Agricultural and Forest Meteorology 355 (2024) 110153

Contents lists available at ScienceDirect

Agricultural and Forest Meteorology

journal homepage: www.elsevier.com/locate/agrformet

The impact of the spatial resolution of vegetation cover on the prediction of airborne pollen concentrations over northern Italy

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ARTICLE INFO

Keywords:
Pollen modelling system
Vegetation cover maps
High spatial resolution
Geographical environment
Dispersion model
Europe

ABSTRACT

Accurate pollen forecasting models can help the self-management of allergic respiratory diseases. Our study introduces and validates, for the first time, a pollen modelling system covering the Veneto Region (Italy) at the 3 km spatial resolution for 2019. The model simulated the pollen dispersion, diffusion and deposition processes, using vegetation cover (VC) maps, phenological pollen emission algorithms, and meteorological forecasting. We have specifically analysed the influence of the spatial resolution of VC maps on predicted airborne pollen concentrations for alder, birch, olive, grass, and ragweed. Two VC datasets were used: CAMS VC: the European CAMS dataset at ca. 10 km horizontal resolution; detailed VC: high-resolution datasets (from 250 m to 1 km spatial resolution). Predicted daily averaged concentrations obtained with CAMS and detailed VC were compared to the observations collected at 15 monitoring stations using model performance indicators and pollen seasonal-derived parameters. A stratified analysis assessed performance variations in lowland versus mountain environments. The results showed a reduction of the root mean square error (RMSE) for alder and birch pollen using the detailed VC (detailed VC vs. CAMS VC: 15.7 vs. 133.6; 17.8 vs. 52.5 p/m^3, respectively), while higher RMSE resulted for grass (24.5 vs. 20.7 p/m^3). Similar RMSEs were obtained for olive and ragweed pollen (3.8 vs. 4.0; 3.9 vs. 3.9 p/m^3, respectively). Results from the differences in Seasonal Pollen Integrals (SPIn) were consistent with the RMSE patterns. The onset of pollen seasons was more accurately predicted than their end. The general improvement of pollen predictions obtained with the detailed VC was particularly evident in the mountains. Incorporating data from detailed vegetation maps into atmospheric dispersion models has significantly improved predictions for arboreal pollen (alder, birch, olive), especially in complex surfaces where high-resolution input data is crucial.

1. Introduction

Pollen-induced allergies affect approximately 20 % of the world's population (D'Amato et al., 2016, 2007). Despite the evidence is still inconsistent, it seems that climate change may contribute to the increasing trend of allergies (Choi et al., 2021; Lake et al., 2017; Wise et al., 2023). Indeed, the presence of pollen in the atmosphere depends on climate, geography, and vegetation (D'Amato et al., 2007). Changes in temperature, precipitation, and CO_2 concentrations, may play a role in increasing pollen load and in anticipating and extending the pollen seasons (Choi et al., 2021; Lake et al., 2017; Vélez-Pereira et al., 2021). The lack of water and the expansion of droughts could shift up plant species towards higher latitudes (Case and Stinson, 2018; Pörtner et al., 2023). Furthermore, cultural exchanges (e.g. plants' importation)

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https://doi.org/10.1016/j.agrformet.2024.110153
Received 30 January 2024; Received in revised form 17 June 2024; Accepted 5 July 2024
Available online 13 July 2024

promote the introduction of alien species causing environmental changes (D'Amato et al., 2007). All these factors progressively expose people to an increased pollen load and novel allergens (D'Amato et al., 2007).

Aerobiological monitoring is necessary to estimate population exposure to pollen, even though it has several limitations. Dense pollen monitoring networks are lacking due to the high costs of manual pollen counting (Picornell et al., 2019; Sofiev et al., 2020). Pollen counts are affected by the visual pollen recognition skills of the operator, which account for 20–30 % of measurement error (Sofiev et al., 2020). Pollen bulletins are issued weekly due to the need of manual counting, making it challenging to provide more frequent updates (Sofiev et al., 2020). As a result, the allergic population is informed on the basis of weekly retrospective pollen concentrations with a poor spatial and temporal accuracy, making exposure prevention unfeasible (Sofiev et al., 2020; Suanno et al., 2021). Recently, more precise automated devices have been developed, although their adoption remains limited for now (Sofiev et al., 2020).

In the last 20 years, the number of studies on pollen modelling have notably increased (Vélez-Pereira et al., 2021). Pollen forecasting models have the potential to provide accurate estimates of pollen concentrations even in areas that are not covered by monitoring networks, as already occurs with chemical air pollution (Picornell et al., 2019; Stafoggia et al., 2019).

Implementing high-resolution models will provide valuable information to vulnerable populations (e.g. patients with asthma or allergies) regarding pollen concentrations and the onset of pollen seasons (Picornell et al., 2019; Sofiev et al., 2020). E-Health (national/international websites) and m-Health (smartphone apps) platforms are being developed to provide pollen forecasts to individuals with pollen allergies, serving as a prevention tool to avoid exposure, manage and treat pollen allergies (Bastl et al., 2017; Suanno et al., 2021). Smartphone apps offering pollen forecasts are most frequently utilised during pollen seasons, highlighting the need for this tool (Bastl et al., 2017). However, a study on nine mobile apps providing pollen information and forecasts highlighted the need for improvement in the quality of pollen forecasts (Bastl et al., 2017).

To model pollen emissions, simple (e.g. statistical regression) to very complex algorithms (phenological) have been used (Picornell et al., 2019; Suanno et al., 2021). Pollen dispersion models simulate the dispersion and long-range transport of pollen in the atmosphere, incorporating data from vegetation cover (VC) maps, pollen emission algorithms, and meteorological forecasting (Suanno et al., 2021; Vélez-Pereira et al., 2022).

The Copernicus Atmosphere Monitoring Service (CAMS) provides four-day operational forecasts over Europe of the EU-WHO regulated pollutants, other air quality pollutants, aerosol tracers, as well as alder, birch, grass, mugwort, olive, and ragweed pollen (https://atmosphere.copernicus.eu/charts/packages/cams_air_quality/products/europe-air-quality-forecast-pollens). This service is based on eleven individual state-of-the-art systems that are used in the operational ensemble. The operational system MINNI (Italian National Integrated Model to support the international negotiation on atmospheric pollution), developed and operated by the Italian National Agency for New Technologies, Energy and Sustainable Economic Development (ENEA), joined the CAMS European air quality ensemble in June 2022 (https://atmosphere.copernicus.eu/cams-european-air-quality-ensemble-forecasts-welcomes-two-new-state-art-models). MINNI is based on the Flexible Air quality Regional Model (FARM) (Bessagnet et al., 2016; Gariazzo et al., 2007; Silibello et al., 2008) that accounts for the transport (advection and turbulent diffusion), chemistry (gas-phase, with flexible mechanism configuration, and aerosol module) and dry/wet removal of atmospheric pollutants. MINNI includes modelling of the allergen pollen species mentioned above. It is based on the phenological emission algorithms of the Finnish Meteorological Institute (FMI), which ranges from heat sum accumulation models for birch and olive to fixed calendar days for grasses (Prank et al., 2013; Siljamo et al., 2013; Sofiev et al., 2013, 2006; Verstraeten et al., 2021).

