Author response to the referee comments to the paper by Sofiev et al:

Multi-model ensemble simulations of olive pollen distribution in Europe in 2014

First of all, we would like to thank both reviewers for their efforts and comments, which helped us improving the paper. Below, we address them one by one (the comments themselves are included in *italic*).

A general remark.

We would like to emphasize that this is the first-ever experiment of numerical modelling of the European-scale olive pollen dispersion. It was stated in the introduction of the original paper and stressed more in the revised paper, starting from the slightly modified title. Therefore, revealing the issues with the models performance and reporting them to the scientific community was one of the goals of the paper. The issues are reported upfront, were discussed already in the initial paper and addressed in more details in the revised manuscript. In particular, we added a new section 5.4, which summarizes the challenges.

Responses to individual comments of the referees

Referee 1, Slawomir Potempsky

The ensemble setup is based on 6 models, 5 of them using the same meteorological data (ECMWF IFS). This means that this ensemble concerns, in principle, dispersion models – meteorological variety is practically disregarded. From statistics point of view such number of the models can be not enough in real application, but can be treated as a first step. It seems that adding models driven by different meteo data could be important in case of building operational system of this type modelling.

We agree that the current ensemble is at the lower edge of reasonable sizes of such ensembles. Within CAMS, work is going on to increase the number of models up to 10. Possibility to expand the ensemble using perturbed-meteorology forecasts certainly deserves consideration. A sentence stressing the same-meteo-same-source limitation was added in section 5.2.1 and the summary.

The authors proposed also an "optimized ensemble" model basing on properly chosen linear combination. This model has shown good skills although the choice of some parameters (like alpha, beta) seems to be rather art than to be based on pure mathematical approach.

We have tested several levels for the regularization strength and the selected values have come out of these tests. The limited size of the datasets and short duration of the season constrained the possibilities for data-driven selection of the regularization strength.

The presented results have shown some capabilities of the constructed ensemble but also indicated problems like the shift of the whole season. This needs further research and is strictly related to meteorological forecast.

We agree, the corresponding sentences are included in section 5.2.1 and newly created sub-section 5.4. Future challenges

1. Paragraph at lines 186-197

This paragraph needs to be revised in order to precisely define the quantities in the formulas (1) and (2) . In the first formula the meaning of t is ambiguous: a_m(t) means coefficients depending on the interval t while c_m(....,t) means concentration at time t. I think it's better to use parameter "tau" for the period (as in the second formula) and t for time point. Thus c_opt should depend on both tau and t and in the second formula A should depend on tau. There are no definitions of a_0 (bias depending on ?) in formula (1) and c_0 (observations I guess) in formula (2). Functional J should be rather a function of time t than the period tau (unless the average over time is considered – but even then the average period time can differ from the period tau used for the analysis).

Corrected

2. Definition of SPI – Seasonal Pollen Index – is this follows the description given at the beginning of section 3.3 ? It would be good to know whether this index is related to exceeding some threshold limit used for allergy risk.

Clarification is added in sections 3.3. What concerns the relation to the allergy-relevant threshold, unfortunately, there is no unified value for it. Extensive discussions have this-far led to conclusion that it is person-specific and chances for generalization are thin. More than that, experience of

HIALINE project showed a large variability of the amount of allergen content in the pollen grains, which creates further problems in automatic projection of the pollen forecasts to allergy. References are added to introduction and section 4.1.

3. Relating to the previous comments what seems important is to show the agreement of the model predictions with the observations basing on the exceedance of threshold limit (as used, for example, in allergy forecast). Fig. 4 shows hourly olive pollen concentration – this picture could be accompanied by the other presenting agreement on threshold level with the observation.

Unfortunately, as it follows from the above, such threshold does not exist. We have calculated parameters, such as odds ratio etc, in previous papers for birch but the thresholds were each time picked as “expert guess” and criticized in follow-up discussions. Therefore, for the current paper, we concentrated on quality of representation of the season propagation.

4. As accumulation heat is one of the crucial parameter the question arises whether it can be somehow taken from observations and data assimilation technique can be applied to include such information into ensemble modelling.

Temperature is among the most-heavily assimilated meteorological parameters, so bringing it here once again looks like a double-counting. The problem definitely exists but may have more dimensions. In the revised paper, we stressed that it is the combination of the heat-sum accumulation procedure, the flowering threshold, and characteristics of meteorological data that comprise the quality of the season forecast.

5. A delicate matter is the calculation of the source term. Thus the question arises whether uncertainty of the source term could be a part of modelling i.e. the whether the models’ simulation could be also performed with perturbations of source term. This, with no doubts, would be time consuming, nevertheless having an ensemble system with such capability would be an added value. This can be one of the possibility of further development of the system.

We agree. The possibility of perturbing also the source term characteristics is now mentioned in the discussion.

Technical remarks

1. Quality of some figures could be improved:

a) On Fig. 3 observation points are not well visible – some example locations could be shown on separate graph – for example the ones with high values.

b) Zooming maps on Figs 5 and 6 can improve quality.

c) parts of Figs 10 and 11 are not well visible.

The figure 3 has been split to two and zooming sub-picture added. The maps were zoomed-in, their color coding improved for better visibility. Figures 10 and 11 are made with high resolution, which allows their zoom at the screen.

Anonymous Referee 3

2. The paper presents an existing concept – the MACC pollen dispersion modelling ensemble published by Sofiev et al (2015). As such the idea and the concept has already been published. The ensemble is applied on a new pollen type.

Not quite. This paper, indeed building on the existing CAMS ensemble principles, also significantly develops them in several directions. First of all, this is the first numerical simulations for olives made at European level. Secondly, we expanded the ensemble technology of CAMS by constructing the first-ever fusion model for pollen forecasts – and demonstrated its superiority over the simpler ensemble techniques. These main steps forwards are highlighted in the revised paper.

The model manuscript use observations, but there is no station list and no accurate numerical or accurate description of observations.

We have created the full list of stations and reported the basic statistical metrics for all models. Due to its size, the table is put into supplementary material.

3. There are substantial conclusions in the manuscript. However these conclusions do not appear to be founded with data presented in the study. One example is the systematic bias in surface temperatures as a cause of model uncertainties. However the manuscript does not contain data (Figures or tables) concerning surface temperatures.

There seems to be a misunderstanding: our conclusions do not have any sentence regarding the temperature bias of the IFS meteo model. The only reverberation on the quality of this parameter refers to section 5.1 (second paragraph) but that one discussed WRF rather than the core meteo data of IFS. We removed that sentence and reformulated the one in the first paragraph to avoid confusion and to stress that the problem originates from the inconsistency between the features of the temperature forecasts and way they are treated by the source term.

Another example is the conclusion that the model calculations represent large scale transport fairly well. However the results do not seem to agree with previous observations of olive pollen in Europe (Sofiev and Bergmann, 2013). This conclusion there needs better support in the manuscript. The maps in figure 3 show that both the ensemble mean and ensemble median calculates a relevant seasonal pollen index in Northern France, UK, Germany, Poland. For individual models this is extended even to Norway. To my knowledge, olive pollen are rarely or have never been reported from those regions. This shows that the ensemble overestimate the large scale atmospheric transport. The authors clearly write that the sources in France, presented in the source map, are unrealistic low. Adding the missing sources in France must be expected to increase the calculated pollen index in nearby regions such as Germany, UK, Poland, Netherlands etc even more. How much is naturally not known. Nevertheless, the arguments described above, disagrees with the conclusion that the ensemble represent large scale transport fairly well by using the available material in the manuscript.

This is indeed a very relevant discussion and the revised paper has more support for the claim. In particular, we expanded the list of stations including Israel (with own olive plantations but remote from major sources in Western Mediterranean). We also refer to Hungarian observations and the corresponding SILAM predictions, albeit made for 2016. Since Hungary has no olive plantations, all pollen there is long-range – and the main episodes were predicted by the model.

Also, one limitation has to be kept in mind: The SPI below several tens of pollen day m^{-3} is generally irrelevant from allergy point of view and is very inaccurately observed. The Hirst trap is unreliable up to concentrations as high as 5-10 pollen m^{-3} – such days should be disregarded (Buters et al., 2015, 2012; Galan et al., 2013). In Central- and Northern-European countries, olive pollens are not counted / reported due to their low contribution to the allergy level, high uncertainty and noticeable costs of inflating the list of reported pollens. Therefore, we could not use their data and the evaluation of the transport events inevitably relied on the same network of stations as for the main season. However, looking at northern Spain, it is seen (just qualitatively) that the decrease of modelled total load is as fast as or even faster than that in the observations. Since the French level is much less than that of Spain, there seems to be no evidence of over-estimation of the transport distance.

4. The scientific methods and assumptions are generally both valid and clearly outlined? However, when they filter the observational record, then they exclude stations with low amounts of pollen. The threshold is 25 pollen day m-3. This is not appropriate. Stations with both high and low numbers should be included in the evaluation of the model simulations.

We respectfully disagree. As stated above, Hirst trap data are very uncertain for low pollen concentrations. The uncertainty of daily (!) values is generally considered to be around 5-10 pollen m^{-3}. Therefore, our current filtering threshold is actually very soft.

5. The results are not sufficient to support the interpretations and conclusions? This is partly caused by the design of figures. As an example, Figure 3 shows simulated (maps) and observed (dots) pollen index. The maps are good for a broad picture, but the accuracy at the sites cannot be assessed with the maps. Ideally this should be combined with a table that demonstrate model results vs observations. Figure 5 shows maps with observed start dates and the corresponding calculations. The chosen color scale makes it almost impossible to see any variations. A difference between 114 and 126 is from on type of green to another, but cover almost 14 days. This means that differences and agreements between observations cannot be assessed to an accuracy of less than 14 days. A table would make this much more clear. Same arguments on accuracy assessments are relevant for Figure 6. This would also have been better in a table. As the manuscript hardly uses the spatial representation of the maps with the dots (Fig 3,5,6), then there is limited argument for showing these comparisons on a map. Using tables instead of figures would therefore improve transparency substantially.

We have added supplementary table repeating the information provided by maps. Also, the color legend was revised to improve the readability of the maps.

The authors claim a strong forecasting skill in the summary. However Figure 7 clearly shows very low correlations (from below 0.1 to less that 0.4) and the RMSE (also figure 7) ranges from about 80 grains/m3 to 120 grains/m3. As far as I know this level is the typical level for severe warnings of *tree pollen. If the typical error is of the same level as the warning level and the correlations generally low, then I do not find sufficient support for the statement concerning a strong forecasting skill.*

This is confusing: we do not claim strong forecasting skill in the summary. To the opposite, the paper states "noticeable deviations from both observations and each other" in the abstract and discusses the season shift in the summary. What concerns "decent level of reproduction of short-term phenomena", this is confirmed by the sensitivity runs: as soon as the season timing is crudely corrected the correlation nearly doubles, thus suggesting that the short-term features of the time series are fine. Therefore, we respectfully disagree with this criticism.

6. The results cannot be reproduced by fellow scientists. The model simulations can be reproduced, but the accuracy assessment cannot be done as there is no description of the observational record.

