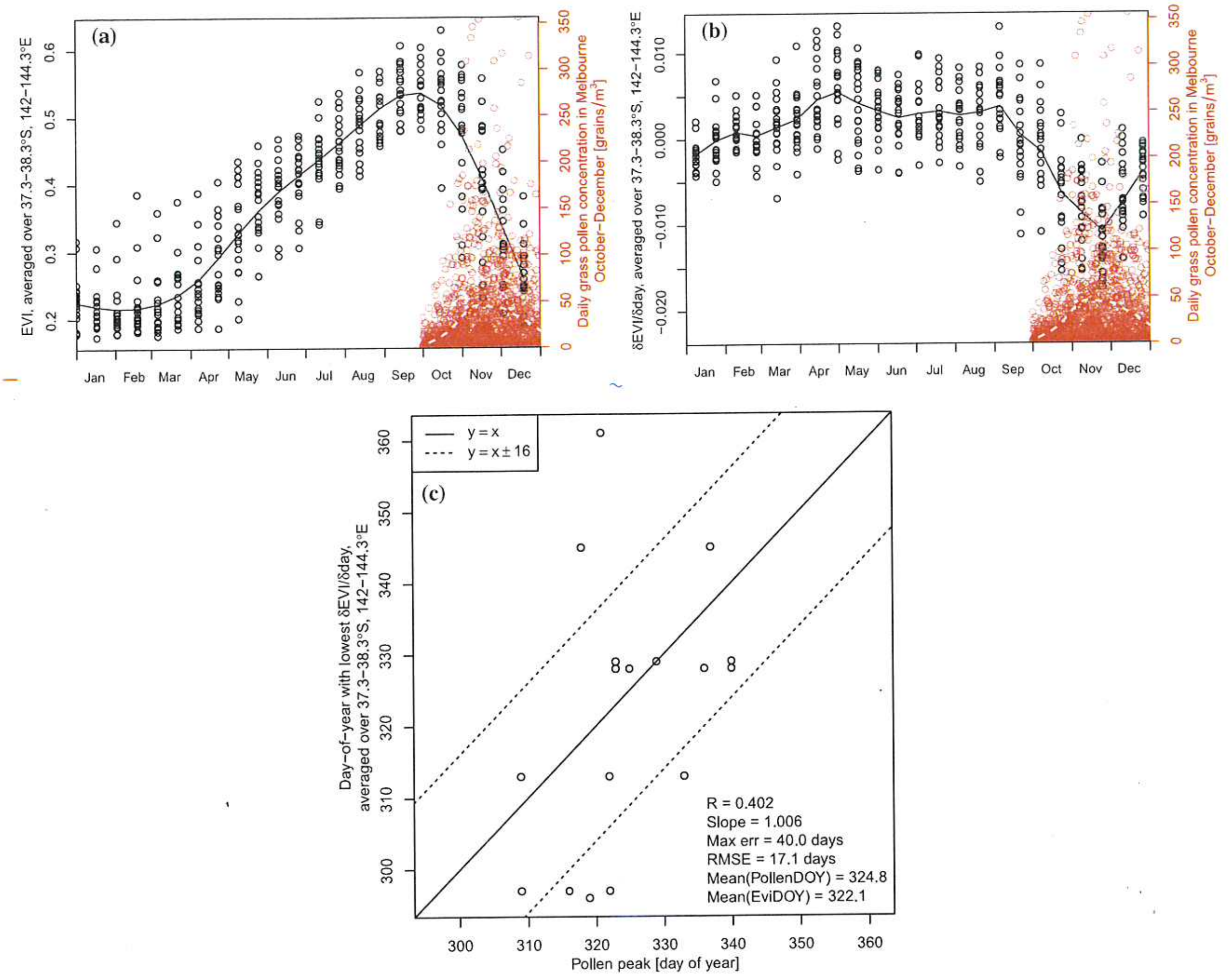


Figure 2. (a) ~~Time series of~~ 16 year climatology in EVI (black) from South West Victoria (averaged over the region 37.3 − 38.3°S and 142 − 143.3°E, shown in each panel of Figure 3) and the grass pollen record in Melbourne (red); the full sequence of data is shown as circles, with a locally-weighted polynomial regression overlaid (?). The EVI data are 16-day composites. (b) As panel (a) except presenting the derivative of the 16-day EVI with respect to time. (c) the day-of-year of the minimum of the $\frac{\partial \mathrm{EVI}}{\partial t}$ for each year plotted against the day-of-year of the maximum pollen; when assessing the timing of the pollen grass pollen peak, the grass pollen time-series was smoothed using a cubic smoothing spline. The dashed lines in (c) represent 16 days either side of a given day, which is the width of the MODIS EVI compositing window.

