



A numerical forecast for birch and grasses pollen concentration in Germany

Mariel Suarez-Suarez · Kabir Medina · Jesus Rojo · Rostislav Kouznetsov · Andreas Uppstu · Anders Stangel · Julia Palamarchuk · Stephanie Dramburg · Jan-Christoph Simon · Robert Gebauer · Inga Wessels · Carsten Schmidt-Weber · Jeroen Buters · Mikhail Sofiev

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Abstract Prevention of pollen exposure is a way to assist allergic individuals to better cope with their disease. To enable this prevention, a prediction of next day(s) pollen flight is needed. The most accurate predictions are from numerical models which calculate the expected airborne pollen concentrations using simulation of emission combined with atmospheric dispersal processes (as in the SILAM model). However, current numerical models are based on historical averages and make predictions for the whole of Europe, which is not always optimal for a specific location. In this study we adapted a continental numerical model forecast to regional conditions in two areas in Germany: Bavaria in the South, and

Leipzig and Berlin in eastern Germany. Eleven automatic pollen monitors were continuously running in these areas, allowing predicted pollen concentrations to be compared with observations. Adaptation of the modelling process to a regional scale increased the correlation (r) between observations and predicted pollen flight by about 38% for birch (up to 0.71 ± 0.07) and 18% for grasses (up to 0.57 ± 0.09). The most effective optimised parameters for birch pollen were; (i) adjusting the grid from a rotated to a non-rotated Latitude–Longitude coordinate system; (ii) updating the distribution and abundance map of potential pollen sources; (iii) adjusting the rate of pollen released in a year; and (iv) the timing based on temperature sum for birch. For grass pollen, the same parameters were optimized, except for the temperature sum. Here, for adjusting the timing, a phenological calendar method was used.

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M. Suarez-Suarez (✉) · K. Medina · I. Wessels · C. Schmidt-Weber · J. Buters
Center of Allergy & Environment (ZAUM), Member of the German Center for Lung Research (DZL), Technical University and Helmholtz Center, Biedersteiner Str. 29, 80802 Munich, Germany
e-mail: mariel.suarez@tum.de

J. Rojo
Department of Pharmacology, Pharmacognosy and Botany, Faculty of Pharmacy, Complutense University of Madrid, Madrid, Spain

R. Kouznetsov · A. Uppstu · A. Stangel · J. Palamarchuk ·

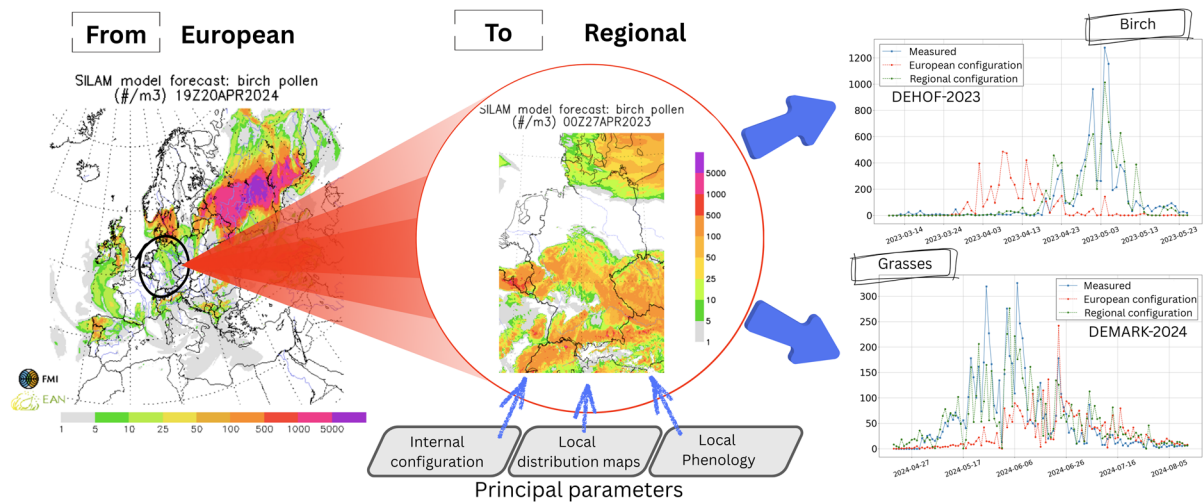
M. Sofiev
Finnish Meteorological Institute, Helsinki, Finland

S. Dramburg
Charité – Universitätsmedizin Berlin, Corporate Member of Freie Universität Berlin and Humboldt-Universität zu Berlin, Berlin, Germany

J.-C. Simon
University of Leipzig Medical Center, Leipzig, Germany

R. Gebauer
IT Consulting Robert Gebauer, Munich, Germany

Graphical Abstract



Highlights

- Adapting the numerical model SILAM from European to regional conditions for birch and grasses pollen clearly improved pollen flight predictions.
- Especially adjusting the internal configuration, phenology (heat sums) and source map improved the forecasts.

Keywords Pollen forecast · Automatic monitors · Hund BAA500 · Regional · Local phenology · SILAM

1 Introduction

Pollen is the main cause of allergic rhinitis and allergic asthma. Birch (Betulaceae) and grasses (Poaceae) are the most important plant pollen that provoke allergic respiratory diseases in Central Europe (Biedermann et al., 2019; García-Mozo, 2017; Jaeger, 2008). Reducing exposure is considered a fundamental tool for limiting allergic symptoms in affected individuals. To better manage their symptoms individuals sensitised to pollen allergens should minimize outdoor exposure during days with high pollen

concentrations. Knowing one's personal current local pollen concentration requires affordable and accurate pollen forecasts to anticipate exceedance of pollen level risk thresholds (Ravindra et al., 2022).

There is a wide variety of pollen prediction models, ranging from probabilistic (e.g. regression models or machine learning techniques) to process-based models estimating the expected airborne pollen concentrations using mechanistic approaches based on the simulation of emission and dispersal atmospheric processes (Scheifinger et al., 2013). In aerobiology, developing a forecast model is still a challenge due to the important stochastic component of the airborne pollen time-series, the complex interrelationships of environmental and human factors involved in pollen dynamics and the intrinsic complexity of given pollen taxa (Hjort et al., 2016; Rojo et al., 2017; Zhang & Steiner, 2022).

In the case of grass pollen, modelling complexity comes from the diversity and ubiquitous nature of grass species belonging to the Poaceae family, which includes more than 11,700 plant species covering a wide range of ecological environments in the world (Soreng et al., 2022). Furthermore, this taxonomic family includes well-known species used by humans such as cereals, bamboos, and grass forage among others. Grasses are thus considered important for the human economy. It is estimated that one-fifth of the Earth's Land is covered by grass-dominated habitats (Grass Phylogeny Working Group et al., 2001). For the reasons previously commented, perhaps one of the main challenges in grass pollen modelling is to determine accurately the main potential spatial sources and to estimate precisely the rate of pollen emission of these areas (Romero-Morte et al., 2018).

Birch pollen come from less species than grass pollen. Here *Betula pendula* Roth and *Betula pubescens* Ehrh. are the dominant species whose distribution in Europe is particularly concentrated in central and northern regions (Beck et al., 2016; Biedermann et al., 2019). Birch species are abundant in broadleaved forests, although birches are also common trees in urban areas (Bogawski et al., 2019). The flowering of birch species shows a marked phenological pattern dominated mainly by temperature as well as other previous and current weather conditions (Dahl & Strandhede, 1996; Hájková et al., 2020; Linkosalo et al., 2010; Picornell et al., 2019). Therefore, the adjustment of the phenological component of the modelling processes is crucial to accurately fit the timing of pollen emission.

One of the most widely used mechanistic numerical models to simulate pollen emission and dispersal is the System for Integrated modeLLing of Atmospheric coMposition (SILAM) which shows robust results when running Europe-wide (Siljamo et al., 2012; Sofiev et al., 2015, 2024, 2013). Applying this model at the regional scale requires optimisation and adjustment for several internal parameters to local conditions in order to achieve the required accuracy (Verstraeten et al., 2021). In Germany, pollen monitoring is now based on automatic pollen monitors belonging to an operative extensive network (Oteros et al., 2020). These devices provide pollen concentration data every 3 h, with a delay of about 4 h. Allergic individuals already benefit from real-time pollen data. The next main topic of interest of allergic individuals is knowing their exposure of

tomorrow. To do so, a precise modelling framework is needed that provides a future forecast.

Thus, our aim was to provide an accurate regional scale forecast of airborne pollen concentrations for the following day, using only historical observations from automatic pollen monitors in a specific area. To achieve this, the SILAM model was adapted to regional conditions by (i) adjusting the internal configuration by changing the grid from a rotated to a non-rotated Latitude–Longitude coordinate system; (ii) updating the distribution and abundance map of potential pollen sources; (iii) fixing the rate of pollen released in a year; and (iv) optimizing the timing of pollen release based on temperature sum for birch, or a phenological calendar method for grasses.