In the present article, we have developed a modelling system to provide high-resolution pollen predictions over the Veneto Region (northern Italy) in the frame of the MEETOUT project (Mitigation of the Effects of Environmental Triggers on the OUTcomes of chronic respiratory diseases). To check the capability of the proposed modelling system in providing realistic pollen forecasts, we implemented an application for the year 2019 considering two VC maps: the ones used by MINNI at the European scale (available at 0.15° x 0.10° regular grid in latitude and longitude) interpolated on the target grid, and high-resolution VC maps derived from different datasets.

2. Materials and methods

2.1. Veneto Region

The Veneto Region is an administrative area in the northeastern part of Italy and occupies approximately 18,400 km^2. About 15 % of its surface is mountainous (in the northern part), 30 % is pre-alpine and hilly, and the remaining 55 % is plain (ARPAV, 2005). The mountainous complexes (Alpine chains and Dolomites) are populated by mixed coniferous and beech forests, and shrubs. The hilly portion (Veneto Prealps) is covered by birch, hornbeam, chestnut, ash, oak, and beech forests. In the plain area, pine, holm oak, and hornbeam forests alternate with crops and meadows. Towards the Adriatic sea (southeastern part), there are wet lagoon environments characterised by hygrophilous and halophilic plants which are interspersed with crops (ARPAV, 2023).

2.2. Pollen monitoring data and study domain

The POLLnet Italian aerobiological monitoring network currently consists of 57 monitoring stations distributed across 15 regions, measuring daily pollen concentrations (pollen/cubic meter, p/m^3) that are collected into a national open-free database (www.pollnet.isprambiente.it). Fig. 1 presents the study domain, the available POLLnet monitoring stations and the topographical map of Veneto Region (NextGIS, 2019). The study domain is 216 × 225 km^2 wide, including the Veneto Region and portions of the surrounding regions, and has a horizontal spatial resolution of 3 km. The 15 monitoring stations are localised in two main topographic territories: mountain (BL1, BL4, BZ2, BZ4, TN2, UD3) and lowland (FE1, PD2, PN1, RO1, TV1, UD1, VE1, VI1, VR1).

2.3. Pollen modelling system

The pollen modelling system was based on FARM (Bessagnet et al., 2016; Gariazzo et al., 2007; Silibello et al., 2008) (Fig. 2), which computes hourly pollen concentration fields by simulating the processes of emission, advection, turbulent diffusion, and dry/wet removal (as pollens were considered passive scalars).

Inputs to the pollen monitoring system were provided by three modules aimed at: (i) producing meteorological fields and related turbulence parameters (meteorology module); (ii) providing spatial data on pollen emission sources (spatial data module), and (iii) including pollen contributions from the surrounding areas (boundary conditions module).

The meteorological module was based on the Weather Forecast and Research (WRF) prognostic non-hydrostatic model (Skamarock et al., 2008) driven by ERA5 reanalyses (Hersbach et al., 2020) produced by ECMWF and distributed by the Copernicus Climate Change Service (https://cds.climate.copernicus.eu/). The configuration of WRF was based on three computational nested domains covering continental Europe, northern Italy, and the Veneto Region, which were characterised by horizontal resolution meshes of 45, 9, and 3 km, respectively. Thirty-five vertical levels were used, with grid spacing increasing with

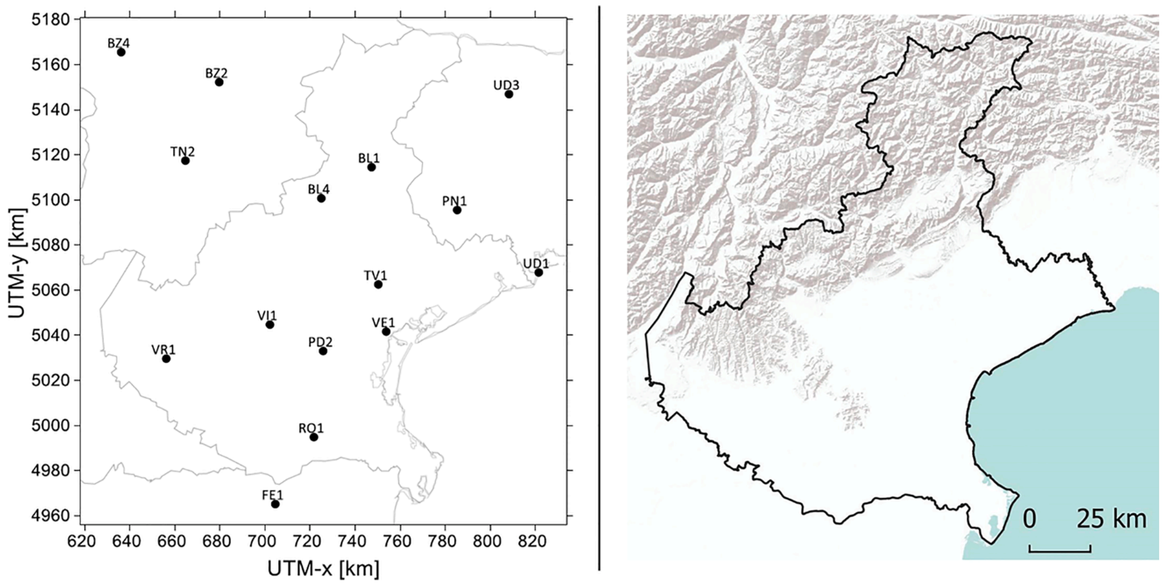

Fig. 1. The study domain with the available POLLnet monitoring stations (left) and the topographical map of Veneto Region (right, Map data: ESRI Terrain).