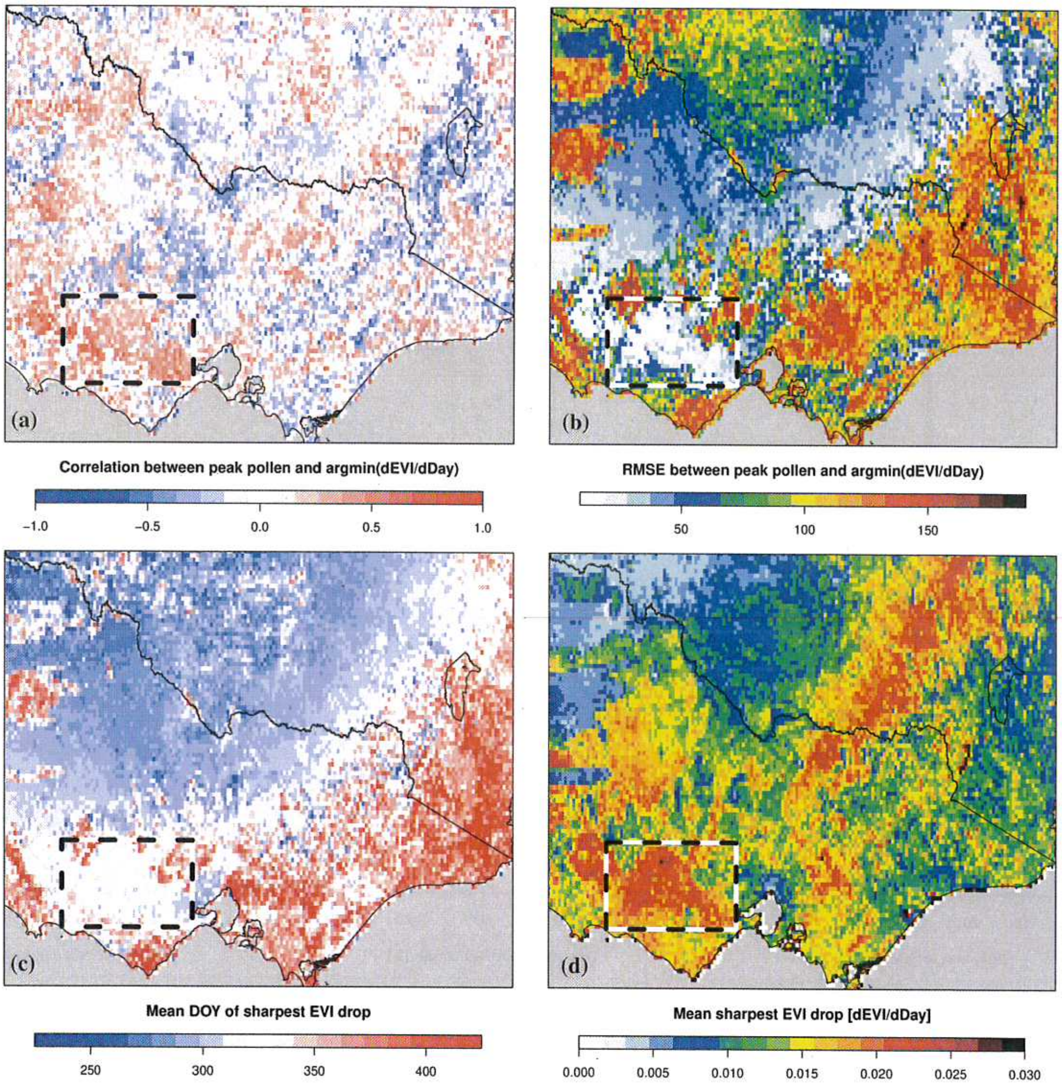


Figure 3. Relationship between the timing of the peak in grass pollen in Melbourne with the timing of the sharpest drop in EVI at each MODIS pixel: correlation (a) and the root mean-squared error in the timing (b). Also shown are the average timing (c) and rate (d) of the fastest fall in EVI at each point in the domain. The dashed rectangle in South West Victoria (spanning 37.3-38.3 °S and 142-143.3 °E) displays the region over which the EVI time-series were averaged for Figure 2.