2 Methods and material

2.1 Study area and pollen observations

The study was conducted in Germany, Central Europe. Pollen observations were collected from a total of eleven automatic pollen monitors, one in Berlin, one in Leipzig, eight from the ePIN network in Bavaria (Oteros et al., 2019) (Altötting, Feucht, Garmisch-Partenkirchen, Hof, Marktheidenfeld, Mindelheim, Munich and Viechtach) and one in Munich at the Center of Allergy and Environment Munich (ZAUM) (www.epin.Bayern.de and www.pollenscience.eu accessed on August 2025). The data collected were from a 5-year period (2021–2025) using the Helmut Hund BAA500 (Bio Aerosol Analyzer) automatic pollen monitors based on image recognition (Oteros et al., 2015, 2020). Although pollen data from these automatic devices has been available since 2019, they could only be used from 2021 onwards because homogeneous predicted meteorological data (needed for the prediction) stemming from the same ICON weather model were only available from 2021 onwards. The temporal resolution was 3 h, from which an average daily value of pollen grains/m³ of air was calculated based on Eq. (1).

$$p_{\text{day}} = \frac{1}{n} \sum_{i=1}^n p_i \quad (1)$$

where: p_{day} = average of pollen concentration on a day, n = numbers of samples collected on the day, and p_i = the pollen concentration of each sample collected.

2.2 Meteorology

Meteorological data from the model ICON (Icosahedral Nonhydrostatic) was downloaded from DWD (Deutscher Wetterdienst, Offenbach, Deutschland, accessed August 2025). The data was provided in an hourly time resolution and on a regular latitude and longitude grid ranging from -3.94 to 20.34 E and 43.18 to 58.08 N with a spatial resolution of $0.02^\circ \times 0.02^\circ$. ICON is run with 65 hybrid-pressure levels from the ground up to the top of the atmosphere, the lowest level placed at a pressure of ~ 300 Pa lower than that at the surface (corresponds to ~ 25 m above the ground in typical conditions). Out of these data, SILAM simulations used 53 lowest levels, thus disregarding the meteorological data above ~ 190 hPa (the stratosphere and the mesosphere) as irrelevant for pollen dispersion.

2.3 Model description

The prediction SILAM model, is an offline 3D chemical transport model (Sofiev et al., 2015) (<http://silam.fmi.fi/>, accessed August 2025). The model is an open-code system (<https://github.com/fmidev/silam-model>, accessed August 2025). This was then set up in the environment of the Leibniz Supercomputing Centre (LRZ) in Garching, Germany using the latest version of SILAM v.5.9.1., with OMP (Open Multi-Processing) plus MPI (Message Passing Interface) parallelization.

SILAM has a variety of transformation modules (chemical and physical), one of which focuses on airborne pollen forecasting. Specifications used for a forecast were pollen species specific. The numerical model for birch pollen is based on a double-threshold temperature sum model (Siljamo et al., 2012; Sofiev et al., 2013). In the case of grasses, emissions are calculated by multiplying the source map for each grid cell with the release rate determined by the combination of different gamma distributions curves, and extended until the end of the season (the timing is

based on a phenological calendar) (Verstraeten et al., 2021).

The model generates a netCDF4 format as output, the tools required to visualise and analyse the results were Python 3.10.12, netCDF4 library, and NASA PanoPly netCDF data viewer (<https://www.giss.nasa.gov/tools/panoply>, accessed August 2025).

2.4 Variables adjusted to regional conditions

For both pollen types, we found that four parameters needed to be modified to adjust to regional conditions, as depicted in Fig. 1. These parameters were (i) adjusting the internal configuration of the model, specially by changing from a rotated grid to a non-rotated grid (coordinate system); (ii) testing different pollen source maps; adjusting phenology; (iii) pollen emission (pollen grains $\text{m}^{-2}\text{yr}^{-1}$, pollen *per area per time*); (iv) the time of flowering of birch and for grass according to regional parameters. Other parameters tested did not show any significant effect and were further omitted in our description, such as threshold temperature (3.5°C) or the start day of temperature accumulation (1st March). There the pre-set values turned out to be already optimal and were employed.

The evaluation parameter for validation of the predictions was the correlation (r) between predicted and observed pollen concentrations of the main pollen season (i.e. timing), and the slope of this curve for the agreement for pollen emission. Each parameter in Fig. 1 was first tested separately and then in combination. For statistical analysis Python 3.10.12, Sklearn and SciPy Stats libraries were used (Virtanen et al., 2020).

2.4.1 Internal configuration

One principal internal configuration adjusted was changing the grid from rotated to a non-rotate latitude–longitude coordinate system. The model was originally configured on a rotated grid in which the origin (0,0) was redefined and located in the centre of Germany. We redefined the origin (0,0) to the usual reference, where the origin is the intersection of the equator and prime meridian. The SILAM model was originally developed especially for Northern countries, where it is necessary to use a rotated grid to reduce distortion during the projection, as the Earth

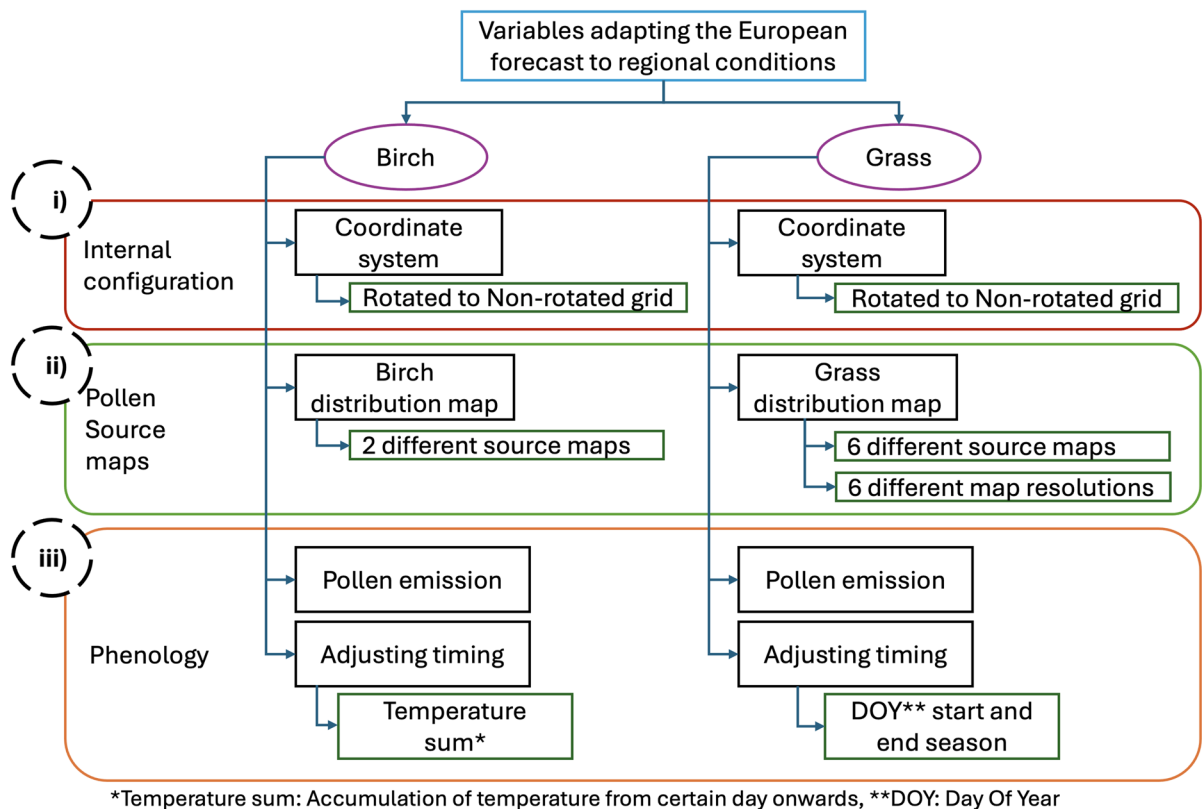


Fig. 1 The principal parameters we investigated for adapting the European forecast to regional conditions are shown for birch (left) and grass (right). Three main groups of parameters were identified: (i) the internal configuration of the model, which involved modifying the grid from rotated to non-rotated

latitude–longitude (i.e. geographical map); (ii) which pollen source maps should we use (we tested two for birch and six for grasses), with resolution is best; and (iii) phenology, optimising pollen emission and local pollination timing (temperature sum for birch and phenological calendar for grasses)

is curved. In our case this was detrimental for our predictions (Bailey et al., 2023; Rauscher et al., 2010) and was eliminated.