Description of the observations is provided in the revised paper as a supplementary table

7. The authors give credit to related work but it is my impression that they have not conducted a sufficient literature review, in particular in relation to other modelling approaches that simulates the start and the strength of the pollen season. This puts limitations to the scientific discussion of the work and the assessment of the quality of the model simulations. A quick search on Google identified studies by Orlandi et al (2006) and Rojo et al (2016). These studies in combination with papers written by the co-authors of this manuscript (e.g. Galan et al, 2005) present methods that seem to have similar or higher accuracy than this study with respect to start of the pollen season as well as the spatial modelling of the season index. This indicates that a deeper literature review is needed in order to position the findings in this manuscript against existing knowledge. The authors claim a strong forecasting skill in the summary. However, all of the models (Figure 7), except SILAM, seem to have a larger error with respect to predicting the start of the season than other multi-site methods presented in scientific literature. It can therefore be questioned if there is a strong forecasting skill of the models and the ensemble with respect to the start of the season.

The topic of comparison of regional numerical transport models with local statistical models (even if the latter ones are based on more than one station) is a large topic, which goes way beyond the current exercise. We discussed it in several previous publications, in particular in recent Ritenberga et al (2016), where showed that even for birch (the most-accurately modelled pollen type) the local model outperforms SILAM. This is how it should be: European-scale models cannot be tuned to a single place in principle, they would inevitably miss rest of Europe. In that sense, for instance, better performance in Perugia of the model made in Perugia (Orlandi et al, 2006) is not surprising. Corresponding discussion is added.

The Rojo et al (2016) paper does not concern the season forecasting, only static dependence of SPI and source map. It is certainly an interesting work and we included it now but its findings are not relevant for the time series analysis.

At the same time, in conclusions we highlight the large season shift as the matter of primary importance, which calls for investigation and, possibly, reparameterization of the source term. And, once again, conclusions did not contain the claim of strong forecasting skills of the ensemble.

8. The title clearly reflects the contents of the paper

9. The abstract provides a concise summary of the study. However as described in the previous sections, then there is not sufficient material in the manuscript to support the findings that are presented in the abstract

See responses to items 5, 6 and 7.

10. The overall presentation is well structured and clear.

11. The language is fluent and precise

12. Equation 1 and 2 are defined. However the scaling factors and *are only partly described as their values could not be identified.*

The omissions are corrected. See response to the Referee 1

13. The figures 3,5,6 are almost impossible to read causing that the findings presented in the conclusion and abstract rely on unclear material

The figure quality has been improved and the table material provided as a supplement.

14. There is about 75 references. Most of these are peer reviewed literature. However a substantial amount of the cited literature appear to be written (as lead or co-author) of the authors to this manuscript. The comments under point number 7 and the large number of references indicates that the authors of this manuscript had put too much weight on own publications and to little weight on publications by other authors.

The current work is a synthetic effort of the many groups playing key roles in the olive pollen aerobiology. We did our best to provide adequate representation of other groups, further expanded the literature review and discussion in the revised paper and included the extra references suggested by the referee. However, one of the suggested papers was also co-authored by the authors of this paper, and we have already quoted two works originated from the same group in the initial paper version. Therefore, we reject the blame of the biased literature review.

15. Supplementary material has not been included

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Multi-model ensemble simulations of olive pollen distribution in Europe in 2014: current status and outlook.

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1. Abstract

The paper presents the first modelling experiment of the European-scale olive pollen dispersion, analyses the quality of the predictions and outlines the research needs. A 6-models strong ensemble of Copernicus Atmospheric Monitoring Service (CAMS) was run through the season of 2014 computing the olive pollen distribution. The simulations have been compared with observations in 8 countries, members of the European Aeroallergen Network (EAN). Analysis was performed for individual models, the ensemble mean and median, and for a dynamically optimized combination of the ensemble members obtained via fusion of the model predictions with observations. The models, generally reproducing the olive season of 2014, showed noticeable deviations from both observations and each other. In particular, the season start was reported too early, by 8 days, but for some models the error mounted to almost two weeks. For the season end, the disagreement between the models and the observations varied from a nearly perfect match up to two weeks too late. A series of sensitivity studies performed to understand the origin of the disagreements revealed crucial role of ambient temperature and consistency of its representation by the meteorological models and by the heat-sum-based phenological model. In particular, a simple correction to the heat sum threshold eliminated the season-start shift but its validity in other years remains to be checked. The short-term features of the concentration time series were reproduced better suggesting that the precipitation events and cold/warm spells, as well as the large-scale transport were represented rather well. Ensemble averaging led to more robust results. The best skill scores were obtained with data fusion, which used the previous-days observations to identify the optimal weighting coefficients of the individual model forecasts. Such combinations were tested for the forecasting period up to 4 days and shown to remain nearly optimal throughout the whole period.

Keywords: olive pollen, airborne pollen modelling, pollen forecasting, multi-model ensemble, data fusion, aerobiology

2. Introduction

Biogenic aerosols, such as pollen and spores, constitute a substantial fraction of particulate matter mass in the air during the vegetation flowering season and can have strong health effects causing allergenic rhinitis and asthma (G D'Amato et al., 2007). One of important allergenic trees is olive.

Olive is one of the most extensive crops and its oil is one of the major economic resources in Southern Europe. The bulk of olive habitation (95% of the total area worldwide) is concentrated in the Mediterranean basin (Barranco et al., 2008). Andalusia has by far the world's largest area given

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over to olive plantations, 62% of the total olive land of Spain and 15% of the world's plantations (Gómez et al., 2014).

Olive pollen is also one of the most important causes of respiratory allergies in the Mediterranean basin (G. D'Amato et al., 2007) and in Andalusia it is considered as the main cause of allergy. In Cordoba City (S Spain), 71-73% of pollen-allergy sufferers are sensitive to olive pollen (Sánchez-Mesa et al., 2005), (Cebrino et al., 2017). High rates of sensitization to olive pollen have been documented in Mediterranean countries: 44% in Spain and 20% in Portugal (Pereira et al., 2006), 31.8% in Greece (Gioulekas et al., 2004), 27.5% in Portugal (Loureiro et al., 2005), 24% in Italy (Negrini et al., 1992), 21.6% in Turkey (Kalyoncu et al., 1995), and 15% in France (Spieksma, 1990). At the same time, relations between allergy and pollen concentrations is person- and case-specific: allergen content of the pollen grains varies from year to year and day to day, as well as the individual sensitivity of allergy sufferers (de Weger et al., 2013; Galan et al., 2013)

Olive is an entomophilous species that presents a secondary anemophily, favored by the agricultural management during the last centuries. This tree is very well adapted to the Mediterranean climate and tolerates the high summer and the low winter temperatures, as well as the summer drought, characteristic for this climate.

Olive floral phenology is characterized by bud formation during summer, dormancy during autumn, budburst in late winter, and flowering in late spring (Fernandez-Escobar et al., 1992; Galán et al., 2005; García-mozo et al., 2006). Similar to some other trees, olive flowering intensity shows alternated years with high and low or even no pollen production. The characteristic quasi-biannual cycles are well visible in observations (Ben Dhiab et al., 2016; Garcia-Mozo et al., 2014). This cycle, similar to other trees, e.g., birch, is not strict and is frequently interrupted showing several years with similar flowering intensity (Garcia-Mozo et al., 2014). Such cyclic behavior is related to the reproductive development, which is completed in two consecutive years. In the first year, the bud vegetative or reproductive character is determined by the current harvest level, since this is the main factor responsible for the inter-annual variation of flowering. In the second year, after the winter rest, the potentially reproductive buds that have fulfilled their chilling requirements develop into inflorescences (Barranco et al., 2008).

After the bud break, certain bio-thermic units are required for the development of the inflorescences. Both the onset of the heat accumulation period and the temperature threshold for the amount of positive heat units might vary according to the climate of a determined geographical area. The threshold level was also reported to decrease towards the north (Aguilera et al., 2013). Altitude is the topographical factor most influencing olive local phenology and the major weather

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factors are temperature, rainfall, and solar radiation that control the plant evapotranspiration (Oteros et al., 2013; Oteros et al., 2014).

Several studies used airborne pollen as a predictor variable for determining the potential sources of olive pollen emission, e.g. Concentric Ring Method (J. Oteros et al., 2015; Rojo et al., 2016), geostatistical techniques (Rojo and Pérez-Badia, 2015) and the spatio-temporal airborne pollen maps (Aguilera et al., 2015).

There is a substantial variability of olive biological characteristics and its responses to environmental stresses. In particular, the allergen content was shown to be strongly different in pollen coming from different parts of the Iberian Peninsula (Galan et al., 2013).

Forecasting efforts of the olive pollen season were mainly concentrated on statistical models predicting the season start and peak using various meteorological predictors. The bulk of studies is based on information from one or a few stations within a limited region (e.g., Orlandi et al., (2006), Moriondo et al., (2001), Alba and Diaz De La Guardia, (1998), Frenguelli et al., (1989), Galán et al., (2005), Fornaciari et al., (1998), etc.). Several wider-area studies were also performed aiming at more general statistical characteristics of the season, e.g. (Aguilera et al., 2014, 2013; Galan et al., 2016).

Numerical modelling of olive pollen transport is very limited. In fact, the only regional-scale computations regularly performed since 2008 were made by the SILAM model (http://silam.fmi.fi) but the methodology was only scarcely outlined in (Galan et al., 2013).

Copernicus Atmospheric Monitoring Service CAMS (http://atmosphere.copernicus.eu) is one of the services of the EU Copernicus program, addressing various global and regional aspects of atmospheric state and composition. CAMS European air quality ensemble (Marécal et al., 2015) provides high-resolution forecasts and reanalysis of the atmospheric composition over Europe. Olive pollen is one of the components, which are being introduced in the CAMS European ensemble in co-operation with European Aeroallergen Network EAN (https://www.polleninfo.org/country-choose.html).

One of possible ways of improving the quality of model predictions without direct application of data assimilation is to combine them with observations via ensemble-based data fusion methods (Potempski and Galmarini, 2009). Their efficiency has been demonstrated for air quality problems (Johansson et al., 2015 and references therein) and climatological models (Genikhovich et al., 2010) but the technology has never been applied to pollen.

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The aim of the current publication is to present the first Europe-wide ensemble-based evaluation of the olive pollen dispersion during the season of 2014. The study followed the approach of the multi-model simulations for birch (Sofiev et al., 2015) with several amendments reflecting the peculiarity of olive pollen distribution in Europe. We also made further steps towards fusion of model predictions and observations and demonstrate its value in the forecasting regime.

The next section will present the participating models and setup of the simulations, the observation data used for evaluation of the model predictions, approach for constructing an optimised multi-model ensemble, and a list of sensitivity computations. The Results section will present the outcome of the simulations and the quality scores of the individual models and the ensemble. The Discussion section will be dedicated to analysis of the results, considerations of the efficiency of the multi-model ensemble for olive pollen, and identification of the development needs.

3. Materials and methods

This section presents the regional models used in the study, outlines the olive pollen source term implemented in all of them, and pollen observations used for evaluation of the model predictions.

3.1. Dispersion models

The dispersion models used in the study comprise the CAMS European ensemble, which is described in details by Marécal et al., (2015) and (Sofiev et al., 2015). Below, only the model features relevant for the olive pollen atmospheric transport calculations are described.

The ensemble consisted of six models.