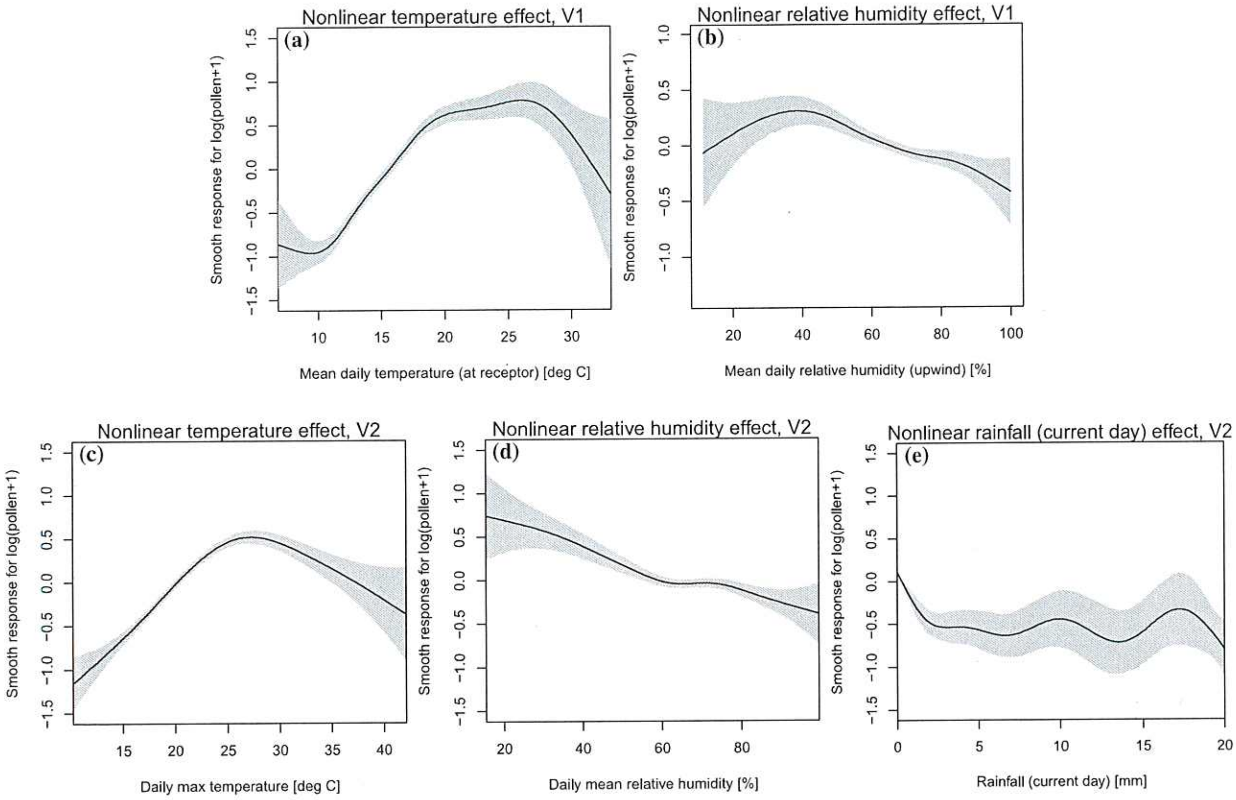


Figure 4. The shape of the non-linear terms in the statistical models related to temperature (a and c), relative humidity (b and d) and rainfall (e) for V1 (top row) and V2 (bottom row). The shaded regions correspond to ± twice the standard error of the GAM term