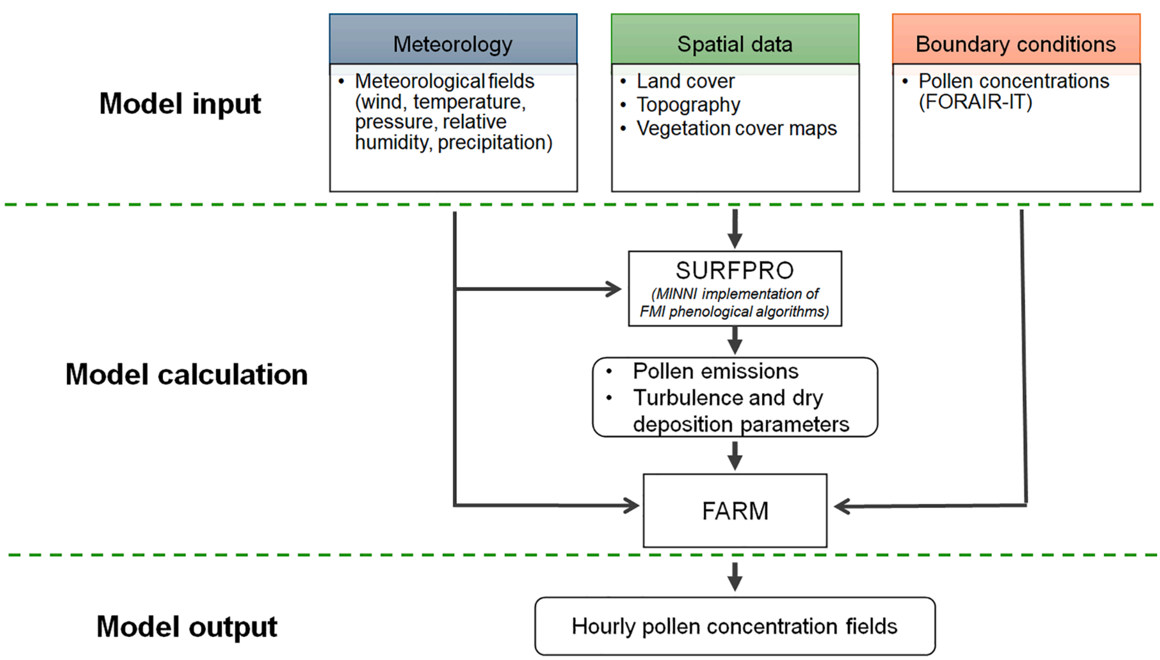

Fig. 2. Scheme of the pollen modelling system. FARM: Flexible Air quality Regional Model; FORAIR-IT: operational air quality forecasting model for Italy; MINNI: Italian National Integrated Model to support the international negotiation on atmospheric pollution; FMI: Finnish Meteorological Institute; SURFPRO: SURface-atmosphere interFace PROcessor.

height, from the surface up to the altitude corresponding to an atmospheric pressure of 50 hPa, with the lowest level located around 25 m over the ground. The calculations were performed in two-way-nesting mode. The WRF meteorological fields together with land cover, topography, and VC maps (spatial data module) were provided to the interface module SURFPRO (SURface-atmosphere interFace PROcessor) (Finardi et al., 2008), which computed deposition velocities, horizontal and vertical diffusivities, and implemented the phenological algorithms adopted by the MINNI modelling system to estimate pollen emissions. The VC maps (details in the next paragraph) were computed as the fraction of vegetation for each grid cell of the modelling domain.

Time-varying pollen boundary conditions to the Veneto Region simulations were provided by the operational forecast system FORAIR-IT, developed by ENEA in 2017, that routinely performs air quality predictions over the Italian peninsula, with a spatial horizontal resolution of 4 km (Adani et al., 2022, 2020). Thanks to the experience gained in CAMS activities, a preliminary version of FORAIR-IT including pollen was applied to the full 2019 year to provide 3-D concentration fields, from which we derived hourly boundary conditions.

2.4. Vegetation cover maps

VC maps were the fundamental input data on pollen emissions. We have considered two vegetation fraction cover datasets:

1. the CAMS VC dataset, available at a horizontal resolution of 0.15° x 0.10° (ca. 10 km);
2. a high-resolution VC dataset (hereafter detailed VC) derived from different sources:
   a. olive and grass: the pan-European CORINE Land Cover (CLC) inventory for 44 thematic classes for the 2012 reference year available at a 250 m spatial resolution (https://land.copernicus.eu/en/products/corine-land-cover);
   b. alder and birch: the European Forest Institute (EFI) dataset on tree species, including the distribution of 20 tree species over Europe at 1 km spatial resolution (https://efi.int/knowledge/maps/treespecies) (Brus et al., 2012);
   c. ragweed: pollen source inventory for Italy available at 1 km spatial resolution (Bonini et al., 2018).

We spatially interpolated both datasets on the target Veneto domain (3 km spatial resolution) (see Fig. S1, Supplementary Material S1). While for olive a single Corine class exists, several classes were available for grasses. Based on a literature review, we considered for the detailed VC the following Corine classes as sources of grass pollen: "Pastures", "Natural grassland", and "Sclerophyllous vegetation" (Hjort et al., 2016; Khwarahm et al., 2017; McInnes et al., 2017; Rojo et al., 2015). In this work, for the detailed VC, we assumed that 66 % of grass-covered areas emit pollen; the choice of this factor is derived from preliminary sensitivity tests performed with the pollen modelling system (other proportions tested were 33 % and 100 %, which resulted in a gross under- and overestimation, respectively). Since no detailed maps were available for mugwort, and the study primarily focused on assessing the impact of different VC datasets on pollen prediction, we did not consider this pollen type in the analysis.

2.5. *Model evaluation*

The statistical analyses were conducted using the R statistical software, version 4.2.2 (RStudio Core Team, 2023). Daily pollen concentrations for 2019 from the 15 POLLnet monitoring stations within the modelling domain (Fig. 1) were downloaded using the R package "pollnet" (https://rpubs.com/gbonafe/pollnet-data-extraction). For each pollen and monitoring station, daily average concentrations predicted from the model fed by CAMS and detailed VC maps were plotted along with observed daily concentrations; differences between predicted and observed daily concentrations averaged over the 15 monitoring stations were plotted to give a summary view. Predicted and observed daily pollen concentrations were then compared using the Spearman's correlation coefficients and the Root Mean Square Error (RMSE) (Suanno et al., 2021). To evaluate model capability in predicting days when pollen concentrations may lead to outbreaks of allergy symptoms, predicted and observed daily pollen concentrations were dichotomised based on the low-concentration class threshold defined by the Italian Society of Aerobiology Medicine and Environment (SIAMA): 0.5 p/m^3 for alder, birch, grass, and olive; 0.1 p/m^3 for ragweed (http://www.pollnet.it/valori_di_riferimento_it.asp). The pollen data distributions did not allow the use of higher thresholds. We calculated model accuracy (MA, the number of correct predictions over the total number of predictions), the probability of detection (POD, the fraction of correct predictions of "events" of threshold exceedance: events/(events + missed events)), and the false alarm ratio (FAR, the fraction of wrong "event" predictions: false alarms/(events + false alarms)) (Mimić et al., 2021; Siljamo et al., 2013; Suanno et al., 2021). For all these indicators, the median values and the 5th and 95th percentiles over the 15 monitoring stations, for each pollen type, are presented (the full results are reported in the Supplementary Material S2).

To further assess model performance, seasonal indexes were calculated for both observed and predicted pollen time series using the R package "AeRobiology" (Rojo et al., 2019). The start and end date of the pollen season were defined at 2.5 % and 97.5 % of the cumulative annual pollen concentration, respectively (Andersen, 1991). The Seasonal Pollen Integral (SPIn, p/m^3) was calculated as the cumulative concentration within the pollen season. The absolute differences between seasonal indexes obtained from predicted and observed daily concentrations were calculated for the 15 monitoring stations and compared graphically using boxplots. For the SPIn, percent relative differences were also calculated as: 100 × (predicted – observed) / observed (%).