Another modification made to the internal configuration was the vertical resolution. Originally, the resolution of the horizontal grid cell was at $0.02^\circ \times 0.02^\circ$, with an uneven vertical resolution of 10 layers with thicknesses of 25, 50, 100, 200, 400, 750, 1200, 2000, 2000, and 2000 m (the three uppermost layers had the same thickness). Other horizontal size of grids resolution was tested, but the original resolution was retained, as our meteorology uses the same resolution. The vertical layers were reduced to 7, based on the configuration used in pollen reanalysis (Sofiev et al., 2024). The new thicknesses were 25, 50, 100, 400, 1000, 2000 and 3000 m, thus reaching up to 6575 m above the ground. The vertical scheme of SILAM

uses the subgrid information, which increases the effective vertical resolution of the model and allows it to run with few thick vertical layers still accounting for the full vertical resolution of meteorological fields (Sofiev, 2002).

The simulations used boundary conditions from the SILAM European simulations that were provided by FMI (Finland) following the Copernicus Atmosphere Monitoring Service standard setup, with the above 10 layers reaching up to 7725 m above the ground. The boundary conditions were provided at hourly temporal resolution. The characteristics of atmospheric boundary layer were computed following the standard SILAM approach (Sofiev et al., 2010).

2.4.2 Pollen source maps

We compared several distribution maps of birch and grasses. The distribution maps originally set up in SILAM for birch and grasses (see Fig. 2 a, c) were compiled and refined at European Scale with a resolution of 5 km (Sofiev et al., 2006, 2013). Two distribution maps were tested for birch: the original map established in the model see Fig. 2a, and a map of probability of abundance of birch species provided by the European Atlas of Forest Tree Species with a resolution of 1 km, see Fig. 2b (Beck et al., 2016; J. San-Miguel-Ayán et al., 2016).

For grasses we tested six different source maps with a spatial resolution of 1 km. The original map of the model (Fig. 2c), and five more specific grass sources characterised as:

- i. Arable land: Derived from the Corine Land Cover (class 2.1) provided by the Copernicus Land Monitoring Service (Copernicus Land Monitoring Service, 2025a). This category comprises agricultural areas dedicated to non-permanent crops (Fig. 2d).
- ii. Cereal crops: Derived from Monfreda et al. (Monfreda et al., 2008), which includes a comprehensive, global-scale inventory mapping all individual cereal crops (Fig. 2e).
- iii. Grasslands: Layer of grasslands provided by the Copernicus Land Monitoring Service (Copernicus Land Monitoring Service, 2025b). This map resource represents permanent, untitled land covered by natural, semi-natural or managed grassy vegetation (Fig. 2f). This map includes pastures and wild grasses.
- iv. Pastures: Derived from the Corine Land Cover (class 2.3) provided by the Copernicus Land Monitoring Service (Copernicus Land Monitoring Service, 2025a). This category comprises permanent, untitled and regularly mowed grasslands, used for grazing (Fig. 2g).
- v. Wild grasses: Layer was generated by combining the Corine Land Cover and Grasslands datasets from the Copernicus Land Monitoring Service (Copernicus Land Monitoring Service, 2025a, 2025b) where pastures were removed from the rest of permanent grasslands. Therefore, the wild grasslands category uniquely

comprises permanent and untitled grasslands that were not mowed for grazing (Fig. 2h).

The Grasslands map was also tested with different spatial resolutions from 100×100 m to 5×5 km grid cell, using the evaluation tool R statistical software (R Core Team, 2021) with the package “terra” (Hijmans R, 2025).

2.4.3 Phenology

For birch, the numerical model was developed based on temperature sums. The accumulation of the temperature sum starts on the 60th day of the year (March 1st) with a threshold temperature of 3.5 °C (Sofiev et al., 2013). When the sum of temperatures reaches 87 ± 2.2 °C, flowering begins. This variable was tested by increasing or decreasing it in steps of 5–10 °C between the range –20 °C to +40 °C, thereby shifting the flowering season’s onset to an earlier or later time. The end of the season was tested on the same way, originally set when the temperature sum reaches a value of around 169 ± 5.2 °C, at which point the season should end. In this case we also tested in steps of 5–10 °C with a range of –30 °C to +40 °C (see Table S1 for the specific values).

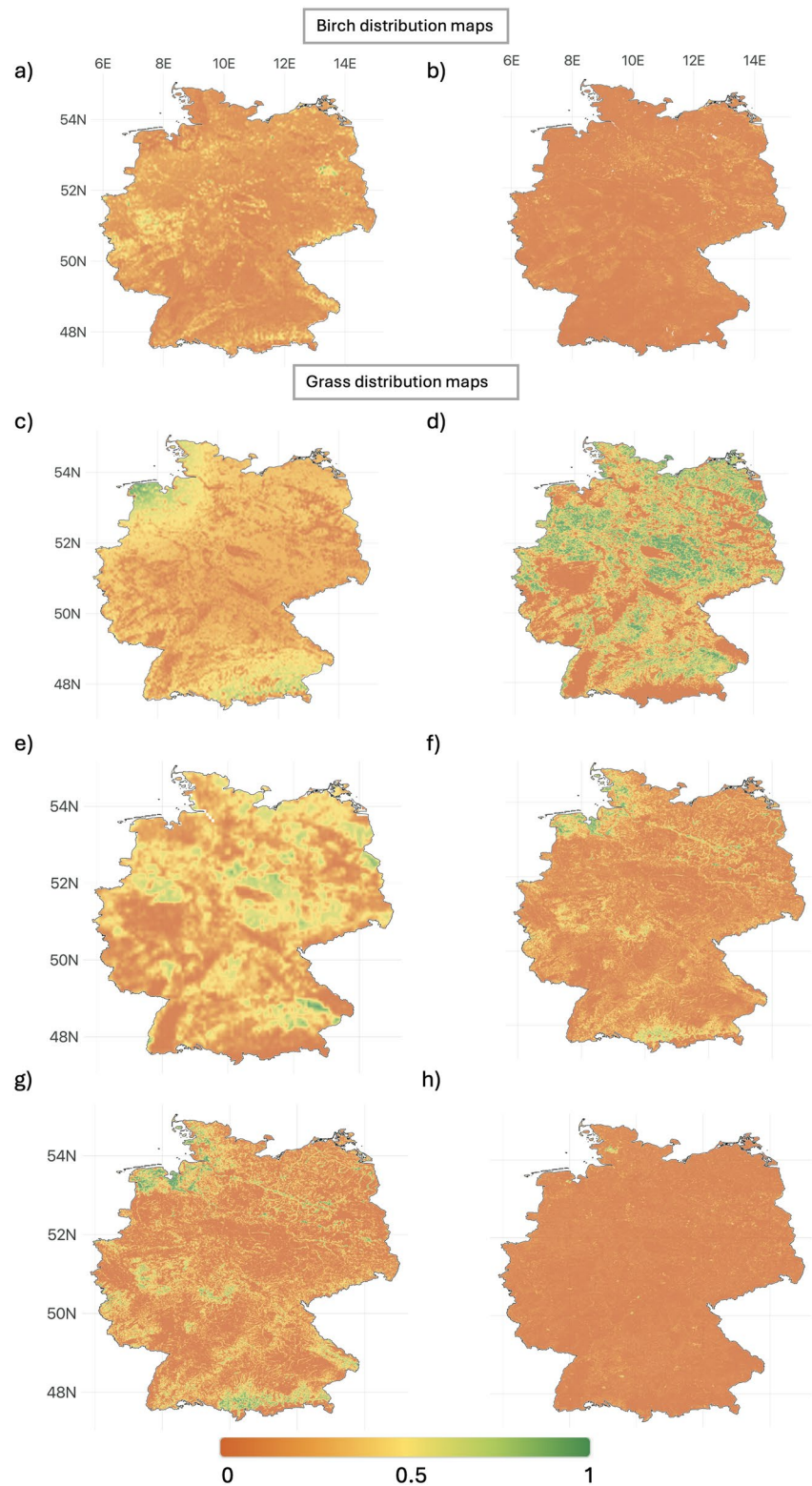
For grasses, the flowering season was adapted to a phenological calendar based on European historical records (Verstraeten et al., 2021). When the model reaches day 145 ± 10 of the year, the season begins, and it ends when day 228 ± 8 of the year is reached. Unlike birch, the predicted grass pollen season started too late when the original settings were used, we therefore brought the season forward in steps of 5–10 days, ranging from 5 to 30 days (see Table S1 for the specific values).