EMEP model of EMEP/MSC-West (European Monitoring and Evaluation Programme / Meteorological Synthesizing Centre - West) is a chemical transport model developed at the Norwegian Meteorological Institute and described in Simpson et al., (2012). It is flexible with respect to the choice of projection and grid resolution. Dry deposition is handled in the lowest model layer. A resistance analogy formulation is used to describe dry deposition of gases, whereas for aerosols the mass-conservative equation is adopted from Venkatram, (1978) with the dry deposition velocities dependent on the land use type. Wet scavenging is dependent on precipitation intensity and is treated differently within and below cloud. The below-cloud scavenging rates for particles are based on Scott, (1979). The rates are size-dependent, growing for larger particles.

EURAD-IM (http://www.eurad.uni-koeln.de) is an Eulerian meso-scale chemistry transport model involving advection, diffusion, chemical transformation, wet and dry deposition and sedimentation of tropospheric trace gases and aerosols (Hass et al., 1995; Memmesheimer et al., 2004). It includes 3D-VAR and 4D-VAR chemical data assimilation (Elbern et al., 2007) and is able to run in nesting mode. The positive definite advection scheme of Bott (1989) is used to solve the advective transport and the aerosol sedimentation. An eddy diffusion approach is applied to parameterize the vertical sub-grid-scale turbulent transport (Holtslag and Nieuwstadt, 1986). Dry deposition of aerosol species is treated size-dependent using the resistance model of Petroff and Zhang (2010). Wet deposition of pollen is parameterized according to Baklanov and Sorensen (2001).

LOTOS-EUROS (http://www.lotos-euros.nl/) is an Eulerian chemical transport model (Schaap et al., 2008). The advection scheme follows Walcek and Aleksic (1998). The dry deposition scheme of Zhang et al. (2001) is used to describe the surface uptake of aerosols. Below-cloud scavenging is described using simple scavenging coefficients for particles (Simpson et al., 2003).

MATCH (http://www.smhi.se/en/research/research-departments/air-quality/match-transport-and-chemistry-model-1.6831) is an Eulerian multi-scale chemical transport model with mass-conservative transport and diffusion based on a Bott-type advection scheme (Langner et al., 1998; Robertson and Langner, 1999). For olive pollen, dry deposition is mainly treated by sedimentation and a simplified wet scavenging scheme is applied. The temperature sum, which drives pollen emission, is computed off-line starting from January onwards and is fed into the emission module.

MOCAGE (http://www.cnrm.meteo.fr/gmgec-old/site_engl/mocage/mocage_en.html) is a multi-scale dispersion model with grid-nesting capability (Josse et al., 2004; Martet et al., 2009). The semi-Lagrangian advection scheme of Williamson and Rasch (1989) is used for the grid-scale transport. The convective transport is based on the parameterization proposed by Bechtold et al. (2001) whereas the turbulent diffusion follows the parameterization of Louis (1979). Dry deposition including the sedimentation scheme follows Seinfeld and Pandis (1998). The wet deposition by the convective and stratiform precipitations is based on Giorgi and Chameides (1986).

SILAM (http://silam.fmi.fi) is a meso-to-global scale dispersion model (Sofiev et al., 2015), also described in the review of Kukkonen et al. (2012). Its dry deposition scheme (Kouznetsov and Sofiev, 2012) is applicable for a wide range of particle sizes including coarse aerosols, which are primarily removed by sedimentation. The wet deposition parameterization distinguishes between sub- and in-cloud scavenging by both rain and snow (Sofiev et al., 2006). For coarse particles, impaction scavenging parameterised following (Kouznetsov and Sofiev, 2012) is dominant below the cloud. The model includes emission modules for six pollen types: birch, olive, grass, ragweed, mugwort, and alder, albeit only birch, ragweed, and grass sources are so-far described in the literature (Prank et al., 2013; Sofiev, 2016; Sofiev et al., 2012).

Three **ENSEMBLE** models were generated by (i) arithmetic average, (ii) median and (iii) optimal combination of the 6 model fields. Averaging and median were taken on hourly basis, whereas optimization was applied at daily level following the temporal resolution of the observational data. For the current work, we used simple linear combination c_{opt} of the models c_m, $m=1..M$ minimising the regularised RMSE J of the optimal field:

(1) $$c_{opt}(i,j,k,t,\tau,A) = a_0(\tau) + \sum_{m=1}^{M} a_m(\tau) c_m(i,j,k,t), \quad A=[a_1..a_M], \quad a_m \geq 0 \ \forall m$$

(2) $$J(t,\tau) = sqrt\left[\frac{1}{O}\sum_{o=1}^{O}\left(c_{opt}(i_o,j_o,k_o,t,\tau,A) - c_o(t)\right)^2\right] + \alpha\sum_{m=1}^{M}\left(a_m(\tau) - \frac{1}{M}\right)^2 + \beta\sum_{m=1}^{M}\left(a_m(\tau-1) - a_m(\tau)\right)^2, \qquad \tau=\{d_{-k}, d_0\}$$

Here, i,j,k,t are indices along the x,y,z, and time axes, M is the number of models in the ensemble, O is the number of observation stations, $\tau=\{d_{-k}:d_0\}$ is the time period of $k+1$ days covered by the analysis window, starting from d_{-k} until d_0, $\tau-1$ is the previous-day analysis period $\tau-1=\{d_{-k-1}:d_{-1}\}$, c_m is concentration of pollen predicted by the model m, c_o is observed pollen concentration, a_m is time-dependent weight coefficient of the model m in the ensemble, a_0 is time-dependent bias correction. In the Eq. (2), the first term represents the RMSE of the assimilated period τ, the second term limits the departure of the coefficients from the homogeneous weight distribution, the third one limits the speed of evolution of the a_m coefficients in time. The scaling values α and β decide on the strength of regularization imposed by these two terms.

The ensemble was constructed mimicking the forecasting mode. Firstly, the analysis is made using data from the analysis period τ. The obtained weighting coefficients a_i are used over several days forwards from day d_0: from d_1 until d_{nf}, which constitute the forecasting steps. The performance of the ensemble is evaluated for each length of the forecast, from 1 to n_f days.

3.2. Olive pollen source term

All models of this study are equipped with the same olive pollen source term, which has not been described in the scientific literature yet. However, it follows the same concept as the birch source (Sofiev et al., 2012) that was used for the birch ensemble simulations (Sofiev et al., 2015). The formulations and input data are open at http://silam.fmi.fi/MACC. The main input dataset is the annual olive pollen production map based on ECOCLIMAP dataset (Champeaux et al., 2005; Masson et al., 2003), Figure 1.

ECOCLIMAP incorporates the CORINE land-cover data for most of western-European countries with explicit olive-plantations land-use type (CEC, 1993). For Africa and countries missing from CORINE, the empty areas were filled manually assuming that 10% of all tree-like land-use types are olives. This way, Tunisian, Egyptian, and Algerian olive plantations were recovered and included in the inventory. In some areas, such as France (Figure 1), the olive habitat looks unrealistically low, probably because the large olive plantations are rare but the trees are planted in private gardens, city park areas, streets, etc. Since these distributed sources are not reflected in the existing land-use inventories, they are not included in the current pollen production map.

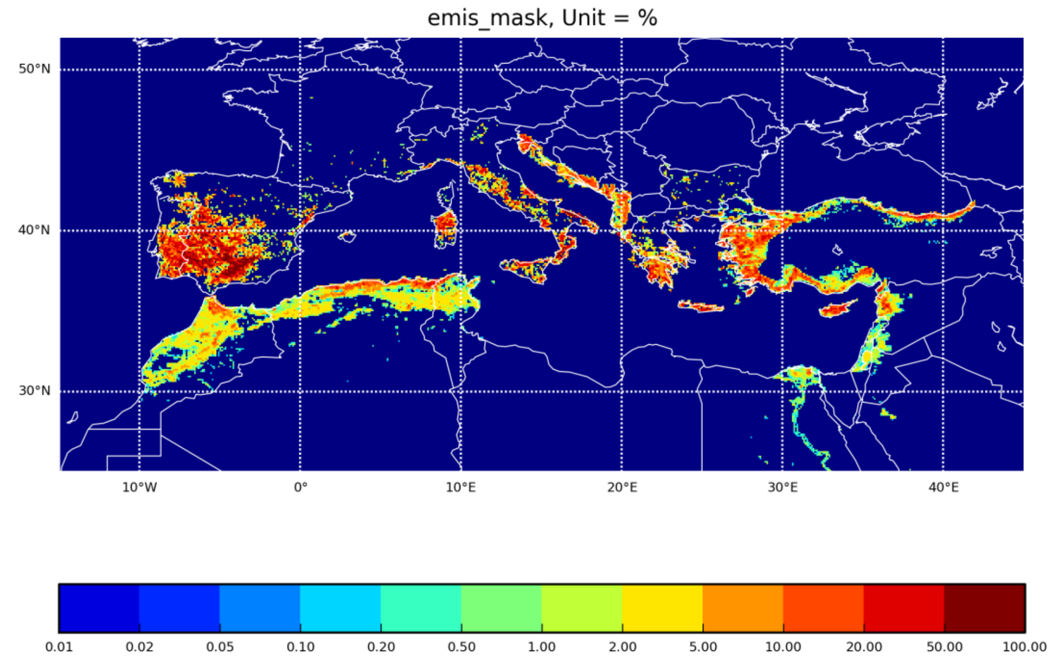

Figure 1. Olive pollen habitat map, percentage of the area occupied by the trees, [%]. Productivity of an area with 100% olive coverage is assumed to be 10^{10} pollen grain m^{-2} $season^{-1}$.

Similar to birch, the flowering description follows the concept of Thermal Time phenological models and, in particular, the double-threshold air temperature sum approach of Linkosalo et al.

(2010) modified by Sofiev et al. (2012). Within that approach, the heat accumulation starts on a prescribed day in spring (1 January in the current setup – after Spano et al. (1999), Moriondo et al. (2001), Orlandi et al. (2005a, 2005b) and continues throughout spring. The cut-off daily temperature below which no summation occurs is 0°C, as compares to 3.5°C for birch, was obtained from the multi-annual fitting of the season start. Flowering starts when the accumulated heat reaches the starting threshold (Figure 2) and continues until the heat reaches the ending threshold (in the current setup, equal to the start-season threshold + 275 degree day). The rate of heat accumulation is the main controlling parameter for pollen emission: the model assumes direct proportionality between the flowering stage and fraction of the heat sum accumulated to-date.