To compare model performance between the mountain and lowland areas, all the previously described analyses were repeated separately for monitoring stations located in these two environments (Section 2.2).

3. Results

3.1. *Daily pollen concentrations*

The comparison of predicted and observed temporal series for each pollen and monitoring station is shown in the Supplementary Material S1 (Figs. S2–S6). The difference between predicted and observed daily pollen concentrations (Δp/m^3) averaged over the 15 monitoring stations is shown in Fig. 3.

The use of detailed VC resulted in a substantial improvement in estimations of alder and birch daily pollen concentrations compared with CAMS VC, which overestimated daily concentrations up to 1000 (alder) and 400 (birch) p/m^3. For both detailed and CAMS VC predictions, olive and grass daily concentrations resulted in over- and underestimations, with a slightly better performance for grass when using CAMS VC. Ragweed mean daily predictions were generally underestimated, without difference between the use of different VC maps. The mean RMSEs over the 15 monitoring stations were consistent with this pattern of the results, indicating that the use of detailed VC resulted in notable enhancements in estimating daily pollen concentrations for alder and birch compared to CAMS VC (Fig. 3). An important reduction in the mean RMSE was obtained for alder and birch pollens when using detailed VC (detailed VC vs. CAMS VC: 15.7 vs. 133.6; 17.8 vs. 52.5 p/m^3, respectively). For grass, the mean RMSE resulted higher when using detailed VC (24.5 vs. 20.7 p/m^3). Similar mean RMSEs were obtained for olive (3.8 vs. 4.0 p/m^3) and ragweed pollen (3.9 vs. 3.9 p/m^3).

The Spearman's correlation coefficients and the threshold-based statistics were similar between models using CAMS and detailed VC, with slightly better values using CAMS (Table 1).

The median correlation coefficients ranged from 0.45 (olive) to 0.82–0.84 (grass). Model accuracy was high (between 0.70 and 0.93), as was the probability of detection (between 0.75 and 0.90, except for grass, detailed VC: 0.53), while the false alarm ratio ranged from very low (0.03–0.12 for grass) to high (0.61 for olive).

3.2. *Pollen seasonal indexes*

The maps representing the predicted SPIn spatial distributions over the modelling domain are shown in Fig. 4.

The SPIn predicted using CAMS VC was higher compared with the detailed VC for all pollens, except for grass. In line with the vegetation distribution (Fig. S1), the SPIn for alder and birch was higher in the mountains compared to the lowlands. This difference was more pronounced in the map obtained from CAMS VC. For olive, the hotspots of SPIn aligned with the plant distribution depicted in Fig. S1, with an additional contribution from the Eastern margin of the modelled domain. For grass, the SPIn appeared more produced in the lowland environment, and it was generally higher when using detailed VC. For ragweed, the SPIn showed higher values at the margins of the modelled domain, especially when using the CAMS VC.

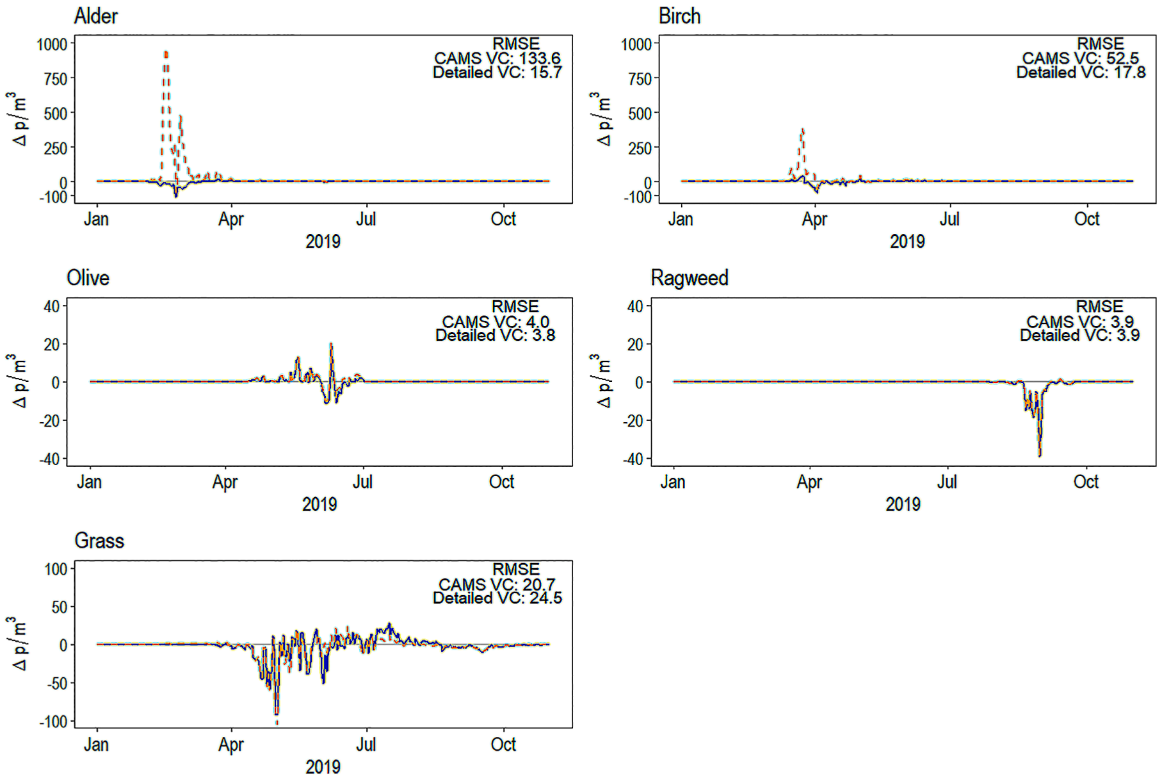

Fig. 3. Difference between predicted (CAMS VC: dashed-orange line; detailed VC: solid blue line) and observed daily pollen concentrations averaged over the 15 monitoring stations. The horizontal grey line at 0 p/m^3 represents the equality between predicted and observed daily concentrations.

Table 1
Median (5th and 95th percentiles) validation metrics for the model fed by CAMS and detailed vegetation cover maps.