To estimate the pollen emission rate in our regional conditions, we based our calculations on the Season Pollen Integral (SPIn) for each year from the model versus observations Eq. (2).

$$pe_{i,y} = \frac{(SPIn_{obs})_{i,y}}{(SPIn_{for})_{i,y}} \times pe_{standard} \quad (2)$$

where $pe_{i,y}$ is the pollen emission calculated by year (y) and station (i), based on the SPIn observations and forecast, the $pe_{standard}$ is the pollen emission originally established for the SILAM model. The pollen

Fig. 2 Pollen source maps specific for Germany; for birch trees (a) compiled by SILAM and (b) European Atlas (finally selected). For grasses, six different source maps were tested: (c) compiled by SILAM, (d) Arable land, (e) Cereal crops, (f) Grasslands (finally selected for our model), (g) Pastures, (h) Wild grasses. For the source of the maps see text. The left y-axis and top x-axis indicate the map coordinates. The colour scale at the bottom represents the occurrence intensity (0–1) for all maps



emission per area per year in the original model was set at 10^8 pollen grains $\text{m}^{-2}\text{yr}^{-1}$ for birch and 2×10^6 pollen grains $\text{m}^{-2}\text{yr}^{-1}$ for grasses. These values were calculated using database at European scale and were used as the original model emission estimates (Sofiev et al., 2024) (Verstraeten et al., 2021). The calculations from Eq. (2) offer a general indication of the extent to which the model differs from the observations. The results of these calculations by station and year are given in Table S3 and S4.

The differences between observations and modelled forecasts were quantified, and the pollen emission was adjusted on a yearly basis accordingly. For birch, as the model was always overestimating, this was reduced over a range between -5% to -80% . On the contrary for grasses the model was underestimating the pollen emission rate, and the number was increased up to 16 times (details of the specific values tested can be found on Table S2).

The phenology was optimised on an annual basis, resulting in a specific configuration for each year. This was then averaged to derive a generalized configuration. The phenology parameters were systematically adjusted, either increasing or decreasing the original value. The configuration that best aligned the observations with the forecast was then selected. The adjustment process continued until no further improvements could be made to the model, at which point the model began to degrade. This process was carried out for both pollen types. This procedure resulted in year-specific values from which a uniform average value was calculated to fit all years.

2.4.4 Pollen emission bias factor

After the above adjustments, a different bias factor (BF) was calculated for each station, using a method similar to other studies in aerobiology. We used the BF to compare the automatic device's observations with the forecast (the slope i.e. pollen emission observed vs predicted per day) Eq. (3). When $\text{BF} > 1$ (higher), it indicates that the model was systematically underestimating, and if $\text{BF} < 1$ (lower) the model was systematically overestimating the pollen emission for that location. We calculated bias factors for each station for each individual year.

$$\text{BF}_{s,y} = \frac{\text{SPIn}_{\text{obs},s,y}}{\text{SPIn}_{\text{forecast},s,y}} \quad (3)$$

where, $\text{BF}_{s,y}$ is the bias factor for station s in year y , $\text{SPIn}_{\text{obs},s,y}$ is the observe SPIn value at station s in year y , and $\text{SPIn}_{\text{forecast},s,y}$ is the corresponding forecast SPIn value from the model.

3 Results

The results of the individual parameters are presented first, followed by the results obtained from their combination.

3.1 Internal configuration

The SILAM model is configured by default with a rotated longitude-latitude grid (coordinate system), which we modified to a non-rotated grid. Figure 3a shows that using a non-rotated grid improved the correlation between the predicted and observed values for birch pollen concentrations, with a significant difference in almost all years. However, the slopes (pollen emission) in Fig. 3b were not significantly affected in almost all years. Similarly, changing the configuration of the grid also affected grass pollen predictions. In Fig. 3c we show in some years the impact on the correlation increased in other it did not. In general, the impact of changing from a rotated to a non-rotated grid was smaller than for birch pollen. In the slope (Fig. 3d) we observed a positive effect in some years, but not significantly different between the groups for all years.

As the meteorology is provided in a non-rotated grid, not applying this extra transformation into a rotational grid also reduced computational power. Using the non-rotated longitude-latitude grid and reducing the vertical layers from 10 to 7, we reduced the processing time by 20%. The subsequent experiments were then performed using the non-rotated latitude–longitude grid and 7 vertical layers.

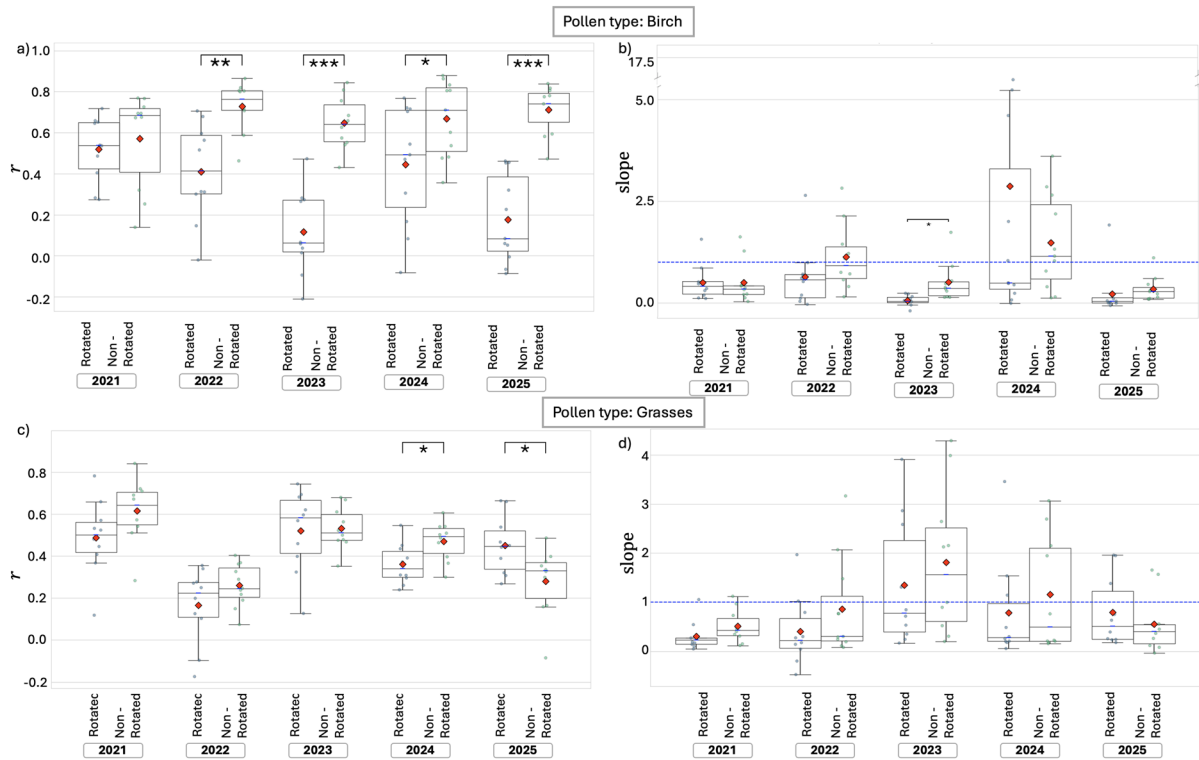


Fig. 3 Effect of adjusting the SILAM internal configuration parameters: changing the grid configuration from rotated to non-rotated latitude-longitude (coordinate system) per year (2021–2025) for (a) and (b) birch or (c) and (d) grass pollen. The mean and 75% (box) and 95% (whiskers) ranges of all eleven stations and years are given. (a) and (c): Correlation (r ,

agreement between measured and predicted in pollen timing), (b) and (d): Slope of the curve (agreement in pollen emission intensity between measured and predicted). The respective significant differences (t-test) are noted at the top of the figures, along with the corresponding p-values

3.2 Pollen source maps and phenological optimisation

3.2.1 Pollen source maps

Two birch distribution maps were evaluated, as shown in Fig. 2 a, b. The evaluation parameters were the timing of the main pollen season (r), Fig. 4a and the pollen emission (slope, Fig. 4 b) of the curves for predicted versus observed pollen concentrations (shown by years on Fig. S1). The results show that, in general, the correlation is slightly higher when using the European Atlas map than when using the map compiled by SILAM, for all years and all stations. Using the European Atlas map also reduces the number of underestimated stations in terms of pollen emission.

For grasses pollen we experimented with different six source maps, due to species belonging to this

family grow in very diverse environments like for instance wild grasslands, pastures, croplands, peri-urban and urban areas, and others (Grass Phylogeny Working Group et al., 2001). In Fig. 5 we show the results of testing these grass distribution maps on a) the correlation and b) the slope (shown by years on Fig. S2). The Grassland and Pastures maps performed best, the map compiled by SILAM performed moderately, and the Arables, Cereals and Wild maps performed worst.