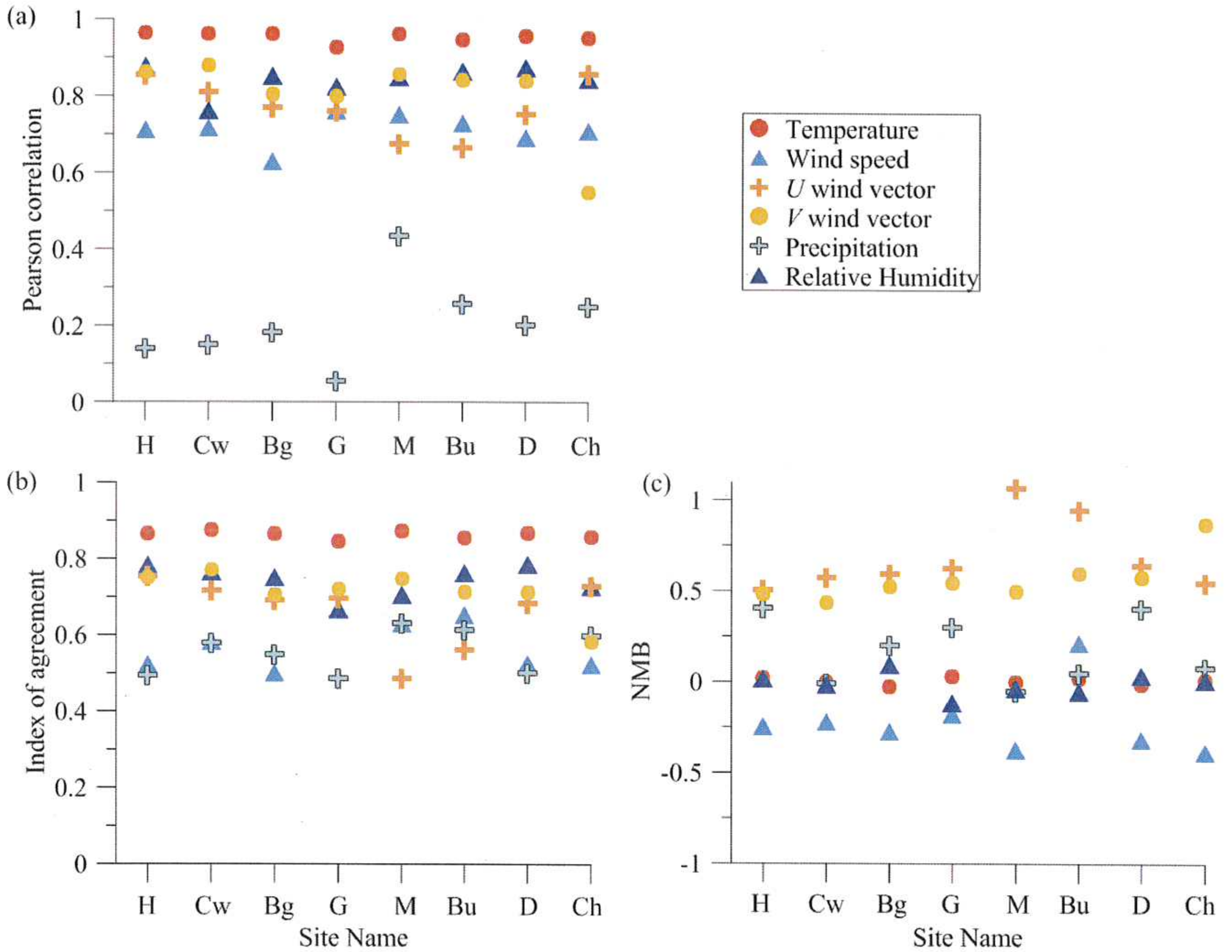


Figure 5. Comparison of observed and modelled meteorological variables at Automatic Weather Stations sites nearest to the pollen observation sites. (a) Pearson correlation. (b) index of agreement. (c) normalised mean bias.