Pollen	Simulation	Corr median (5p-95p)	MA median (5p-95p)	POD median (5p-95p)	FAR median (5p-95p)
Alder	CAMS VC	0.65 (0.50–0.69)	0.83 (0.67–0.86)	0.90 (0.62–1.00)	0.45 (0.31–0.73)
	Detailed VC	0.61 (0.45–0.68)	0.84 (0.70–0.88)	0.83 (0.54–0.99)	0.42 (0.28–0.63)
Birch	CAMS VC	0.56 (0.40–0.66)	0.84 (0.76–0.89)	0.79 (0.67–0.98)	0.45 (0.25–0.57)
	Detailed VC	0.55 (0.40–0.62)	0.84 (0.77–0.88)	0.75 (0.64–0.94)	0.44 (0.25–0.57)
Olive	CAMS VC	0.45 (0.23–0.62)	0.88 (0.81–0.93)	0.86 (0.46–1.00)	0.61 (0.41–0.94)
	Detailed VC	0.45 (0.23–0.56)	0.88 (0.81–0.93)	0.82 (0.38–0.96)	0.61 (0.36–0.94)
Ragweed	CAMS VC	0.56 (0.30–0.62)	0.93 (0.87–0.95)	0.77 (0.64–0.87)	0.19 (0.06–0.74)
	Detailed VC	0.56 (0.30–0.62)	0.92 (0.89–0.95)	0.83 (0.57–0.87)	0.22 (0.04–0.74)
Grass	CAMS VC	0.84 (0.79–0.89)	0.84 (0.82–0.91)	0.90 (0.80–0.99)	0.12 (0.03–0.23)
	Detailed VC	0.82 (0.77–0.87)	0.70 (0.56–0.89)	0.53 (0.38–0.90)	0.03 (0.00–0.13)

Corr: Spearman's correlation coefficient; MA: model accuracy; POD: probability of detection; FAR: false alarm ratio.

The distribution of absolute (panel a) and relative (panel b) differences between SPIn from predictions and observations at the 15 monitoring stations is shown in Fig. 5.

The boxplots reflect the spatial distribution of the seasonal pollen load in Fig. 4. Regarding arboreal pollen (alder, birch, olive), the median SPIn value was closer to the observed SPIn when using detailed VC, and the boxes were narrower, suggesting higher prediction accuracy. The use of CAMS VC overestimated the SPIn up to 12,000 % higher values for alder. The SPIn was similarly underestimated for ragweed with both CAMS and detailed VC (almost 100 % lower compared to observed SPIn), although the relative error was lower when using detailed VC. For grass, the SPIn was better estimated using CAMS VC.

Performance in the prediction of the season start date was similar between models using CAMS and detailed VC, except for grass, whose season was markedly shifted toward earlier and later dates using CAMS VC and detailed VC, respectively (left panel of Fig. S7, Supplementary Material S1). The start date of the olive pollen season was strongly shifted towards earlier timing, in both predictions, by a median of 40 days. The estimation of the season end dates was less accurate compared to the estimation of the season start dates (Fig. S7, right panel).

3.3. Geographical-stratified analysis

The difference in model performance appeared magnified according to the geographical area (Fig. 6). Regarding alder and birch pollen, the improved prediction of daily concentrations using detailed VC was particularly evident in the mountain environment compared to the lowlands, consistently with the mean RMSE values (CAMS VC vs. detailed VC in the mountains: 304.9 vs. 11.9 p/m^3, for alder; 93.8 vs. 22.5 p/m^3, for birch). The predictions of olive and ragweed daily concentrations were similar using different VC maps in both environments. The higher performance of daily grass pollen predictions using CAMS VC compared to detailed VC did not depend on the environment.

The distribution of absolute and relative differences between observed and predicted SPIn at the monitoring stations divided by geographical area was shown in the Supplementary Material S1

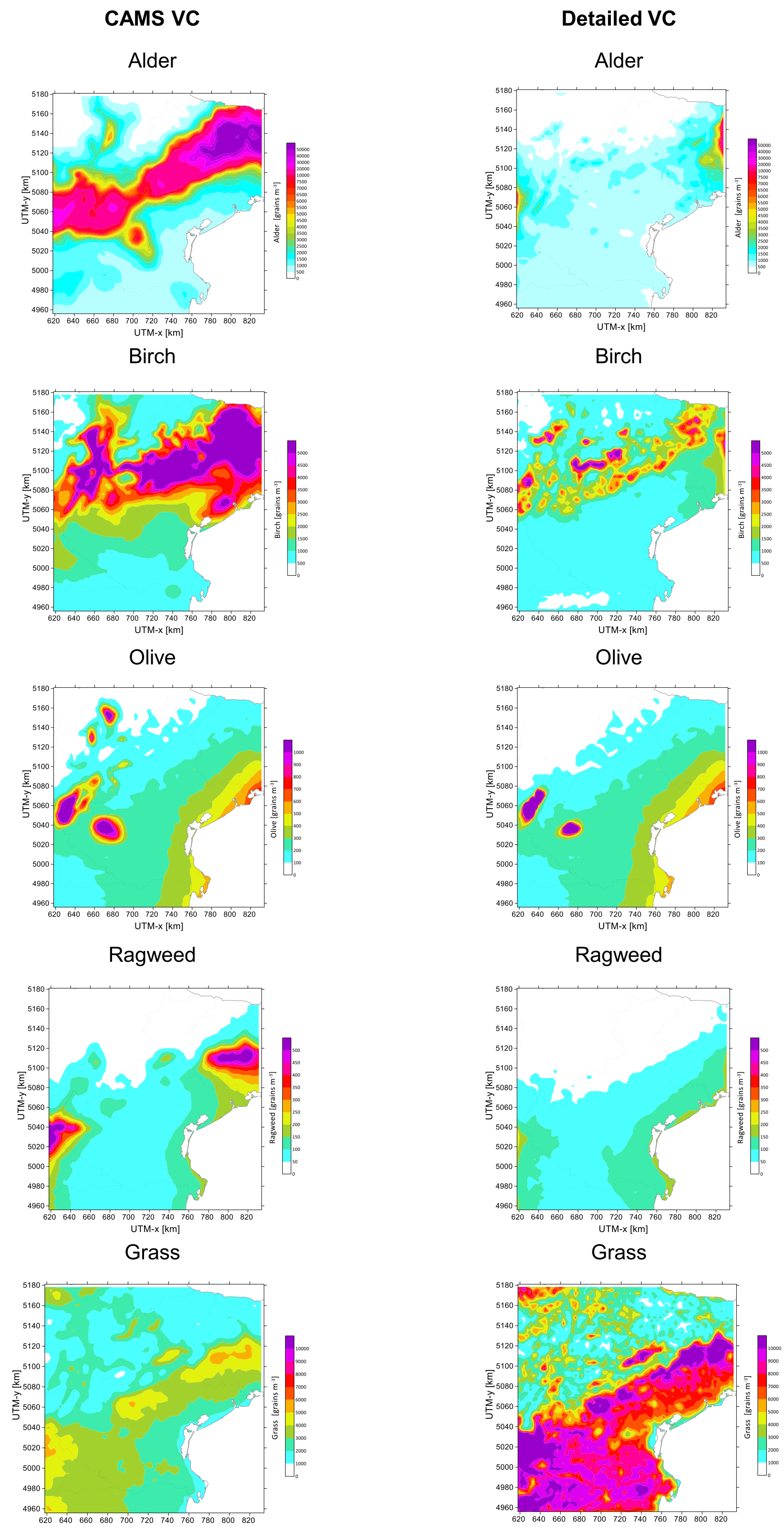

Fig. 4. Seasonal Pollen Integral (SPIn, grains m^{-3}) estimated across the study domain using model fed by CAMS (left) and detailed (right) Vegetation Cover datasets. Each map is obtained for the period calculated from the earlier start to the later end of the observed pollen season across the 15 monitoring stations: alder (26/01/2019 – 08/07/2019), birch (27/02/2019 – 04/06/2019), olive (03/05/2019 – 02/07/2019), ragweed (13/06/2019 – 30/09/2019), grass (30/03/2019 – 05/10/2019).