Nowadays, grasses distribution maps with a higher resolution exist. To test whether a higher-resolution map would benefit the model, we compared maps with grid cells ranging from 100×100 m to 5×5 km, as shown in Fig. 5c–d. The results showed that the model started to degrade when the map resolution was lower than 1×1 km grid cell, and that it showed the same performance up to 5×5 km grid cells.

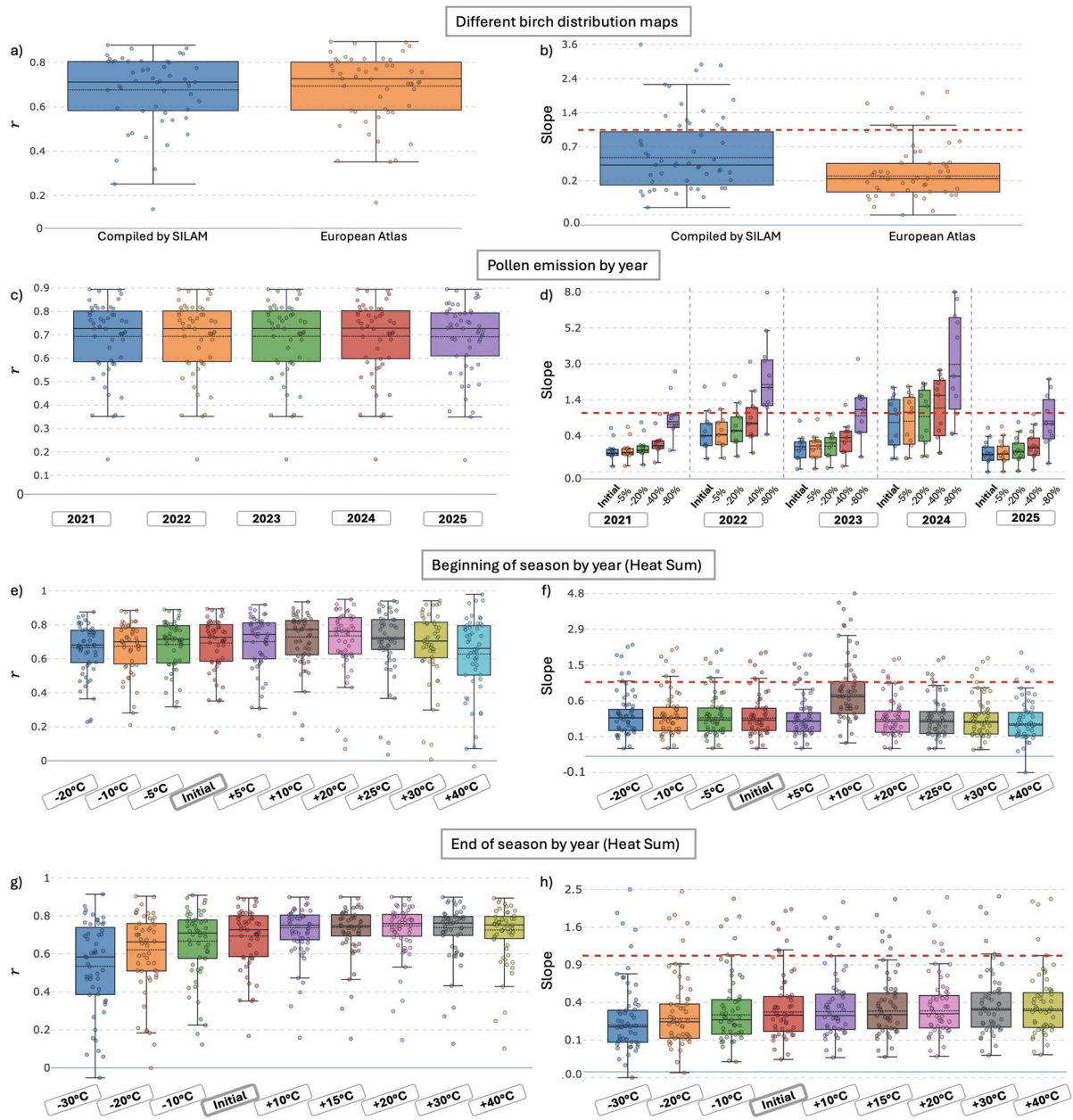


Fig. 4 Airborne birch pollen: Effect of changes of map distributions and phenological parameters on correlation (timing) or slope (pollen emission) of the curve of predicted values compared to those observed at the eleven stations in the years 2021–2025; (a) a comparison of two distribution maps on correlation and (b) on the slope of the curve; (c) effect of changing the pre-set pollen emission released by the model during a season on correlation and (d) on the slope, the pollen emission rate (10⁸ pollen grains m⁻²yr⁻¹) was reduced in

steps from -5% to -80%; (e) and (f) changes in correlation and slope when adjusting the temperature sum for the start of flowering season (around 87 ± 2.19 °C), which was gradually decreased to -20 °C or increased +40 °C; (g) r and (h) slope for the end of the flowering season, temperature sum around 169 ± 5.18 °C, gradually decreased to -30 °C and increased to +40 °C. The y-axis of the slope is shown on a square-root scale

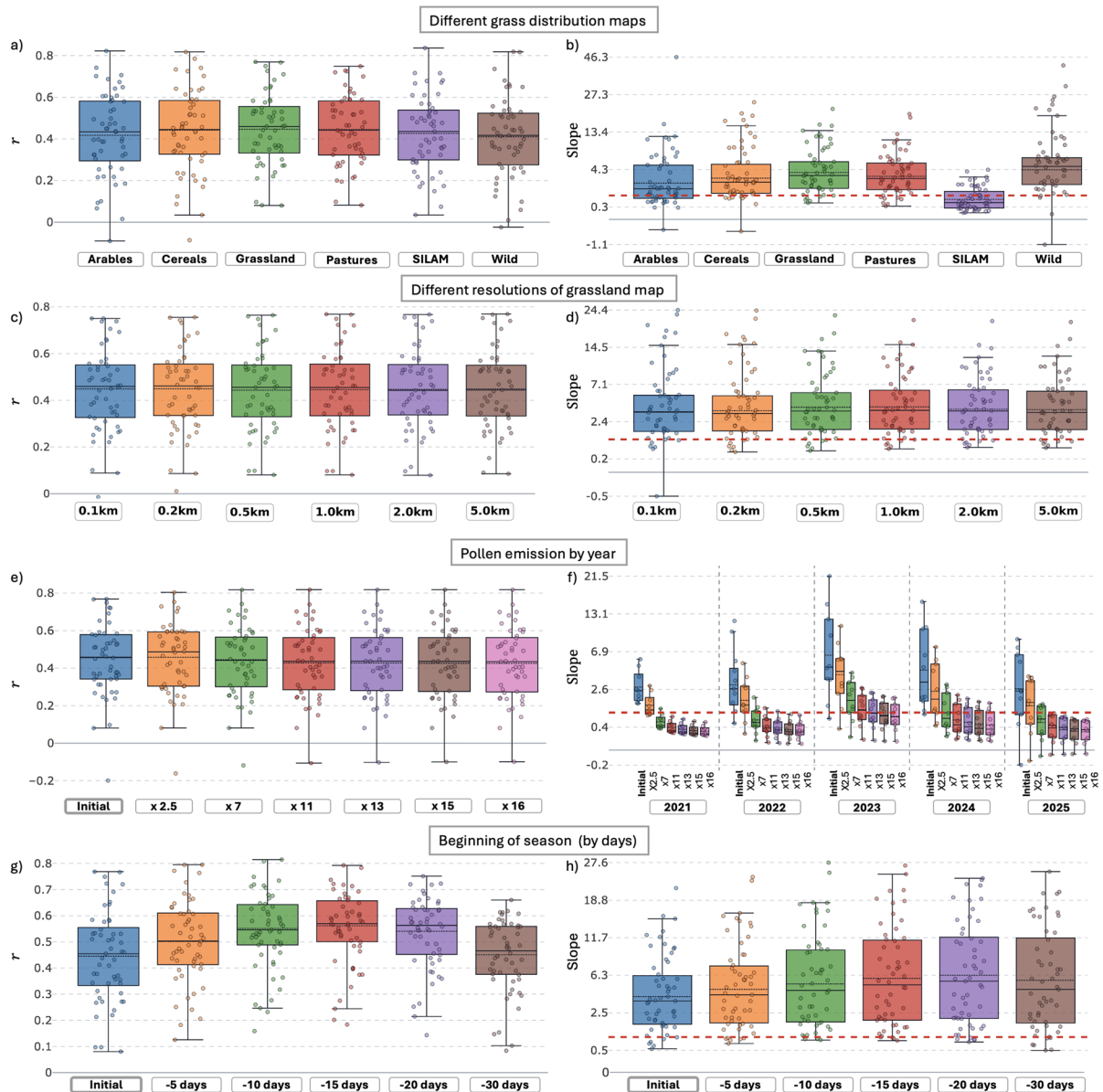


Fig. 5 Airborne grasses pollen: Effect of changes in map distribution (with different resolutions) and phenological parameters on the correlation (timing) or slope (pollen emission) of the curve of predicted values compared to those observed at the eleven stations in the years 2021–2025; (a) the effect on correlation and (b) the slope of six different distribution maps; (c) r and (d) slope of the comparison of maps of different res-

olution (from 100×100 m to 5×5 km grid cell; (e) changes in correlation and (f) slope when increasing the pollen emission rate (2×10^6 pollen grains $m^{-2}yr^{-1}$) in steps from 2.5 to 16 times; (g) r and (h) slope of modifying the beginning of the flowering season around day 145 ± 10 of the year which was gradually reduced to 30 days. The y-axis of the slope is shown on a square-root scale