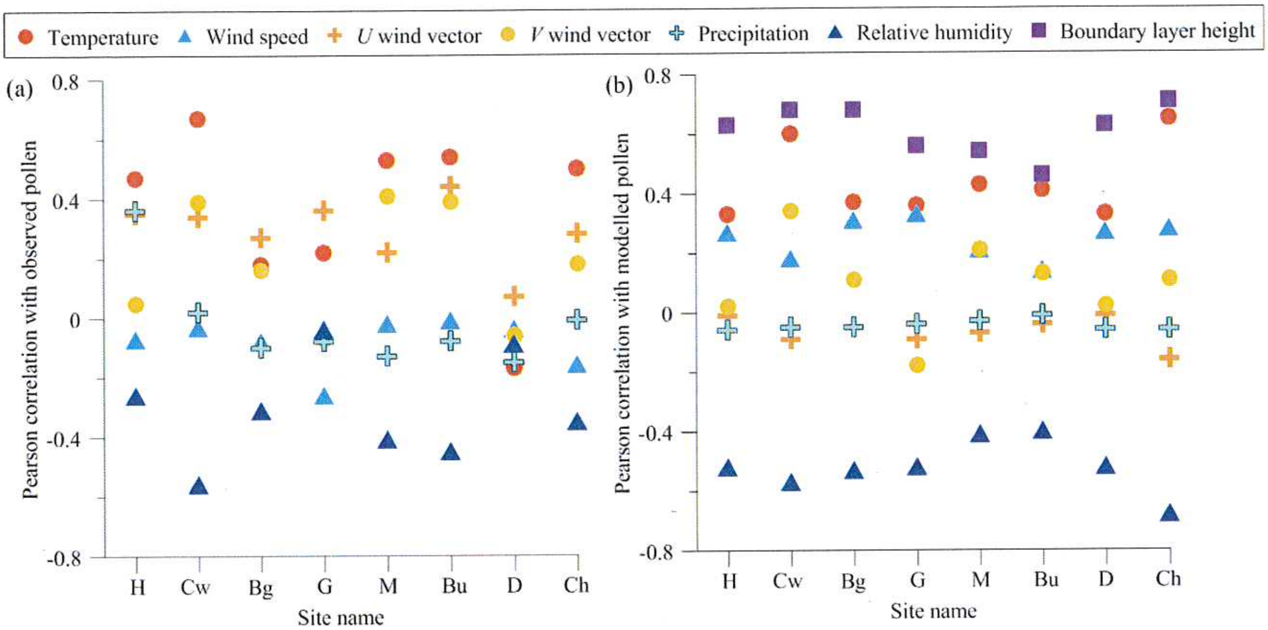


Figure 6. Pearson correlations of (a) observed pollen with observed meteorological variables from nearest Automatic Weather Station and (b) modelled pollen with modelled meteorological variables.