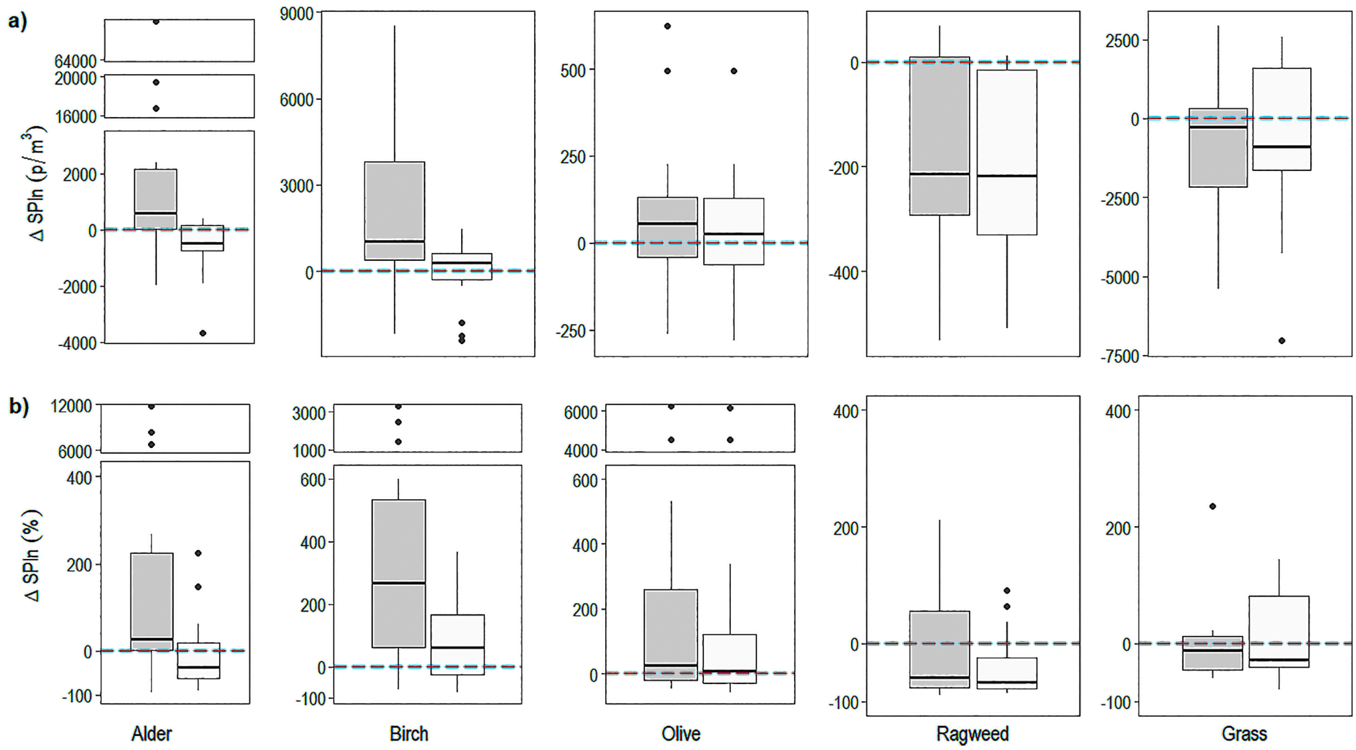

Fig. 5. Distribution of absolute (a) and relative (b) differences between Seasonal Pollen Integrals (ΔSPIn) predicted (CAMS VC: grey box; detailed VC: white box) and observed at the 15 monitoring stations.

(Fig. S8). The results are in line with the previous ones (Fig. 6), pointing out the higher accuracy in the SPIn estimations in lowland environment compared to the mountains (except for ragweed), and better performance for the mountain environment when using the detailed VC (except for grass).

4. Discussion

A modelling system implementing phenological emission algorithms was used to simulate dispersion, diffusion and deposition of allergological pollens over a domain including the Veneto Region in northern Italy. The use of high-resolution VC data turned out in improved predictions of arboreal pollen (alder, birch, olive), especially in mountain environment. More accurate predictions have been obtained in areas where the density of the plants and pollen emissions were higher, usually corresponding to the lowland environment.

Some authors have outlined that the performance of pollen prediction models depends on the study area and the vegetation inventories used (Suanno et al., 2021; Vélez-Pereira et al., 2022). With this respect, we have assessed the sensitivity of pollen predictions to the spatial resolution of VC maps (high versus low resolution). Similar approaches have been used in the literature: integration of pollen data among source maps for pollen dispersion models, alone or in combination with land-use information; use of ecological models combining plant inventories along with habitat suitability; update of source maps with more detailed ones (Kurganskiy et al., 2020; Mimić et al., 2021; Prank et al., 2013; Verstraeten et al., 2021, 2019; Zink et al., 2017).

The detailed VC maps exhibited significant differences compared to the coarser CAMS VC maps, even up to orders of magnitude for alder and ragweed. Since there are no available detailed descriptions of the study area in biogeographic terms, it has not been possible to determine which of the VC maps offered the most accurate representation of the actual distribution of plants. Nevertheless, it is documented in the literature that ragweed is not widely spread in the Veneto Region (Bonini et al., 2018), thus the CAMS distribution map seems to be implausible. In Italy, the colonisation of ragweed started in the Province of Milan, Lombardia Region (a western area outside the study domain) where significant concentrations of ragweed still persist; then, it spread to the Po Valley in northern Italy (including the lowlands in our study domain) (Bonini et al., 2018). Ragweed is uncommon in the mountain environment and is not locally transported due to the barrier effect of the Alpine mountain chain.

Various metrics were considered for the validation of prediction models, in accordance with the literature (Mimić et al., 2021; Prank et al., 2013; Siljamo et al., 2013; Suanno et al., 2021). A good agreement between the metrics employed (graphical methods (boxplots), RMSE, seasonal indexes) was found, except for threshold-based statistics, which showed apparently contradictory results. Threshold-based statistics were probably not appropriate for our data, due to the low density of plants and low pollen concentrations. In fact, we used the phenological algorithms developed for the SILAM model by the Finnish Meteorological Institute, focusing on pollens that are uncommon in our study domain (alder, birch, ragweed, and olive). For this reason, unlike other studies (Mimić et al., 2021; Siljamo et al., 2013), in our analysis there were few days when pollen concentrations exceeded the medium or high concentration thresholds set by the SIAMA. Consequently, it was impossible to evaluate the models' ability to predict medium to high concentrations.