3.2.2 Phenological optimisation

In terms of phenology, the results showed that the model overestimated the emission of birch

pollen per area in all years. To address, this issue, we adjusted the initial pollen emission rate of 10^8 pollen grains $m^{-2}yr^{-1}$ by values ranging from -5 to -80% . This reduction was done based on the results

of applying Eq. (2), for which the SPIn values for the forecast and observation were calculated for each year and then multiplied by the pollen emission rate (see Table S3). This table shows the deviation between the forecast and the observations. Figure 4 shows the (c) correlation and (d) slope of the predicted versus observed values. The results show that a reduction of up to 80% was required for the years 2021, 2023 and 2025, whereas for the other two years a reduction of 20% or 40% was sufficient for the years 2022 and 2024. After this point, the model started to underestimate. The correlation remained unaffected, as this variable primarily adjusts the pollen emissions.

The model however underestimated the pollen emission for grasses. Therefore, we increased the original model's pollen emission rate per area (2×10^6 pollen grains $\text{m}^{-2}\text{yr}^{-1}$) in steps until the model emitted up to 16 times more pollen (see Fig. 5 e–f). As with birch, this increase was based on the results of Eq. (2) (see Table S4). The results showed that a 16-fold increase was required in the year 2023, when the model underestimated the pollen emission the most. An 11-fold increase was required in 2024, a sevenfold increase in the years 2022 and 2025, and only a 2.5-fold increase in 2021. Consequently, we observed that a different adjustment per years were needed to adjust the slope to about 1 (i.e. predicted fitted observed amounts). As expected, the correlation (i.e. timing) remained unaffected by changing the emitted pollen.

The timing of the birch pollen season is based on an accumulated temperature sum (Sofiev et al., 2013). We adjusted the initial start of pollination, which was initially set at around 87 ± 2.2 °C for all the stations. This value was then decreased and increased in steps of 5–10 °C over the range from –20 °C to 40 °C (see Table S1 for specific values). The statistical parameter most affected was the correlation (the evaluation parameter for timing); see Fig. 4 (e) correlation and (f) slope (shown by years on Fig. S1). Increasing the temperature sum by around +20 °C (to 107 ± 2.2 °C) improved the forecast, which then started to deteriorate for the years 2023–2025. This was achieved by increasing the temperature sum by +5 °C (92 ± 2.2 °C) for 2022 and reducing of –5 °C (82 ± 2.2 °C) for the 2021. The slope remained unaffected except in some cases where the temperature sum was increased by +10 °C.

For the end of the flowering season, the original setup for all stations was around 169 ± 5.2 °C. This value also was decreased in steps of 5 °C or 10 °C within the range –30 °C to +40 °C (see Table S1 for the specific values). Figure 4 shows (g) the correlation and (h) the slope (shown by years on Fig. S2). As with the beginning of the season, the correlation improved over the same three years (2023–2025), by increasing the heat sum accumulation by +30 °C (to 199 ± 5.2 °C). In 2022, no increase or decrease was necessary, as the model degraded in both directions. In 2021 a decrease of 20 °C (149 ± 5.18 °C) was required.

Finally, we adjusted the pollination time for grasses, for which the model uses a phenological calendar. Flowering begins around day 145 ± 10 of the year (DOY) and finishes around day 228 ± 8 DOY in all the stations. We observed, in all years, that the model's original forecast was consistently too late compared to the observations. Thus, we tested the effect of reducing the start of the pollen season by gradually decreasing the start day in steps of 5 days or 20 days, ranging from 5 to 30 days earlier (see Table S1 for specific values). The Fig. S2 (g) shows that the maximum improvement in correlation was reached when the season started 15 days (130 ± 10 DOY) earlier in the years 2023–2025, 20 days (125 ± 10 DOY) earlier in 2022, and only 5 days (140 ± 10 DOY) earlier in 2021.

3.3 Adjusted model to regional conditions

After evaluating the different configurations in Sect. 3.1 and 3.2, we combined all the optimal variables. This gave us the best configuration for forecasting both birch and grass pollen at a German regional scale. For birch the results show that, in most of the years it was necessary to increase the temperature sum by 5–20 °C and reduce the pollen emission by 10% compared with the original configuration of SILAM (see Fig. 4 and Table S5). In the case of grasses, the regional season started 5–15 days earlier in all years, and the pollen emission needed to be increased by 2.5–14-folds (see Fig. 5 and Table S5).

The final optimized time series for all the station and seasons are shown in the Fig. S3 (a) birch and (b) grass, where pollen observations from the eleven automatic monitors (blue line) were compared with the initial

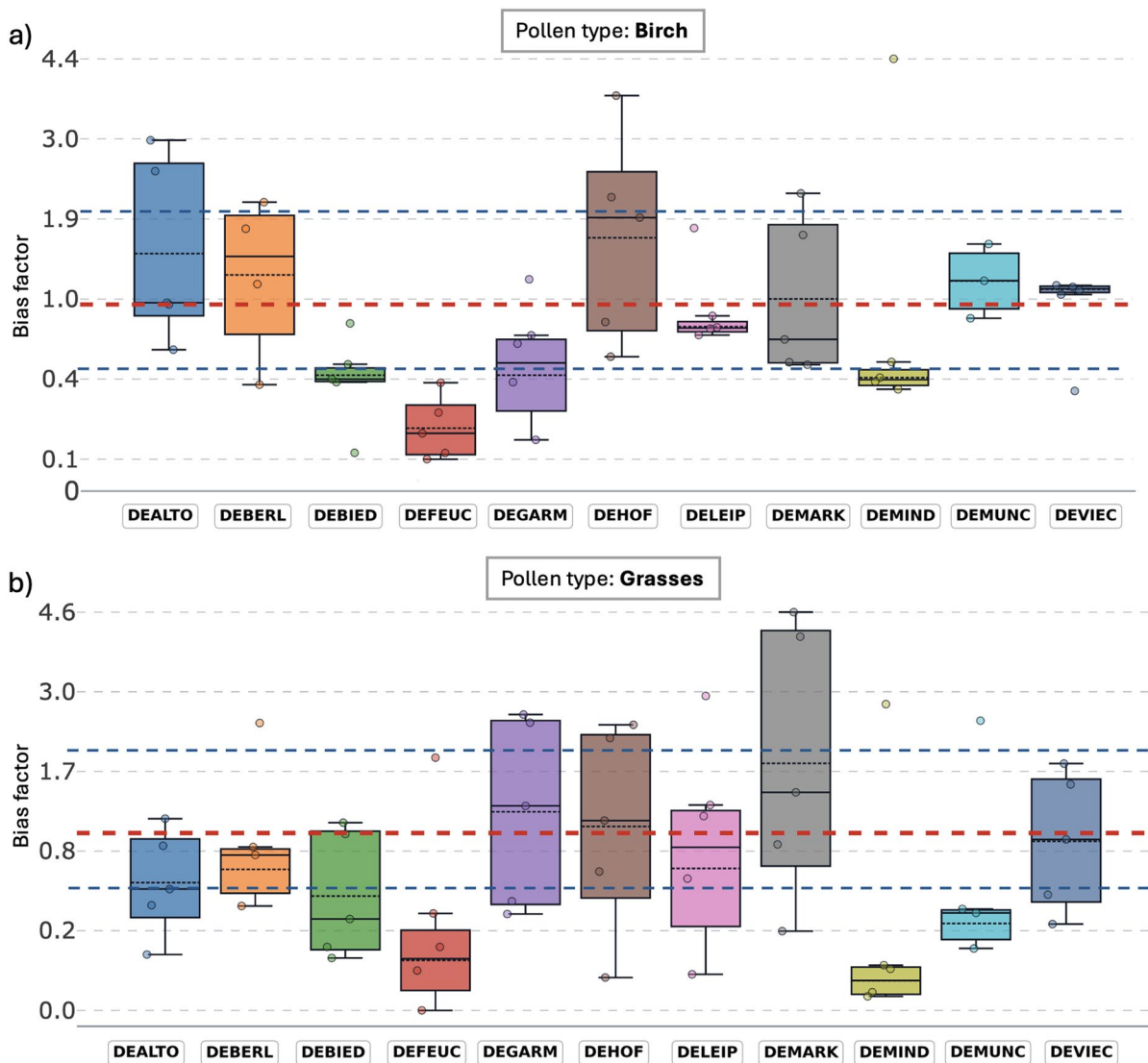


Fig. 6 Systematic over- or underestimation by year and by station for **(a)** birch and **(b)** grasses. The dashed red horizontal line indicates no bias, and the model is correct ($SF=1$, no bias factor), the dashed blue line shows a limit when the model is