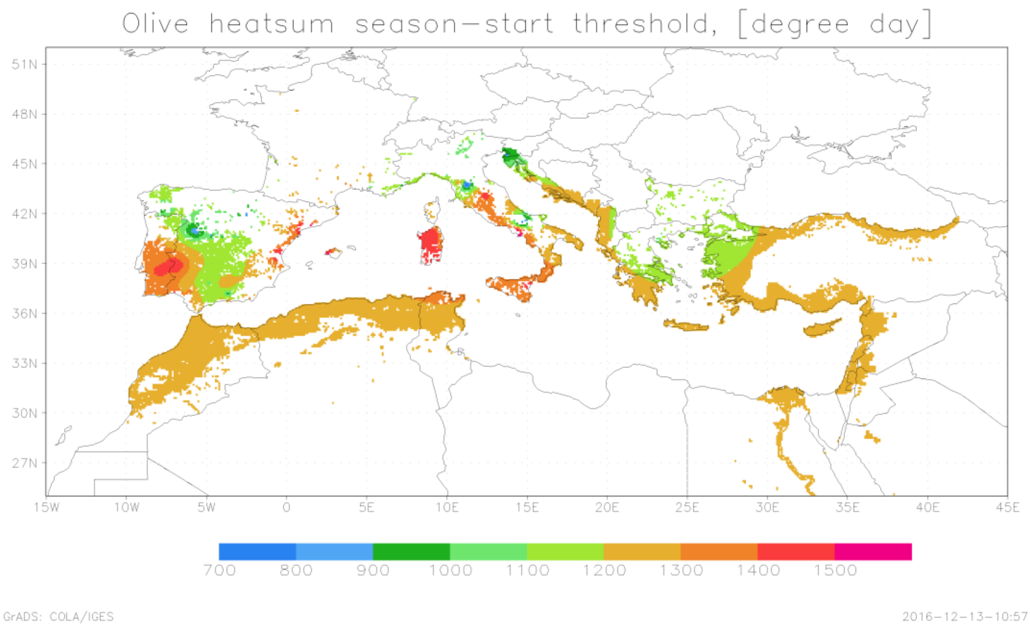

Figure 2. Heat sum threshold for the start of the season. Unit = [degree day]

Similar to birch parameterization of Sofiev et al. (2012), the model distinguishes between the pollen maturation, which is solely controlled by the heat accumulation described above, and pollen release, which depends on other parameters. Higher relative humidity (RH) and rain reduce the release, completely stopping it for RH > 80% and/or rain > 0.1 mm hr^{-1}. Strong wind promotes it by up to 50%. Atmospheric turbulence is taken into account via the turbulent velocity scale and thus becomes important only in cases close to free convection. In stable or neutral stratification and calm conditions the release is suppressed by 50%. The interplay between the pollen maturation and release is controlled by an intermediate ready-pollen buffer, which is filled-in by the maturation and emptied by the release flows.

Local-scale variability of flowering requires probabilistic description of its propagation (Siljamo et al., 2008). In the simplest form, the probability of an individual tree entering the flowering stage can be considered via the uncertainty of the temperature sum threshold determining the start of flowering for the grid cell – 10% in the current simulations. The end of the season is described via the open-pocket principle: the flowering continues until the initially available amount of pollen is completely released. The uncertainty of this number is taken to be 10% as well.

3.3. Pollen observations

The observations for the model evaluation in 2014 have been provided by the following 6 national networks, members of the European Aeroallergen Network (EAN): Croatia, Greece, France, Hungary, Israel, Italy, Spain, and Turkey. The data were screened for completeness and existence of non-negligible olive season: (i) time series should have at least 30 valid observations, (ii) at least 10 daily values during the season should exceed 3 pollen m^{-3}, and (iii) the seasonal pollen index (SPI, an integral of the concentrations over the whole season) should be at least 25 pollen day m^{-3}. After this screening, information of 62 sites was used in the intercomparison. Data from Hungary referred to 2016 and required dedicated computations for evaluating the long-range transport events.

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Pollen monitoring was performed with Burkard 7-day and Lanzoni 2000 pollen traps based on the Hirst design (Hirst, 1952). The pollen grains were collected at an airflow rate of 10 l min^{-1}. The observations covered the period from March until September, with some variations between the countries. Daily pollen concentrations were used. Following the EAS-EAN requirements (Galán et al., 2014; Jäger et al., 1995), most samplers were located at heights of between 10m and 30m on the roofs of suitable buildings. The places were frequently downtown of the cities, i.e. largely represent the urban-background conditions (not always though). With regard to microscopic analysis, the EAS-EAN requirement is to count at least 10% of the sample using horizontal or vertical strips (Galán et al., 2014). The actual procedures vary between the countries but generally comply. The counting in 2014 was mainly performed along four horizontal traverses as suggested by Mandrioli et al., (1998). In all cases, the data were expressed as mean daily concentrations (pollen m^{-3}).

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3.4. Setup of the simulations

Simulations followed the standards of CAMS European ensemble (Marécal et al., 2015). The domain spanned from 25°W to 45°E and from 30°N to 70°N. Each of the 6 models was run with its own horizontal and vertical resolutions, which varied from 0.1° to 0.25° of the horizontal grid cell size, and had from 3 up to 52 vertical layers within the troposphere (Table 1). This range of resolutions is not designed to reproduce local aspects of pollen distribution, instead covering the whole continent and describing the large-scale transport. The 10km grid cells reach the sub-city scale but still insufficient to resolve the valleys and individual mountain ridges. The limited number of vertical dispersion layers used by some models is a compromise allowing for high horizontal resolution. Thick layers are not a major limitation as long as the full vertical resolution of the input meteorological data is used for evaluation of dispersion parameters (Sofiev, 2002).

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The simulations were made retrospectively for the season of 2014 starting from 1 January (the beginning of the heat sum accumulation) until 30 June when the pollen season was over. All models produced hourly output maps with concentrations at 8 vertical levels (near surface, 50, 250, 500, 1000, 2000, 3000 and 5000 metres above the surface), as well as dry and wet deposition maps.

All models considered pollen as an inert water-insoluble particle 28 μm in diameter and with a density of 800 kg m^{-3}.

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Table 1. Setup of the simulations for the participating models

Model	Horizontal dispersion grid	Dispersion vertical	Meteo input	Meteo grid	Meteo vertical
EMEP	0.25° × 0.125°	20 levels up to 100 hPa	ECMWF IFS 00 operational forecast, internal preprocessor	0.25° × 0.125°	IFS lvs 39 – 91 up to 100 hPa
EURAD-IM	15 km, Lambert conformal proj.	23 layers up to 100 hPa	WRF based on ECMWF IFS	Same as CTM	Same as CTM
LOTOS-EUROS	0.25° × 0.125°	3 dyn. lyrs up to 3.5km, sfc 25m	ECMWF IFS 00 operational forecast, internal preprocessor	0.5° × 0.25°	IFS lvs 69-91 up to 3.5km
MATCH	0.2° × 0.2°	52 layers up to 7 km	ECMWF IFS 00 from MARS, internal preprocessor	0.2° × 0.2°	IFS vertical: 91 lvs
MOCAGE	0.2° x 0.2°	47 layers up to 5hPa (7 in ABL)	ECMWF IFS 00 operational forecast, internal preprocessor	0.125° × 0.125°	IFS vertical 91 lvs
SILAM	0.1° × 0.1°	9 layers up to 7.5 km	ECMWF IFS 00 operational forecast, internal preprocessor	0.125° × 0.125°	IFS lvs 62-137 up to ~110hPa

4. Results for the pollen season of 2014

4.1. Observed peculiarities of the season

At French Mediterranean stations (Aix-en-Provence, Avignon, Montpellier, Nice, Nîmes and Toulon), the mean value of the Seasonal Pollen Index (SPI) in 2014 was quite similar to that of 2012 but lower than in 2013 (see (de Weger et al., 2013) for the SPI relevance to allergy).

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The start of the pollen season was earlier than in the previous five years. The duration of the season has been the longest one on Aix-en-Provence, Nice and Nîmes since 2010. On Ajaccio (Corsica) station, the SPI was higher in 2014 than at other stations, similar to the situation in 2012.

In Andalusia, 2014 was the second warmest year during the last decades but more humid than usual, 5% above the typical relative humidity level (https://www.ncdc.noaa.gov/sotc/global/201413). However, after an intense olive flowering in 2013, in 2014 the flowering intensity was lower and similar to 2012, in agreement with the bi-annual alterations of the season severity.

In Northern Italy, the 2014 olive pollen season was less intense than the average of the previous ten years (2004-2013). Instead, in Southern Italy, the 2014 season was more intense in the first part and less intense in the second part (after the beginning of June) than during previous seasons. No differences were noted with respect to the start and the end of the season in both cases.

In Thessaloniki, Greece, in 2014, the pollen season started in the same time as during the last decades (first half of April), but ended about 1.5 month later (last half of October). The pollen season peak has been steadily in May. The SPI was considerably higher in 2014 (418 pollen day m^{-3}), compared against the previous two years (approximately 300 pollen day m^{-3}). The overall shape of the pollen season in 2014 resembled the ones during the last decade, however, with a multi-modal and less peaky pattern.