4.1. Arboreal pollen

Using detailed VC, the greater improvement in predictions of daily pollen concentrations and SPIn was obtained for alder and birch, particularly emerging in the complex and heterogeneous territory of the mountains. About olive, the differences between the two predictions were few and only seemed to be expressed in the BZ2 station (Fig. S4 of Supplementary Material S1).

Our findings highlight that the performance of the model using CAMS VC maps was significantly reduced in the orographic areas, probably attributed to the inadequate description of the spatial

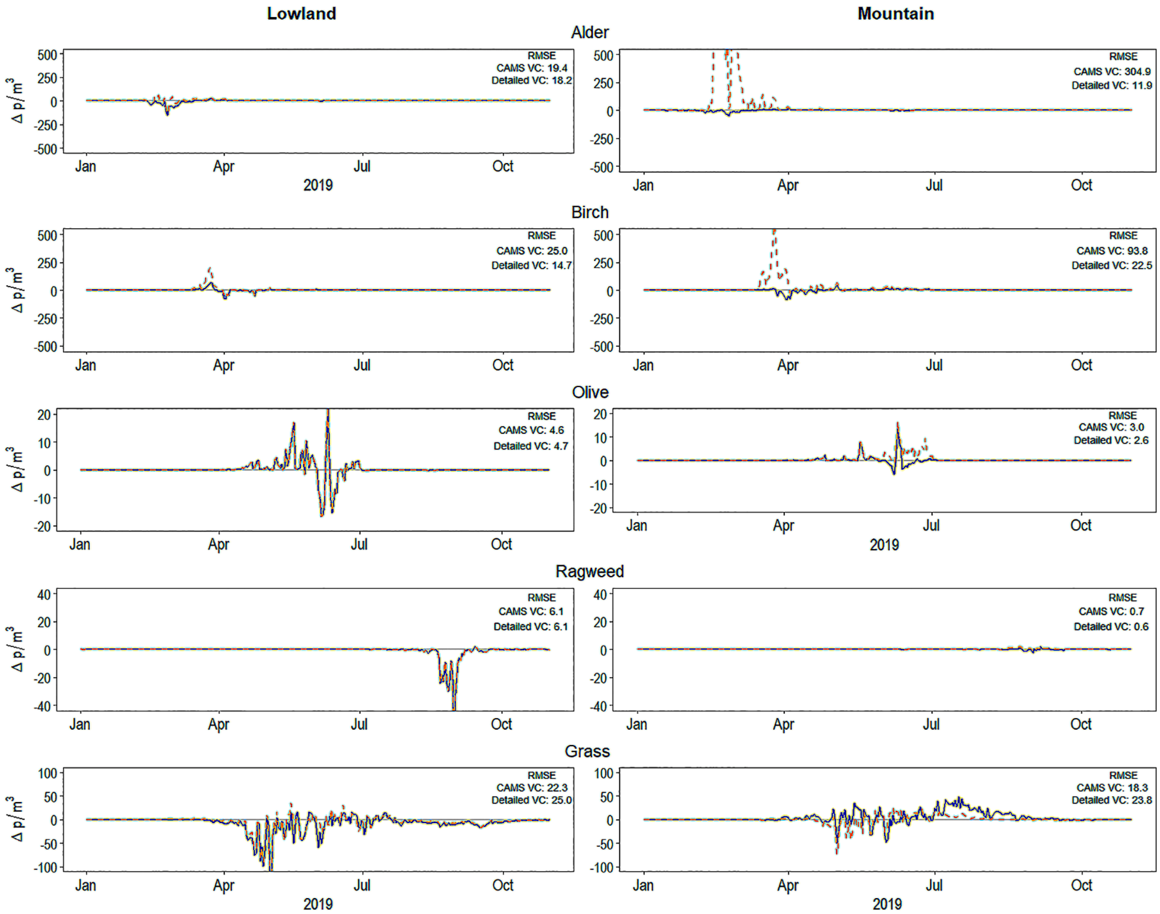

Fig. 6. Difference between predicted (CAMS VC: dashed-orange line; detailed VC: solid blue line) and observed daily pollen concentrations at the monitoring station according to the geographical environment. The horizontal grey line at 0 p/m^3 represents the equality between predicted and observed daily concentrations.

distribution of species in these areas. Indeed, the olive hot-spots in the northwestern part of the domain identified by the CAMS map might be responsible for the slight decreased performance of prediction for this pollen.

The CAMS ensemble models, including MINNI, were originally implemented for large-scale predictions, covering the European domain with a 10 km grid cell size (Sofiev et al., 2017). This resolution is not designed to capture the local pollen distribution, especially in a complex topography, such as valleys and mountains, where the airflow is constrained and the landcover changes over short distances due to the elevation variations (Sofiev et al., 2017, 2013). Our study confirms the potential of the model running at high-spatial resolutions to capture the pollen distribution also in the mountain environment, where the spatial distribution of the emitting species is correctly mapped. Our findings align with Pauling et al. (2020), who demonstrated realistic predictions for birch pollen in the context of the European Alps when incorporating high-resolution datasets in the COSMO-ART model (Pauling et al., 2020).

On the contrary, the start/end dates of alder and birch pollen seasons were better estimated by using CAMS VC. The worse model performance emerged in the prediction of end dates. Nonetheless, for an allergic subject, the correct prediction of the start date of the pollen season is more important than the end (Suanno et al., 2021). From our results, only the start season of olive was not predicted well using both vegetation maps. This error may be due to the phenological emission algorithms, likely not be properly adequate for our region. As reported by Sofiev et al. (2017), the heat-sum formulations, threshold values, and temperature predictions by weather forecasting models result in predicting the start of the olive pollen season too early (Sofiev et al., 2017). In fact, heat-accumulation algorithms for olive are still not well developed and not easily fixable (Aguilera et al., 2014; Sofiev et al., 2017).

4.2. Herbaceous pollen

Our results showed no difference in ragweed pollen predictions between models using CAMS and detailed VC, but important differences in grass pollen predictions. Ragweed daily concentrations and SPIn predictions were generally underestimated, in accordance with Mimić et al. (2021). However, this underestimation primarily affected lowland areas, potentially due to the inability of the model to predict occasional transport events coming from eastern Europe (Pannonian Plain). These phenomena are well-known and are responsible for high concentrations peaks detected by monitoring stations in the Veneto territory (https://www.arpa.veneto.it/temi-ambientali/pollini/articoli-1) (D'Amato et al., 2007; Prank et al., 2013). As depicted in our maps, the spatial distributions of the SPIn for ragweed suggests a likely contribution of pollen transported from the margins of the domain, but the model failed to predict these peaks (Fig. S5 of the Supplementary Material S1). As these transport events do not affect the mountain environment, the SPIn predictions obtained with detailed VC resulted more accurate in this environment, although differences in RMSE were minimal. This discrepancy could be attributed to the incompleteness of the CAMS VC map (unrealistically low and patchy distribution of the plant) and the method of model calibration, which may have introduced a systematic error in the emission model (Prank et al., 2013). Nonetheless, the model was able to predict the main features of the ragweed season in Europe (Mimić et al., 2021; Prank et al., 2013). From our results, the end of ragweed season was reproduced better than the start, consistently with

Prank et al. (2013).