2 times lower (underestimating), and 0.5 when the model is 2 times more than the observations (overestimating). The y-axis is shown on a square-root scale to improve the visibility of values close to one

forecast conditions (red line) and the forecast adjusted to regional conditions (green line).

Even after using all optimised parameters, we still observed that the pollen levels were systematically over- or underestimated depending on the stations and year. To verify which stations were still over- or underestimating the pollen emission, a bias factor (BF) was calculated for each station and year. See Fig. 6 (a) birch and (b) grasses. Here the red dashed horizontal line

$BF=1$ means that there is no bias. The blue dashed line $BF=2$ indicates that the model underestimates by factor of two, while $BF=0.5$ indicates that the model overestimating by a factor of two. For birch and grass, around 50% of the stations were over- or underestimated. The name of each station is abbreviated: the first two letters DE, which stand for Deutschland (Germany), plus the first four letters of each city's name.

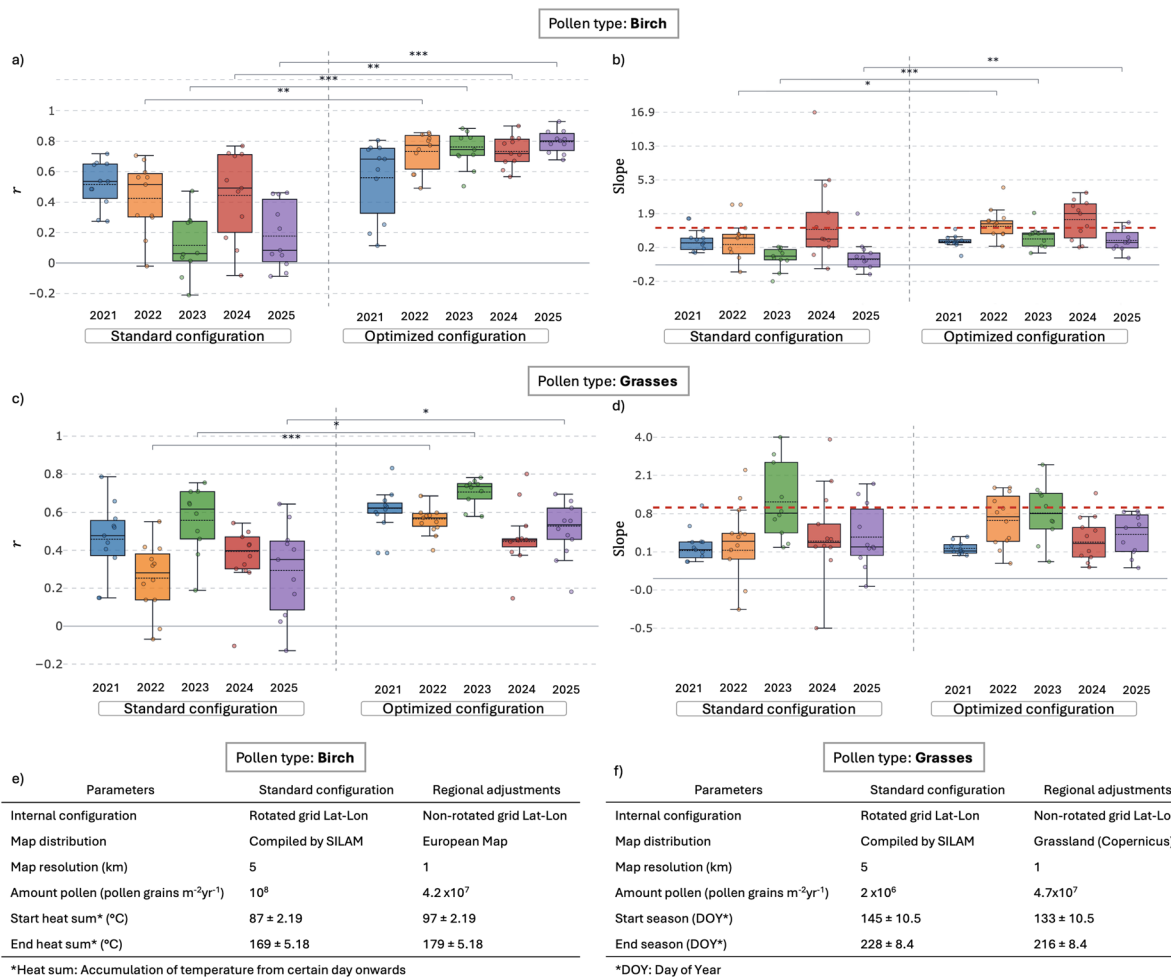


Fig. 7 Comparison of the standard configuration with the configuration adjusted to regional conditions. For birch (**a**) correlation and (**b**) slope. For grasses (**c**) the correlation, (**d**) the slope. The y-axis of the slope is shown on a square-root scale.

Having obtained an optimal configuration for each year (see Fig. S3), we analysed the pattern across all years and all stations. Figure 7 shows a comparison between the standard configuration and the one common optimal configuration for all the years. For birch, Figure 7a shows that the correlation improved significantly for almost all years, except at three stations in 2021. As for the slope Fig. 7b, we were able to adjust the pollen emission predictions to be close to 1. Similar results were obtained for grasses. Fig. 7c shows that the correlation improved in all the years, and Fig. 7d shows that the slope also improved, although not being an exact match with the observations.

The respective significant difference (t-test) is shown at the top of the figures with the respective p -value. The principal parameters are detailed for (**e**) birch and (**f**) grasses

4 Discussions

4.1 Internal configuration

The first parameter we adjusted to go from European to regional scale was the internal configuration, which was changed from a rotated to a non-rotated Latitude–Longitude grid. Although this should not affect the forecast result, Fig. 3 shows that it did influence the predictions for both pollen types. These differences may be attributed to the remapping of the grid, since the geometry of the grid can influence the numerical solutions of atmospheric models

and can shift precipitation (Bailey et al., 2023) and temperature (Rauscher et al., 2010) patterns. Additionally, errors may have been introduced during the transformation of the meteorological grid (Nievinski & Santos, 2007). Consequently, changes in meteorological conditions may affect the pollen forecast as we observed in this case.

Although both pollen type forecasts showed a change in performance, the birch pollen forecast benefitted most compared to the grasses pollen forecast. The birch pollen forecast is highly sensitive to changes in meteorological parameters because its timing is based on accumulated temperature sums (Siljamo et al., 2012; Sofiev et al., 2013). It is therefore possible that the temperature was affected during the grid transformation, which modified the forecast.

4.2 Vegetation maps

The distribution of pollen sources, including their presence and abundance, is considered as ‘crucial’ and a ‘key input’ for pollen forecasting (Kurganskiy et al., 2020; Zhu et al., 2024; Zink et al., 2017). Without these sources maps, the model cannot realistically calculate the pollen emissions or their origin (Katz & Batterman, 2019; Kurganskiy et al., 2020; Zink et al., 2017). Changing the source in other studies has been shown to affect the simulated pollen, demonstrating the model’s high sensitivity to source distribution (Tagliaferro et al., 2024). In this context, different vegetation maps were tested for both, birch and grasses.

The European Atlas of Forest Tree Species showed a better performance for birch (see Fig. 4a). This may be because it is a rigorous, up-to-date map of birch tree abundance (J. San-Miguel-Ayanz et al., 2016). The map was also used in a previous study which compared historical pollen observation from manual traps in Bavaria. That study showed that the abundance of birch trees explained the spatial variability of the annual pollen load quite well (Rojo et al., 2021). The following tests, such as adjusting the phenology were performed using this map.