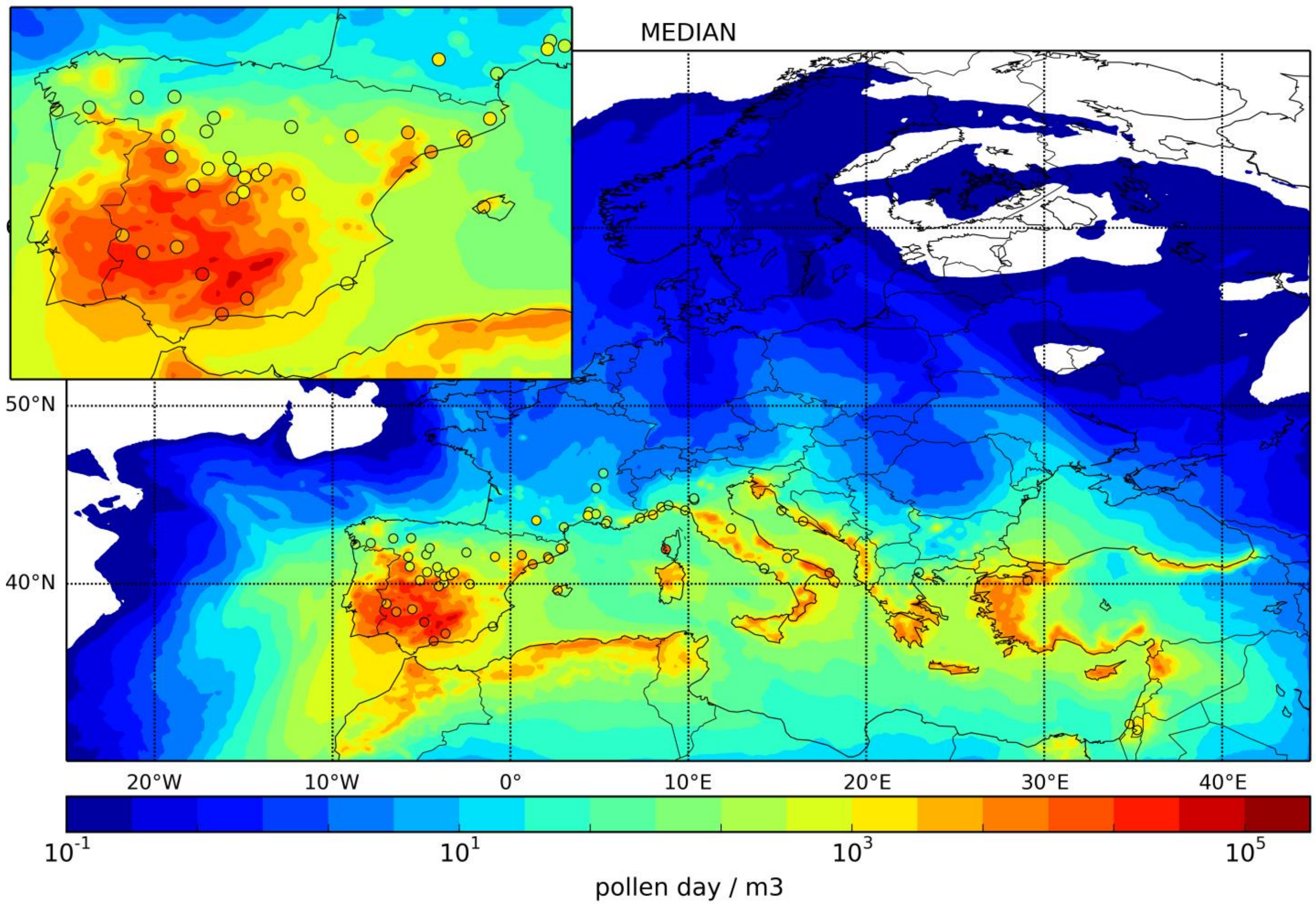
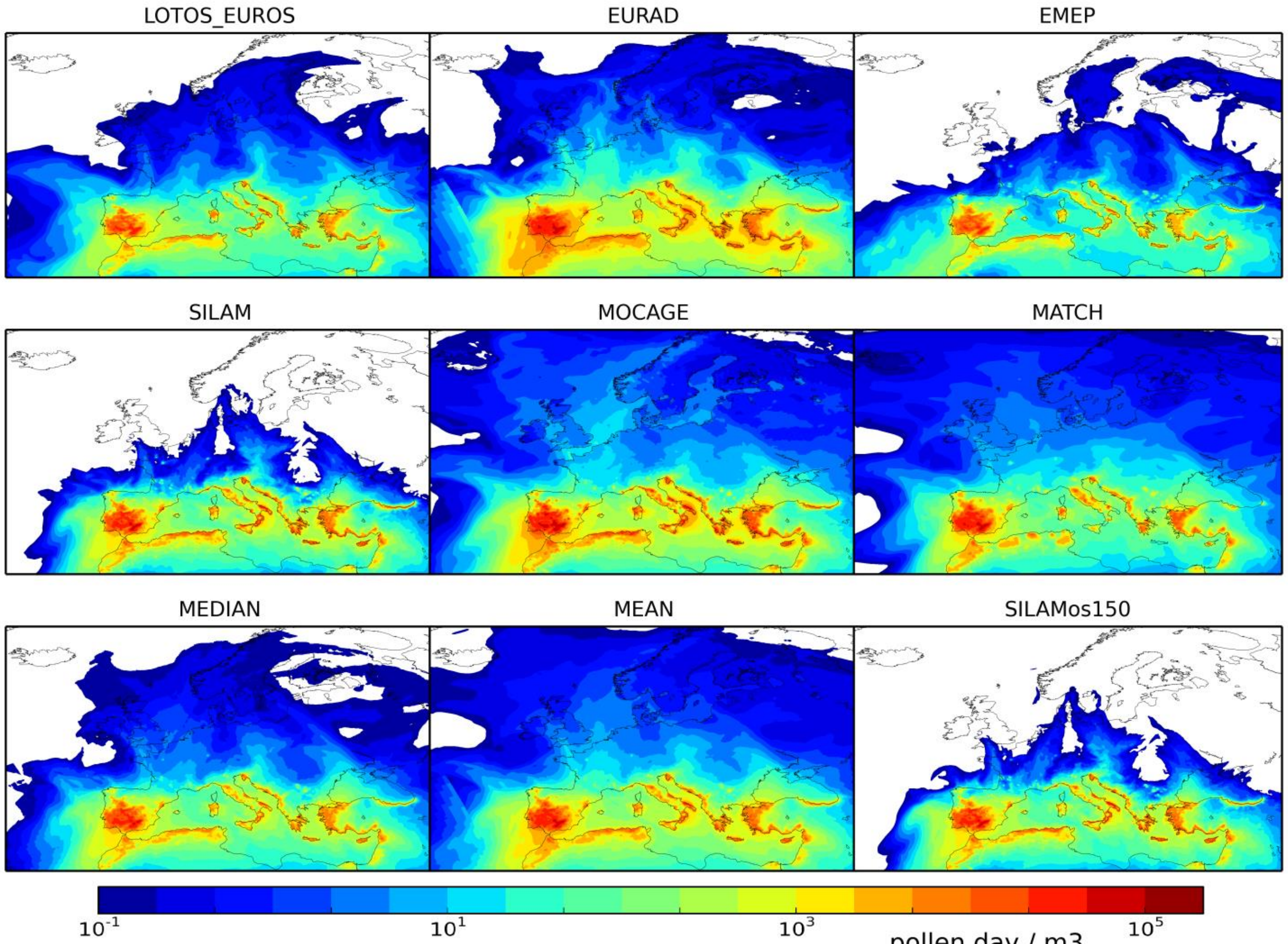


Figure 3. Observed (dots) and MEDIAN-model predicted (shades) Seasonal Pollen Index (SPI, sum of daily concentrations), 2014, [pollen day m^{-3}].



626 **Figure 4.** Modelled Seasonal Pollen Index (SPI) by the individual ensemble members and mean models, 2014, [pollen day m^{-3}].

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4.2. Model results

The total seasonal olive pollen load (Figure 3, Figure 4) expectedly correlates with the map of olive plantations (Figure 1), which is also confirmed by the observations (Figure 3). The highest load is predicted over Spain and Portugal, whereas the level in the Eastern Mediterranean is not so high reflecting smaller size of the areas covered by the olive trees and limited long-range transport over Mediterranean. The model predictions differ up to a factor of a few times (Figure 4), reflecting the diversity of modelling approaches, especially the deposition and vertical diffusion parameterizations (see Table 1 and section 3.1).

Since the olive plantations are located within a comparatively narrow climatic range, flowering propagates through the whole region within a few weeks starting from the coastal bands and progressing inland (not shown).

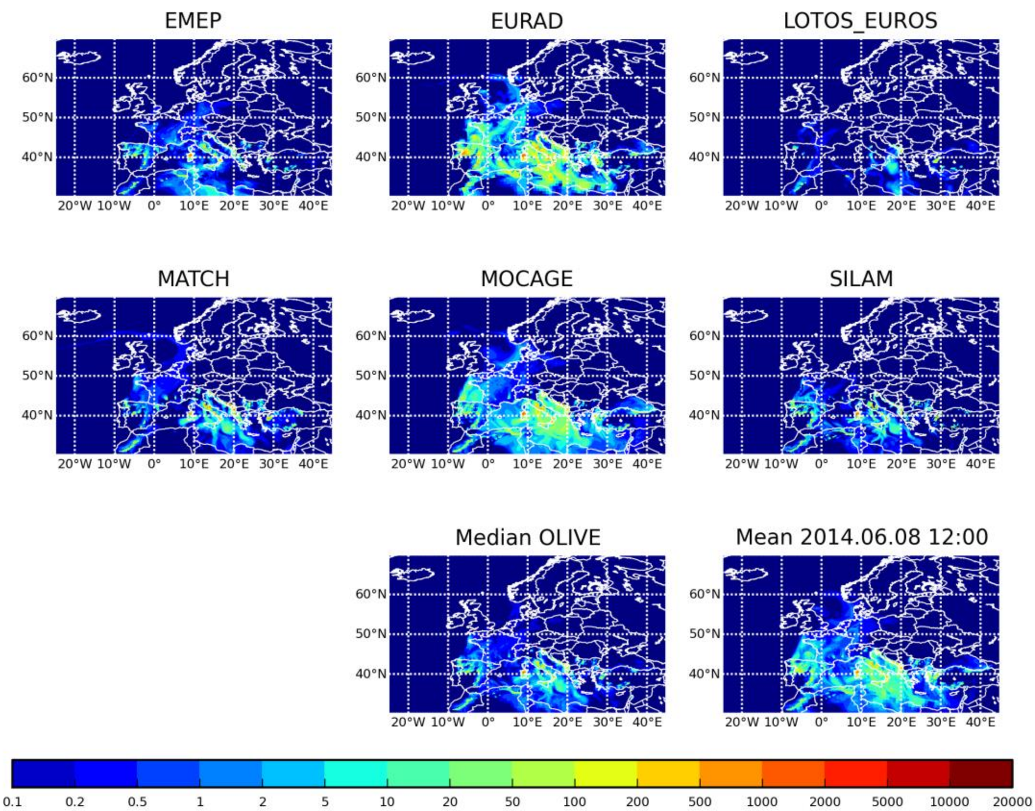

Figure 5. Example of hourly olive pollen concentrations, 12 UTC 08.06.2014, [pollen m^{-3}].

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Hot weather during the flowering season leads to strong vertical mixing and deep atmospheric boundary layer (ABL), which in turn promotes the pollen dispersion. As seen from Figure 5, the pollen plumes can reach out over the whole Mediterranean and episodically affect Central Europe. Both Figure 4 and Figure 5 illustrate the differences between the models, e.g. substantially higher concentrations reported by EURAD-IM and MOCAGE as compared to other models. What regard to pollen transport, the shortest transport with the fastest deposition is manifested by LOTOS-EUROS (also, showed the lowest concentrations), while the longest one is suggested by MOCAGE.

The most-important general parameters describing the season timing are its start and end (Figure 6). Following Andersen (1991), these dates are computed as dates when 5% and 95% of the SPI are reached.

Computations of the model-measurement comparison statistics faces the problem of non-stationarity and non-normal distribution of the daily pollen concentrations (Ritenberga et al., 2016). For such processes, usual non-parametric statistics have to be taken with high care since their basic assumptions are violated. Nevertheless, they can be formally calculated for both individual models and the ensemble (Figure 7, Figure 8). The main characteristic of the ensemble, the discrete rank histogram and the distribution of the modelled values for the below-detection-limit observations (Figure 9) show that the spread of the obtained ensemble is somewhat too narrow in comparison with the dynamic range of the observations. The same limitation was noticed for the birch ensemble.

The patterns in Figure 6 and Figure 7 reveal a systematic early bias of the predicted season start and end, which is well seen from normalised cumulative concentration time series (Figure 10). This bias is nearly identical for all models, except for EURAD-IM, which also shows higher correlation coefficient than other models. The reasons for the problem and for the diversity of the model response are discussed in the next section.