Using detailed VC maps, the predictive performance of grass pollen was consistently lower across all the validation statistics considered (although the difference was small in terms of RMSE): this was amplified in the mountain environment. These findings could be related to the arbitrary selection of the Corine classes, a task further complicated by conflicting opinions on emitting species in the literature (Hjort et al., 2016; Khwarahm et al., 2017; McInnes et al., 2017; Prieto-Baena et al., 2003; Rojo et al., 2022, 2015; Verstraeten et al., 2021). We selected the "Natural grasslands", "Sclerophyllous vegetations", and "Pastures" as potential emitting classes, aligning with studies suggesting higher pollen production in natural areas than in agricultural ones (Hjort et al., 2016; Khwarahm et al., 2017; McInnes et al., 2017; Prieto-Baena et al., 2003; Rojo et al., 2022, 2015; Verstraeten et al., 2021). Predicting grass pollen is inherently challenging due to the variety and quantity of characterising species that shape the larger extension of the pollen season (Verstraeten et al., 2021). This complexity holds significant importance when considering the pollen load. The lack of specific grass emissions maps (Vélez-Pereira et al., 2022) leads to increased error in the predictions. Actually, not all grasses emit pollen and pollen production is variable across species; currently no maps differentiate between emitting and non-emitting species (Verstraeten et al., 2021).

4.3. Strengths and limitations

A strength of this study, compared to existing literature, was the availability of a high number of monitoring stations (15) belonging to a standardised network within a relatively small territory. This enabled the evaluation of model performance even in a complex topography, such as the Alpine mountain chain. For the pollen dispersion model validation in Belgium and Serbian (region of Vojvodina, Pannonian Plain) studies, only five monitoring stations were used (Mimić et al., 2021; Verstraeten et al., 2021, 2019). Kurganskiy et al. (2020) compared predictions with measurements from 12 stations located in Finland, Denmark, and Russia (Kurganskiy et al., 2020). Sofiev et al. (2017) did not validate the European olive model in our study area although they considered the Italian territory; we provided a first validation for olive pollen in this region (Sofiev et al., 2017).

As our study aimed to assess the impact of using more detailed vegetation cover data on estimated pollen concentrations, we restricted the analysis to a single year. We selected the year 2019 due to the potentially smaller impact of the exceptionally high temperatures recorded in 2021 and 2022, and, more importantly, the absence of monitoring data for olive pollen before 2019. As a consequence, we could not assess interannual variability, which is important as evidenced by previous research that has shown considerable changes of the SPIn over time, particularly for some plants like birch (Dąbrowska-Zapart and Niedźwiedź, 2022; Fernández-Llamazares et al., 2014; Spieksma et al., 2003). However, it is essential to note that the phenological algorithms were previously validated over multiannual periods within the context of CAMS (Prank et al., 2013; Sofiev et al., 2017, 2013, 2006). Given that vegetation maps remain static over time, the main parameter affecting variations in pollen seasonality was weather, which was not the focus of the present study.

Another limitation is the lack of pollen emission maps to be used for model input, necessitating the use of VC maps as proxy indicators for emission sources. Moreover, the available VC maps were not homogeneously coded and managed, requiring processing to obtain the reference landcover (Vélez-Pereira et al., 2022).

5. Conclusions

Our findings indicate that incorporating detailed maps into pollen dispersion models can improve prediction accuracy, particularly in complex surfaces where high-resolution input data are crucial. Yet, the success of enhancing local-scale models mainly depends on sufficiently detailed maps describing the spatial distribution of the relevant species, which are still unavailable. Future research efforts will be dedicated to investigating the capability of the pollen modelling system to simulate interannual variability, and to develop new models for pollen taxa that are better representative of the Italian territory (e.g. Corylaceae and Urticaceae). Considering the ongoing changes in pollen patterns due to climate change, a future perspective should also consider the development of new emission algorithms to overcome the limitation of the actual phenological emission models based on fixed seasonal periods. Addressing these challenges can enhance short-term pollen forecasts and improve the quality of life of individuals affected by allergies. In fact, accurate forecasts can help individuals in planning their activities, taking precautions for self-protection, and ensuring timely medication during pollen outbreaks (Suanno et al., 2021). Moreover, accurate forecasts can enable community-based prevention strategies, such as scheduling lawn mowing before the release of grass pollen or organising public activities outside peak-pollen periods (Geller-Bernstein and Portnoy, 2019).

CRediT authorship contribution statement

Sofia Tagliaferro: Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Investigation, Formal analysis, Data curation. **Mario Adani:** Writing – review & editing, Visualization, Software, Resources, Methodology, Investigation, Formal analysis, Data curation. **Nicola Pepe:** Writing – review & editing, Methodology, Data curation. **Gino Briganti:** Writing – review & editing, Resources. **Massimo D'Isidoro:** Writing – review & editing, Software, Resources, Methodology, Investigation, Data curation. **Maira Bonini:** Writing – review & editing. **Antonio Piersanti:** Writing – review & editing. **Sandro Finardi:** Writing – review & editing, Software, Resources, Methodology, Investigation, Data curation. **Pierpaolo Marchetti:** Writing – review & editing, Visualization. **Francesco Domenichini:** Writing – review & editing. **Mihaela Mircea:** Writing – review & editing. **Maria Gabriella Villani:** Writing – review & editing, Resources. **Alessandro Marcon:** Writing – review & editing, Visualization, Supervision, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Conceptualization. **Camillo Silibello:** Writing – review & editing, Writing – original draft, Visualization, Supervision, Software, Resources, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

Alessandro Marcon reports financial support was provided by European Union. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Acknowledgments

A.M. has been awarded grants from the European Union through the Italian Ministry of University and Research to carry out the MEETOUT research project under the ESF REACT-EU Green and Innovation funding programme (Ministerial Decree 1061/2021) and the NextGenerationEu funding programme (Ministerial Decree 737/2021). We thank the ARPAV pollen monitoring team (Drs. Damaris Selle, Morena Nicolis, Barbara Dall'Ara, Stefania Lazzarin) for their information about pollen behaviour and distribution in Veneto Region. Finally, thanks to Dr.

Giovanni Bonafè for making the R package "pollnet" available and Dr. Daniela Barbero for WRF simulations.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.agrformet.2024.110153.

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