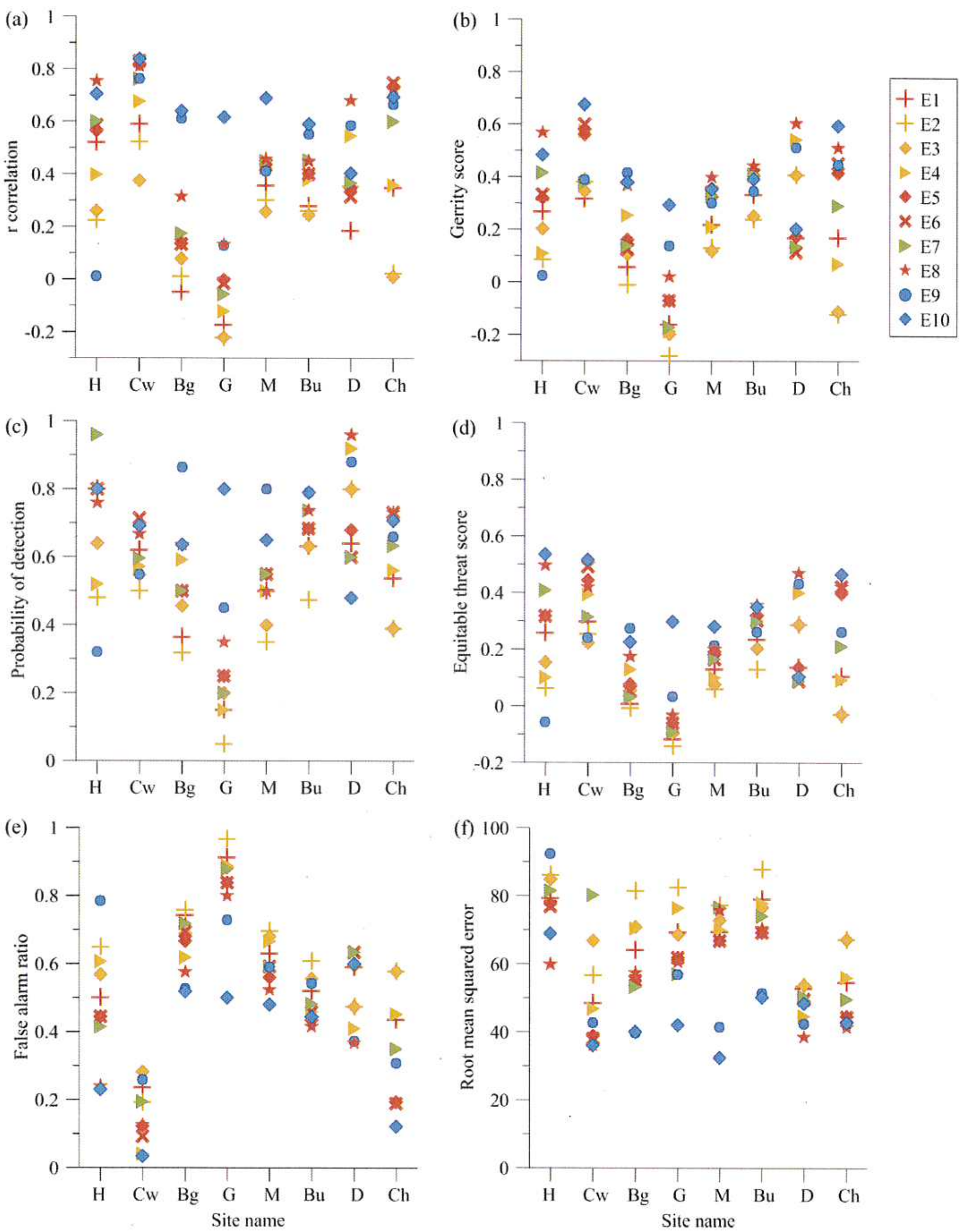


Figure 7. Results from the pollen emission methodology scenarios (a) Pearson correlation (b) Gerrity score (c) POD (d) ETS (e) FAR (f) RMSE. The sites are presented from west to east, and coloured red relating to Gaussian methodologies, yellow for ∂EVI methodologies, green for the production and loss model and blue for statistical methodologies. A higher score is better for the Pearson correlation, Gerrity score, POD and ETS. A lower score is better for the FAR and RMSE.

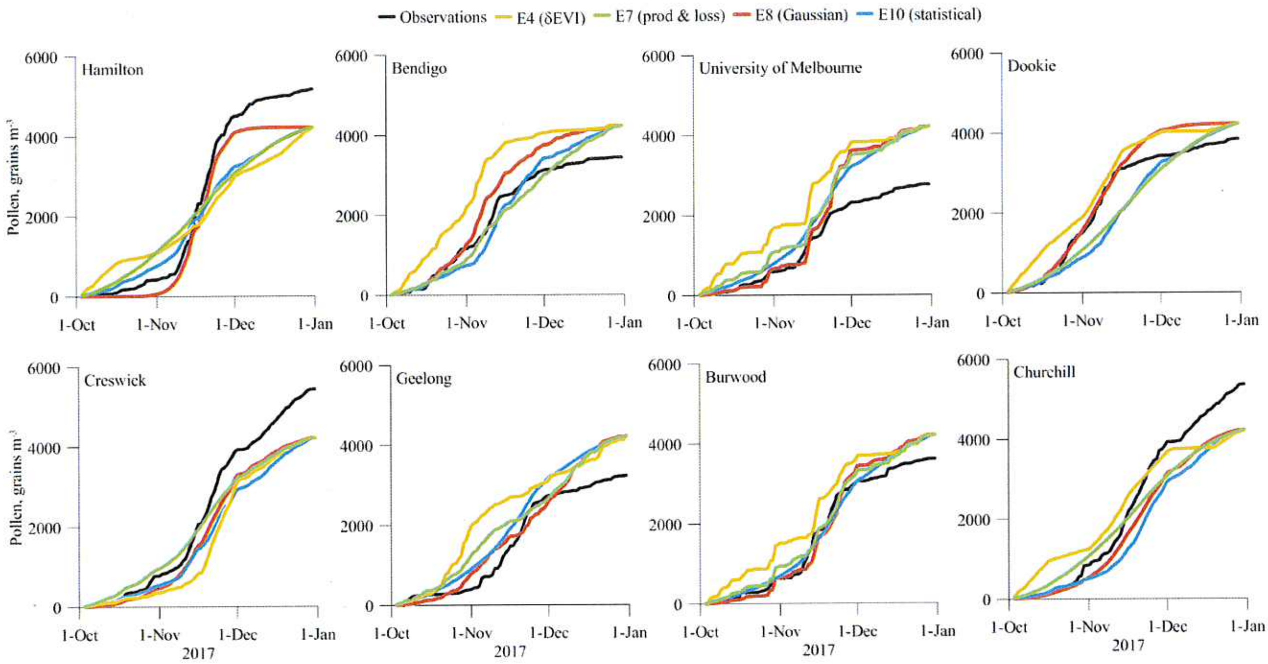


Figure 8. Cumulative time series in pollen across the 2017 season. Sites arranged from west to east.