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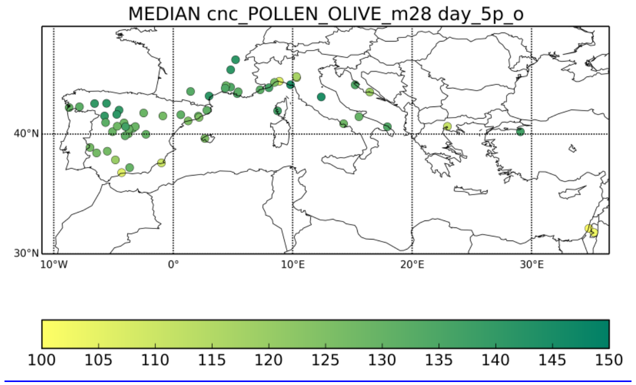
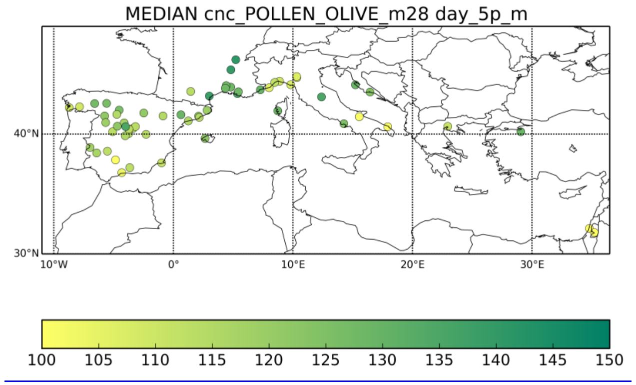
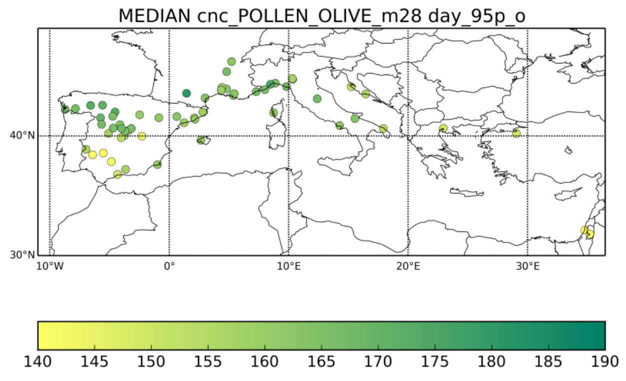


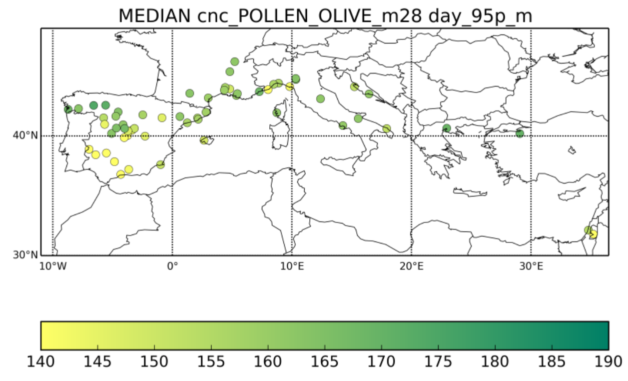
Season start day, 5%, observed



Season start day, 5%, ensemble median



Season end day, 95%, observed



Season end day, 95%, ensemble median

Figure 6. The start (date of 5% of the cumulative seasonal concentrations) and the end (95% of the cumulative seasonal concentrations) of the olive season in 2014 as day of the year, predicted by the median of the ensemble and observed by the stations with sufficient amount of observations.

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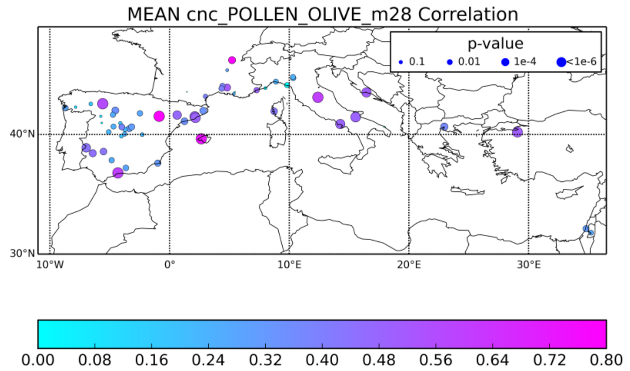
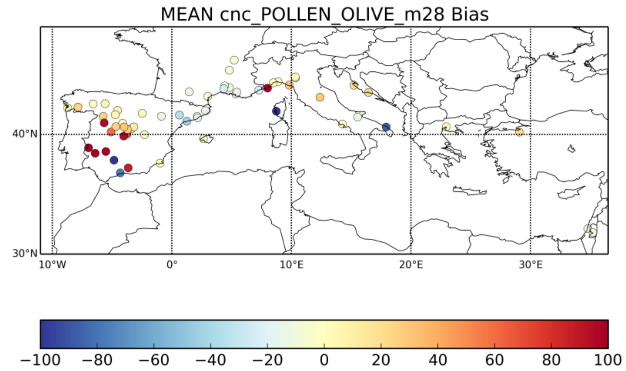
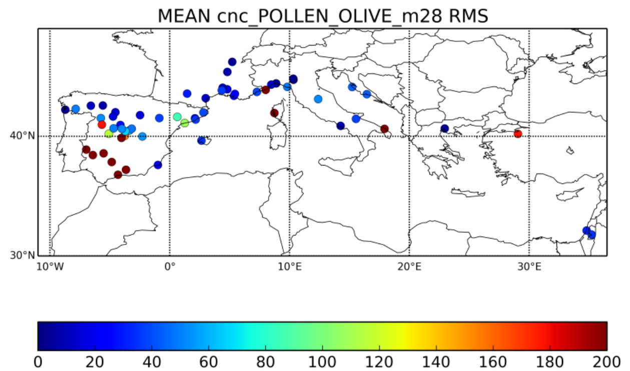


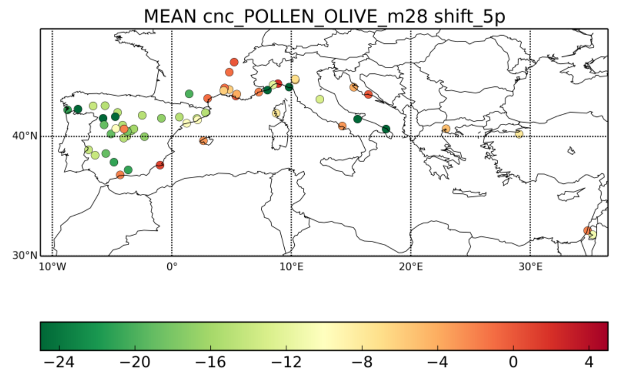
Correlation coefficient, dot size refers to p-value



Absolute bias, mean April-June, [pollen m^{-3}]



RMSE, [pollen m^{-3}]



Error in the season start, days

Figure 7. Results of model-measurement comparison for the ensemble mean: correlation coefficient for daily time series, mean bias April-June (pollen m^{-3}), RMSE (pollen m^{-3}), error in the season start (days).

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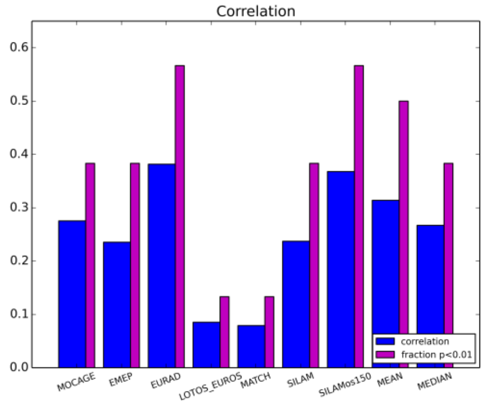
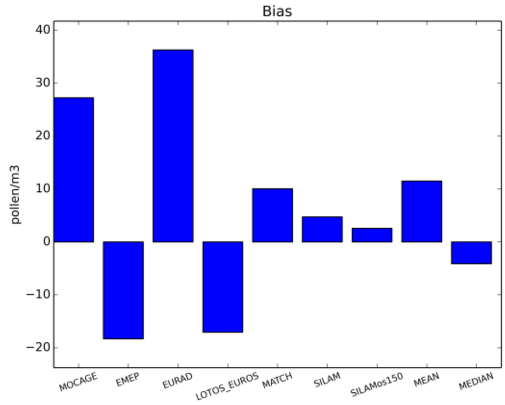
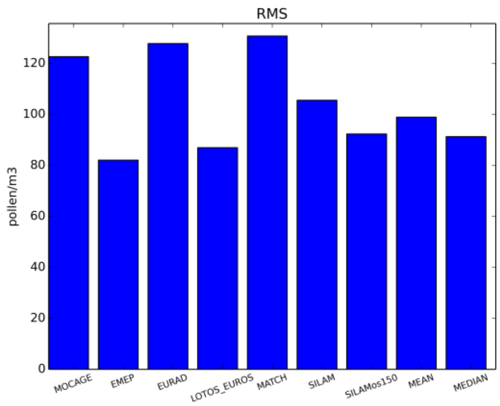


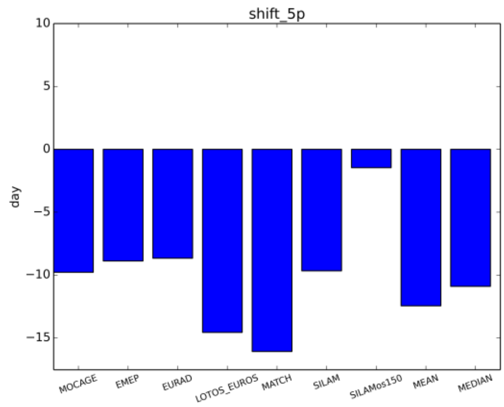
Correlation coefficient and fraction of $p<0.01$



Absolute bias, mean April-June [pollen m^{-3}]



RMSE, [pollen m^{-3}]



Error in the season start, days

Figure 8. Scores of the individual models, mean over all stations. The same parameters as in **Figure 7**. The sensitivity run SILAMos150 is explained in the discussion section

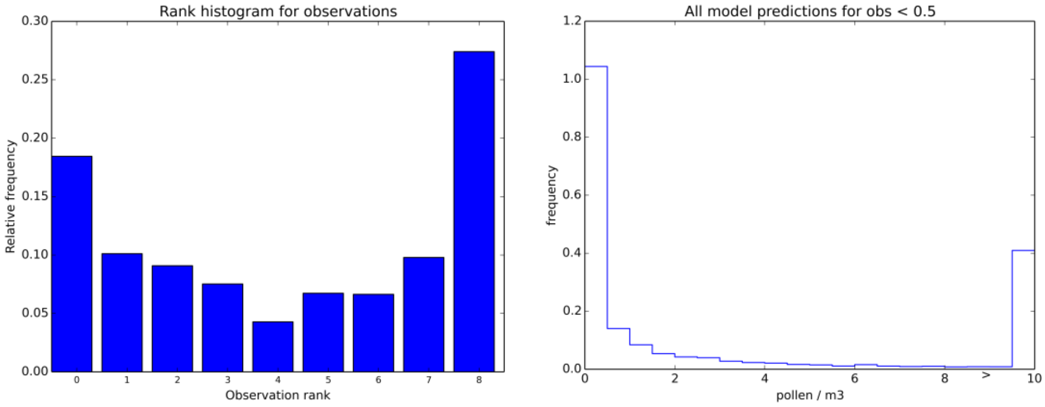


Figure 9. Ensemble characteristics. Left: discrete rank histogram for the constructed ensemble (daily concentration statistics); right: histogram of model predictions when observations were below the detection limit 0.5 pollen m^{-3},