For grasses, the results (Fig. 5a) shows that the Grasslands map produced the best results for almost all years. In agreement with other studies conducted in Bavaria also demonstrated the impact of Grasslands on pollen concentrations (Jung et al., 2022). For grasses, we demonstrate that a higher

spatial resolution does not improve the forecast results (Fig. 5c), contrary to our expectation and to the findings of other studies (Frisk et al., 2022; McInnes et al., 2017; Tagliaferro et al., 2024). While high resolution preserves many useful details, most models are less capable of predicting them. Therefore, an optimal resolution that balances the costs and benefits of increasing resolution is required (Costanza & Maxwell, 1994). Conversely, using a coarse land cover only can lead to larger errors and the mislocation of peaks, as demonstrated in other studies (Kurganskiy et al., 2020; Tagliaferro et al., 2024; Zhu et al., 2024). Based on these results and the literature, we selected the map with a 1 × 1 km resolution for our area, which was also more efficient in terms of computing time.

4.3 Phenology

4.3.1 Pollen emission

Two parameters were tested: the first was pollen amount emission and the second was the pollen flowering timing for birch and grasses. In the case of pollen emission for birch, the model tended to overestimate (see Fig. 4 d and Table S3), so we reduced emission for each year. There was a tendency of a bi-annual rhythm of pollen production. Similar bi-annual patterns were reported for arboreal species, which are affected by the tree’s physiological balance with previous year environmental conditions (Latorre, 1999; Nilsson & Persson, 1981; Rodríguez-Rajo et al., 2004). We know from longer observation periods using manual pollen traps that this bi-annual rhythm is not stable in the southern Germany (see pollenscience.eu, accessed October 2025). In other words, it cannot be periodically established as a time-series cycle.

In the case of grasses, unlike to birch, the model underestimated the emitted pollen. In this case, each year has its own characteristics: some years required a significant increase in pollen emission (up to 16-fold), while other required only a moderate increase (11-fold) or a small increase (2.5-fold) (see Fig. 5f). This variation in the grasses pollen emission may be due to different factors, such as management practices at each station (Jung et al., 2022).

For birch and grass pollen a bi-annual rhythm in pollen emission released by the trees or grasses in

an area was documented (Smith et al., 2009). This pattern can be observed for birch in our stations between 2021 to 2025 (see Fig. 4d). Unfortunately, we cannot adjust for this, as this rhythm appears to be consistent in Scandinavian countries, but not in Central Europe.

Additionally, a general validation was conducted to evaluate the remaining deviation between the model predictions and the observations. A bias factor was calculated to quantify this, enabling the identification of stations where the model was still systematically over- or underestimating the observed values (see Fig. 6). The bias might be due to unexplained biological variability, not accounted for by the vegetation maps. For instance, when the vegetation changes over time but the new maps are not available yet. The results showed that, even after adjusting the pollen emission specific for each location, 50% of stations were still over- or underestimating. It appears that more factors affect the pollen emission in a single year. This means that the pre-set value for pollen emission to be released in an upcoming year is not sufficiently accurate, and we have to use an average value over the years. We think that enabling SILAM to work with a dynamic pollen emission map (predicting the variability between locations per year) could increase the accuracy of the predictions. For instance, one station is always higher in pollen emission compared to another station (then use a bias factor), but both stations could be higher in pollen emission next year (use a SPIn prediction). However, our proposal would imply changing the source code of the model, which was out of the scope of this paper as we focused on adapting the available SILAM model to local conditions.

4.3.2 Timing flowering

In the case of birch flowering, the prediction was too earlier compared to the observations in most of the years. The results showed that the temperature sum required for the start and end of the flowering season was around +10 to +20 °C higher than that originally set in the standard SILAM configuration (Fig. 4e). This could be because the SILAM model was validated in northern countries, where the trees need to hurry up and a lower temperature sum is required for flowering than in Central Europe (Linkosalo et al.,

2010; Sofiev et al., 2013). The same was reported for other models (Boreczek et al., 2025).

For grasses, the predicted start of the flowering season was too late; it had to be set around 10–15 days earlier (see Fig. 5g). Studies showed that many plants start flowering earlier in spring than in the past, with flowering advancing by 2.5–8.3 days per decade (Menzel et al., 2006; Templ et al., 2017). The SILAM model was developed over ten years ago (Sofiev et al., 2015). While it may have been accurate at the time, due to climate change, it now needs to be adjusted to German conditions. After adjusting the timing for each year, the correlation improved, in agreement with another study in Belgium (Verstraeten et al., 2021).

4.4 Adjusting the model to regional conditions

Once the optimal configuration was established for each year, a single configuration was established for both pollen types (birch and grasses). The SILAM model that was adjusted to regional conditions showed a better correlation for almost all stations and all years compared with the standard SILAM configuration did (Fig. 7a and c). The improvement for birch was between 0.6 and 0.8 on the correlation, meaning that the adjustments made to the model were effective. For grasses the correlation was also improved after adjustment to local conditions, but only around 0.4 and 0.6, which is lower than for birch pollen. This could be due to the management of grasses that affects the pollen collected; frequent cutting or grazing for example could suppress pollen emission (Jung et al., 2022). We are also validating the model against the automatic pollen monitors. It is well known that the location of the pollen monitor affects the results, with lower pollen counts being found in urban areas where high local movements significantly reduces emissions (Jetschni & Jochner-Oette, 2021).

For pollen emission (represented as the slope in Fig. 7b and d), an improvement after local adjustment can be observed, but it is still not as accurate as expected. This may be because we are using an average of pollen emission calculated over several years. While this adjusts the model to regional conditions, the model is still unable to account for these variations between years (i.e. uses a fixed value for all years). To further improve the emission parameter, we need to adjust it before each pollen season, as is done

for birch in some other countries in the north (Ritenberga et al., 2018). However, this published method cannot be directly applied to Central Europe, as the bi-annual rhythm contrary to Scandinavian countries only seldom occurs. This situation is most complex in the case of grasses, as this family comprises annual, biennial and perennial species (Hodkinson, 2018), unlike birch plants, which are strictly perennial and the pollen emission depend on conditions in the previous year (Ritenberga et al., 2018).

5 Conclusions

The numerical pollen forecast model developed for European conditions can be optimized by adapting it to regional conditions. We adapted the SILAM forecast to regional conditions, thereby improving the correlation (r) between measured pollen concentrations and predicted pollen concentrations from eleven monitoring stations in Germany by about 38% for birch (from 0.33 ± 0.05 to 0.71 ± 0.07) and 18% for grass (from 0.39 ± 0.12 to 0.57 ± 0.09).

The most effective parameters used to adapt the forecast to regional conditions were the internal configurations, specifically changing the grid from rotated to non-rotated longitude-latitude (coordinate system), updating the phenological maps, adapting the pollen emission released in a year, and the flowering time based on temperature sum for birch. For grasses, the same parameters were optimized except the temperature sum. In this case a phenological calendar method was optimized.

Although we managed to improve our correlation between observed and predicted values for timing, the absolute numbers of pollen in the air varied between years. A method for predicting the “pollen emission expected for the coming year” would further improve our predictions by adjusting the emission rate parameter of the model. Additionally, applying the 4D-Var data assimilation technique, where actual pollen concentrations are automatically assimilated into the SILAM model, could further improve the forecast. Nevertheless, our adaptations to regional conditions already greatly improved predictions.

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Author Contribution **M.S.S.** Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Software, Validation, Visualization, Writing—original draft. **K.M.** Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Software, Validation, Visualization, Writing—review & editing. **J.R.** Conceptualization, Data curation, Formal analysis, Methodology, Software, Validation, Visualization, Writing—review & editing. **R.K.** Data curation, Formal analysis, Investigation, Methodology, Software, Writing—review & editing. **A.U.** Data curation, Formal analysis, Investigation, Methodology, Software, Writing—review & editing. **A.S.** Data curation, Investigation, Software, Writing—review & editing. **J.P.** Conceptualization, Data curation, Formal analysis, Methodology, Software, Writing—review & editing. **S.D.** Data curation, Writing—review & editing. **J.C.S.** Data curation, Writing—review & editing. **R.G.** Data curation, Investigation, Software, Writing—review & editing. **I.W.** Conceptualization, Investigation, Methodology, Project administration, Supervision, Writing—review & editing. **C.S.W.** Formal analysis, Investigation, Methodology, Project administration, Supervision, Writing—review & editing. **J.B.** Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Resources, Software, Supervision, Validation, Visualization, Writing—review & editing. **M.S.** Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Software, Validation, Visualization, Writing—review & editing.

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Data Availability No datasets were generated or analysed during the current study.

Declarations

Conflict of interest The authors declare no competing interests.

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