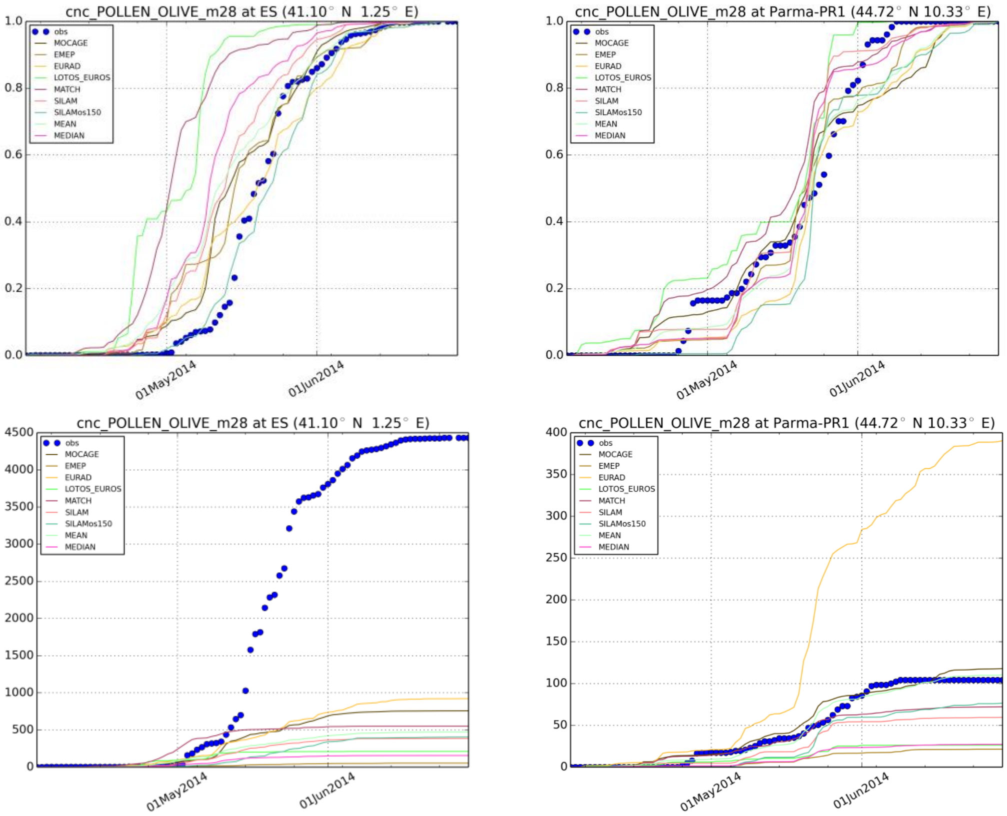


Figure 10. Cumulative time series of olive concentrations at Tarragona (Spain) and Parma (Italy). Upper row: normalized to the seasonal SPI [relative unit], lower: absolute cumulative concentrations [pollen day m^{-3}].

5. Discussion

In this section, we consider the key season parameters and the ability of the presented ensemble to reproduce those (section 5.1), the added value of the multi-model ensembles, including the optimized ensemble (section 5.2), the main uncertainties that limit the model scores (section 5.3), and the key challenges for future studies (section **Error! Reference source not found.**).

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5.1. Forecast quality: model predictions for the key season parameters

The key date of the pollen season is its start: this very date refers to adaptation measures that need to be taken by allergy sufferers. Predicting this date for olives is a significantly higher challenge than, e.g., for birches: the heat sum has to be accumulated starting from 1 January with the season onset being in mid-April, whereas for birches it is 1 March and mid-March, respectively. As a result, prediction of the olive season start strongly depends on the temperature predictions by the weather prediction model and the way this temperature is integrated into the heat sum. Inconsistency between these, even if small, over the period of almost 4 months can easily lead to a week of an error. As one can see from Figure 8 and Figure 7, there is a systematic, albeit spatially inhomogeneous bias of all models by up to 10 days (too early season). Exception is the SILAMos150 sensitivity run, which used the higher heat sum threshold, by 150 degree-days (~10%), than the standard level (Figure 2). No other sensitivity runs, including the simulations driven by ERA-Interim fields, showed any significant improvement of this parameter. Importantly, EURAD-IM, which is driven by WRF meteo fields, also showed a similar bias. Finally, the shift varies among the stations: from near-zero (France, some sites in Italy, Croatia, Greece, and Israel) up to almost three weeks in North-Western Spain. It means that no "easy" solution exists and calls for an analysis of long-term time series, aiming at refinement of the heat sum formulations and threshold values.

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The end of the season showed an intriguing picture: EURAD-IM, despite starting the season as early as all other models, ends it 2 days too late instead of 5 days too early as all other models (see examples for two stations in Figure 10). This indicates that WRF, in late spring, predicts lower temperature than IFS, which leads to longer-than-observed season in the EURAD-IM predictions. Other models showed correct season length and, due to initial early bias, end it a few days too early. The de-biased run SILAMos150 run shows almost perfect shape and hits both start and end with 1 day accuracy, which supports 250 degree day as a season length parameter.

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The most-diverged model predictions are shown for the absolute concentrations (Figure 8). With the mean observed April-June concentration of 35 pollen m^{-3} the range of predictions spans over a factor of four: EURAD-IM and MOCAGE being twice higher and EMEP and LOTOS-EUROS twice lower. Shifting the season by 5 days in the SILAMos150 run also changes the model bias, reflecting differences in the transport patterns and the impact of stronger vertical mixing in later spring. Spatially, the bias is quite homogeneous, except for southern Spain, where heterogeneous pattern is controlled by local conditions at each specific site (Figure 7).

Temporal correlation is generally high in coastal areas (Figure 7) but at or below 0.5 in terrestrial stations of Iberian Peninsula (the main olive plantations). This is primarily caused by the shifted season: the simulations with more accurate season showed the highest correlation among all models with ~60% of sites with significant correlation ($p<0.01$, Figure 8).

Comparison with local statistical models made for single or a few closely-located stations expectedly shows that local models are usually comparable but somewhat more accurate (at their locations) than the European-scale dispersion models (see also discussion in (Ritenberga et al., 2016)). Thus, (Gala et al., 2001) analyzed performance of three popular local models for Cordoba, with the best one showing the mean error of the start of the season of 4.7 days but reaching up to 14 days in some years. Similar error was found for Andalusia (Galán et al., 2005) and two sites (Perugia and Ascoli Piceno) in Italy (Frenguelli et al., 1979) – 4.8 and 4.33 days of the standard error, respectively. A recent study (Aguilera et al., 2014) constructed three independent statistical models for Spain, Italy and Tunisia and ended up with over 5 days of a standard error for the Mediterranean. In another study, the authors admitted the scale of the challenges: "The specific moment for the onset of the olive heat accumulation period is difficult to determine and has essentially remained unknown" (Aguilera et al., 2013).

One of the strengths of continental-scale dispersion models is their ability to predict long-range transport events. However, direct evaluation of this feature for olive pollen is difficult since countries without olive plantations usually do not count its pollen. One can however refer to Figure 3 (zoomed map of Spain), which shows that the ensemble successfully reproduces the drastic change of the SPI from nearly 10^5 pollen day m^{-3} in the south of Spain down to less than 100 pollen day m^{-3} in the north. Episode-wise, an example of a well-articulated case of olive pollen transport from Italy to Hungary in 2016 was brought up by Udvardy et al., (2017), who analyzed it with adjoint SILAM simulations. The episode was also well-predicted by the forward computations.

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5.2. Ensemble added value

Arguably the main uncertainty of the model predictions was caused by the shift of the season start and end – the parameters heavily controlled by temperature, i.e. least affected by transport features of the models. As a result, application of the "simple" ensemble technologies does not lead to a strong improvement. Some effect was still noticed but less significant than in case of birch or traditional AQ forecasting. Therefore, in this section we also consider a possibility of ensemble-based fusion of the observational data with the model predictions. All ensembles were based on operational models, i.e. the SILAMos150 run was not included in either of them.

5.2.1. Mean ensembles: arithmetic average and median

Considering the mean-ensemble statistics, one should keep in mind that both the meteorological driver and the source term parameterization were the same for all models (except for EURAD driven by WRF). This resulted in the under-representative ensemble (Figure 9), where several good and bad features visible in all models propagate to the mean ensembles.

Among the simple means, arithmetic average performed better than the median, largely owing to strong EURAD-IM impact. That model over-estimated the concentrations and introduced a powerful push towards extended season, thus offsetting the early bias of the other models. Since median largely ignored this push, its performance was closer to that of other models. Nevertheless, both mean and median demonstrated low RMSE, median being marginally better.

5.2.2. Fusing the model predictions and observations into an optimized ensemble: gain in the analysis and predictive capacity

Developing further the ensemble technology, we present here the first attempt of fusion of the observational data with the multi-model ensemble for olive pollen.

In the Section 3.1, the Eq. (2) requires three parameters to prescribe: the regularization scaling parameters α and β, and length of the assimilation window *T*. For the purposes of the current feasibility study, several values for each of the parameters were tested and the robust performance of the ensemble was confirmed with very modest regularization strength and for all considered lengths of the analysis window – from 1 to 15 days. Finally, $\alpha = 0.1,\ \beta = 0.1,\ T = 5\,days$ were selected for the below example as a compromise between the smoothness of the coefficients, regularization strength and the optimization efficiency over the assimilation window.

The optimized ensemble showed (Figure 11, left-hand panel) that each of the 6 models had substantial contribution over certain parts of the period. Over some times, e.g. during the first half of May, only one or two models were used, other coefficients being put to zero, whereas closer to the end of the month, all models were involved. Finally, prior to and after the main season, concentrations were very low and noisy, so the regularization terms of Eq. (2) took over and pushed the weights to a-priori value of 1/6.

The bulk of the improvements came in the first half of the season (Figure 11, middle panel). After the third peak in the middle of May, the effect of assimilation becomes small and the optimization tends to use intercept to meet the mean value, whereas the model predictions become small and essentially uncorrelated with the observations. This corroborates with the observed 8-days shift of the season, which fades out faster in the models than in the observed time series (Figure 10).

There was little reduction of the predictive capacity of the optimized ensemble when going out of assimilation window towards the forecasts. In-essence, only the first peak of concentrations (and RMSE) is better off with shorter forecasts. For the rest of the season (before and after the peak) the 5-day assimilation window led to a robust combination of the models that stayed nearly-optimal over the next five days.

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Comparison with other forecasts expectedly shows that the optimized ensemble not only has significantly better skills than any of the individual models, but is up to 25-30% better than mean and median of the ensemble (Figure 11, middle panel). A stronger competitor was the “persistence forecast” when the next-day(s) concentrations are predicted to be equal the last observed daily value. The one-day persistence appeared to be the best-possible “forecast”, which shows at the beginning of May almost twice lower RMSE than the one-day forecast of the optimal ensemble (Figure 11, right-hand panel). However, already two-days persistence forecast had about-same RMSE as the ensemble, and 3- and 4- days predictions were poor.

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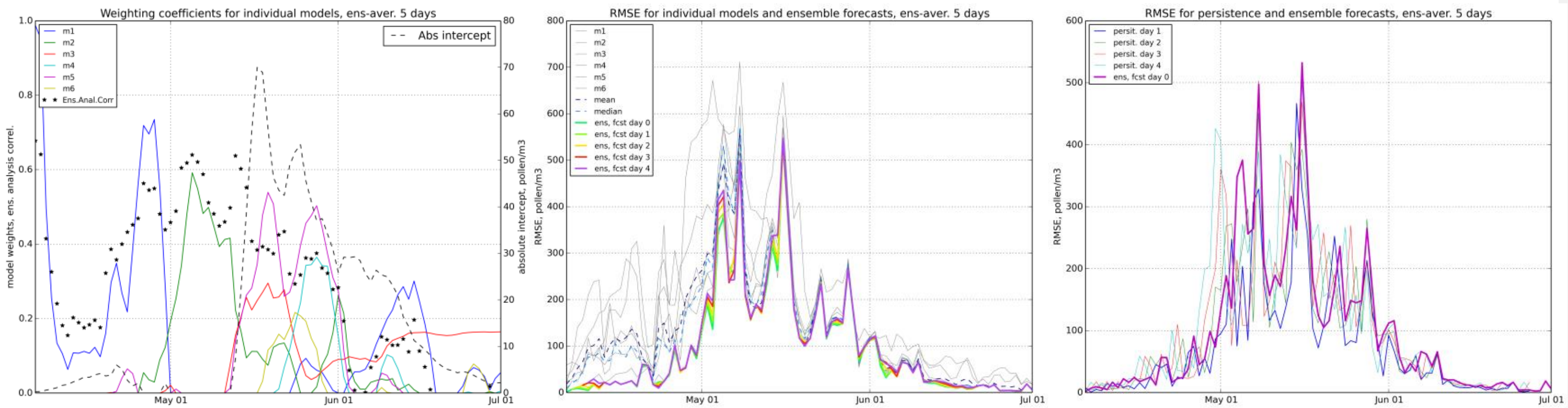

Figure 11. Optimal weights of the individual models and ensemble correlation score over the 5-days-long assimilation window (left panel); RMSE of the of individual models and the optimal ensemble forecasts against those of individual models and simple ensemble means (middle) and against persistence-based forecasts (right-hand panel).

Strong performance of the one-day persistence forecast is not surprising and, with the current standards of the pollen observations, has no practical value: the data are always late by more than one day (counting can start only next morning and become available about mid-day). The second problem of the persistence forecast is that it needs actual data, i.e. the scarcity of pollen network then limits its coverage. Thirdly, persistence loses its skills very fast: already day+2 forecast has no superiority to the optimal ensemble, whereas day+3 and +4 persistence-based predictions are useless. Finally, at local scale, state-of-art statistical models can outperform it – see discussion in (Olga Ritenberga et al., 2016).

One should however point out that one-day predicting power of the persistence forecast (or more sophisticated statistical models based on it) can be a strong argument for the future real-time online pollen monitoring, which delay can be as short as one hour (Crouzy et al., 2016; Oteros et al., 2015). Such data have good potential as the next-day predictions for the vicinity of the monitor.

5.3. Sensitivity of the simulations to model and source term parameters

The above-presented results show that arguably the most-significant uncertainty was due to shifting the start and the end of the season. It originated from the long heat sum accumulation (since 1 January), where even a small systematic difference between the meteorology driving the multi-annual fitting simulations and that used for operational forecasts integrates to a significant season shift by late spring. In some areas, resolution of NWP model plays as well: complex terrain in the north of Spain and in Italy requires dense grids to resolve the valleys. Other possible sources of uncertainties might need attention.

To understand the importance of some key parameters, a series of perturbed runs of SILAM was made:

- **os100** and **os150** runs with the season starting threshold increased by 100 and 150 degree days (the **os150** run is referred in the above discussion as SILAMos150)
- **era** run with ERA-Interim meteorological fields, which were used for the source parameters fitting
- series of 3 runs with reduced vertical mixing within the ABL and the free troposphere
- **smlpoll** run with 20 μm size of the pollen grain
- **smlpoll_coarse** run with 20 μm pollen size and coarse computational grid (0.2°×0.2°)

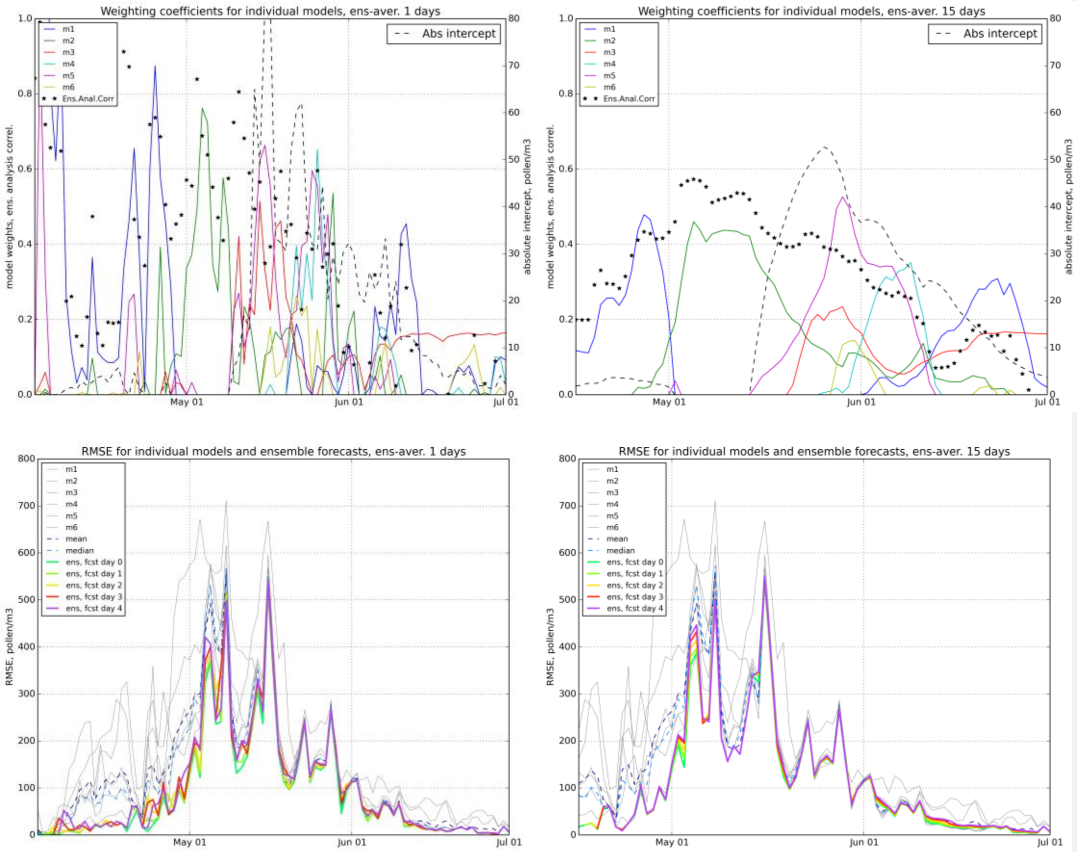

Figure 12. Sensitivity of optimized ensemble to the length of assimilation window. Upper row: optimal weights of the individual models and ensemble score over the 1- (left) and 15- (right) days-long assimilation windows; lower row: RMSE of the of individual models and the optimal ensemble forecasts against those of individual models. Obs. earlier first available date for 1-day-analysis window.

The **era** simulations with ERA-Interim reduced the shift of the season start by 2 days but increased the shift of the end by 3 days, i.e. made the season shorter by 5 days. At the same time, the **os150** run showed that a simple increase of the heat sum threshold by ~10% (150 degree days) essentially eliminates the mean shift – for 2014 – but it remains unclear whether this adjustment is valid for other years.

Variations of the mixing parameterization (perturbing the formula for the K_z eddy diffusivity) did not lead to significant changes: all scores stayed within 10% of the reference SILAM simulations.

Evaluation of the impact of deposition parameterizations was more difficult since they are model-specific. Higher deposition intensity causes both reduction of the transport distance and absolute concentrations. This issue might be behind the low values reported by LOTOS-EUROS and, conversely, high concentrations of EURAD-IM and MOCAGE. Its importance was confirmed by the SILAM sensitivity simulations with smaller pollen size, **smlpoll** and **smlpoll_coarse**. Both runs resulted in more than doubling the mean concentrations but with marginal effect on temporal correlation. They also differed little from each other.

Variations of the fusion parameters showed certain effect. For short averaging window (5 days or less), the variations of weighting coefficients increased and the time series became noisier (Figure 12). On return, the correlation increased almost up to 0.8 – 0.9 for some analysis intervals, though stayed the same for other periods. Also, the one-day forecast RMSE decreased for some days but little difference was found for longer predictions.

5.4. Main challenges for the future

The current study is the first application of numerical models to olive pollen dispersion in Europe. One of its objectives was to identify the most-pressing limitations of the current approach and the extent to which the ensemble and data fusion technologies can help in improving the forecasts.

The most-evident issue highlighted by the exercise is the shift of the pollen season, which is similar in all models suggesting some unresolved inconsistencies between the heat-sum calculations of the source term and the features of the temperature predictions by the weather model. The issue suggests some factor(s) currently not included or mis-interpretted in the source term. One of the candidate processes is the chilling-sum accumulation suggested by some studies, e.g., (Aguilera et al., 2014). A switch to different types of phenological models with genetic differentiation of the populations following Chuine and Belmonte, (2004) is another promising option.

The second issue refers to the under-estimation of the pollen concentration in France, which probably originates from a comparatively large number of olive trees spread in private gardens etc but not accounted for in the agriculture maps of olive plantations.

The third set of questions refers to the pollen load prediction, i.e. a possibility to forecast the overall season severity before it starts. Several statistical models have been presented in the literature, e.g., (Ben Dhiab et al., 2016) for total annual load and (Chuine and Belmonte, 2004) for relative load. Their evaluation and implementation in the context of dispersion models is important.

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An issue, mostly addressing the long-term horizon rather than the short-term forecasts is the validity of the developed models in the conditions of changing climate. The models have to be robust to the trends in meteorological forcing. Purely statistical models are among the most vulnerable in this respect because they just quantify the apparent correlations observed under certain conditions but do not explore the processes behind these relations.

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Finally, already the first steps towards ensemble-based fusion of the model forecasts and pollen observations showed strong positive effect. Further development of these techniques combined with progress towards near-real-time pollen data has very high potential for improving the forecasts.

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6. Summary

An ensemble of 6 CAMS models was run through the olive flowering season of 2014 and compared with observational data of 6 countries of European Aeroallergen Network (EAN).

The simulations showed decent level of reproduction of the short-term phenomena but also demonstrated a shift of the whole season by 8 days (~20% of the overall pollination period). An ad-hoc adjustment of the season-start heat sum threshold by ~10% (150 degree days) resolves the issue and strongly improves the model skills but its validity for other years and meteorological drivers remain unclear.

The ensemble members showed quite diverse pictures demonstrating the substantial variability, especially in areas remote from the main olive plantations. Nevertheless, the observation rank histogram still suggested certain under-statement of the ensemble variability in comparison with the observations. This partly originates from the synchronized source term formulations and meteorological input used by all but one models.

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Simple ensemble treatments, such as arithmetic average and median, resulted in a more robust performance but they did not outrun the best models over significant parts of the season. Arithmetic average turned out to be better than median.

A data-fusion approach, which creates the optimal-ensemble model using the observations over preceding days for optimal combination of the ensemble members, is suggested and evaluated. It was based on an optimal linear combination of the individual ensemble members and showed strong skills, routinely outperforming all individual models and simple ensemble approaches. It also showed strong forecasting skills, which allowed application of the past-time model weighting coefficients over several days in the future. The only approach outperforming this fusion ensemble was the one-day persistence-based forecast, which has no practical value due to the manual pollen observations and limited network density. It can however be used in the future when reliable online pollen observation will become available.

A series of sensitivity simulations highlighted the importance of meteorological driver, especially its temperature representation, and deposition mechanisms. The data fusion procedure was quite robust with regard to analysis interval, still requiring 5-7 days for eliminating the noise in the model weighting coefficients.

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