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A multi-model comparison of meteorological drivers of surface ozone over Europe

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Abstract. The implementation of European emission abatement strategies has led to significant reduction in the emission of ozone precursors during the last decade. Ground level ozone is also influenced by meteorological factors such as temperature, which exhibit interannual variability, and are expected to change in the future. The impacts of climate change on air quality are usually investigated through air quality models that simulate interactions between emissions, meteorology and chemistry. Within a multi-model assessment, this study aims to better understand how air quality models represent the relationship between meteorological variables and surface ozone concentrations over Europe. A multiple linear regression (MLR) approach is applied to observed and modelled time series across ten European regions in springtime and summertime for the period of 2000-2010 for both models and observations. Overall, the air quality models are in better agreement with observations in summertime than in springtime, and particularly in certain regions, such as France, Mid-Europe or East-Europe, where local meteorological variables show a strong influence on surface ozone concentrations.

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Larger discrepancies are found for the southern regions, such as the Balkans, the Iberian Peninsula and the Mediterranean basin, especially in springtime. We show that the air quality models do not properly reproduce the sensitivity of surface ozone to some of the main meteorological drivers, such as maximum temperature, relative humidity and surface solar radiation. Specifically, all air quality models show more limitations to capture the strength of the relationship ozone-relative humidity detected in the observed time series in most of the regions, in both seasons. Here, we speculate that dry deposition schemes in the air quality models might play an essential role to capture this relationship. We further quantify the relationship between ozone and maximum temperature ($m_{o3\text{-}T}$, climate penalty) in observations and air quality models. In summertime, most of the air quality models are able to reproduce reasonably well the observed climate penalty in certain regions such as France, Mid-Europe and North Italy. However, larger discrepancies are found in springtime, where air quality models tend to overestimate the magnitude of observed climate penalty.

1. Introduction

Tropospheric ozone is recognised as a threat to human health and ecosystem productivity (Mills et al. 2007). Moreover, ozone is an important greenhouse gas (IPCC, 2013). It is produced by photochemical oxidation of carbon monoxide and volatile organic compounds (VOCs) in the presence of nitrogen oxides ($NOx=NO+NO2$) (Jacob and Winner, 2009). While it is an important pollutant on a regional scale, due to the long-range transport effect it may also influence air quality on a hemispheric scale (Monks et al., 2015, Hedegaard et al, 2013). Moreover, its strong relationship with temperature represents a major concern, since under a changing climate the efforts on new air pollution mitigation strategies might be insufficient. This effect, referred as climate penalty (Wu et al., 2008), is expected to play an important role on future air quality (Hendriks et al. 2016). Therefore it is essential to better understand the potential implications of climate change on pollutant levels. In a comprehensive review of the existing literature about the robustness of climate penalty on Europe, Colette et al. (2015) concluded that the climate change might act against mitigation measures.

Previous studies have shown that the reduction of emissions of ozone precursors, NOx and VOCs, lead to a decrease in tropospheric ozone concentrations in Europe (Solberg et al. 2005, Jonson et al. 2006). However, there is also a large year-to-year variability due to weather conditions (Andersson et al. 2007). There is a strong correlation between ozone and temperature that has been associated with the temperature-dependent lifetime of peroxyacetyl nitrate (PAN), and also due to the temperature dependence of biogenic emission of isoprene (Sillman and Samson, 1995). Substantial increases in surface ozone have been associated with high temperatures and stable anticyclonic, sunny conditions that promote ozone formation (Solberg et al. 2008). Ozone peak

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concentrations are also affected by closing of the plants' stomata at very high temperatures (Hodnebrog et al. 2012). Several studies have assessed the model dependence of ozone on temperature (e.g. Steiner et al. 2006, Rasmussen et al. 2013). Recently, Coates et al. (2016) used a box model to investigate the influence of temperature and NOx on ozone production. Their analysis suggested that reductions in NOx would be required to offset additional ozone increase due to increasing temperatures under a warmer climate. An extensive review about the impacts of temperature on ozone production can be found in Pusede et al. (2015).

Previous studies have shown the importance of relative humidity on ozone pollution episodes (Camalier et al. 2007, Davies et al. 2011). Regional studies reported a negative relationship between ozone and relative humidity (Dueñas et al. 2002, Elminir 2005, Demuzere et al., 2009). Some authors attributed this negative correlation to the photolysis of ozone and subsequent loss of O1(D) to H_2O (Jacob and Winner). High levels of humidity are usually related with enhanced cloud cover and thus reduced photochemistry (Dueñas et al. 2002, Camalier et al. 2007). Andersson and Engardt (2010) highlighted the importance of including meteorological dependence for dry deposition of ozone to vegetation, also incorporating soil moisture dependence. With a simple modelling approach, Kavassalis and Murphy (2017) found that the relationship ozone-relative humidity was well captured by the inclusion of the vapour pressure deficit-dependent dry deposition, indicating the relevance of detailed dry deposition schemes in the CTMs.

Increasing solar radiation leads to an increase of ozone, though with a weak effect (Dawson et al. 2007) and it has been suggested that it could reflect in part the association of clear sky with high temperatures (Ordónez et al., 2005). Then, changes in cloud cover can also affect the photochemistry of ozone production and loss (Jacob and Winner, 2009). Additionally, low wind speed is usually associated with high ozone pollution levels (Jacob and Winner, 2009).

The influence of climate change on ozone and its precursors can involve multiple processes (Colette et al, 2015). A common approach to study the impact of climate change on air quality requires the use of air quality models that aim to represent dynamic and chemical processes in the atmosphere. The relevance of climate change for future European air quality has been assessed in several studies that also reflect differences depending on the modelling system and future emissions scenarios adopted for each study (e.g. Lagner et al. 2005, Meleux et al. 2007, Anderson and Engardt, 2010).

Air quality models can be divided into two categories: offline chemistry transport models (CTMs) in which the model chemistry runs using meteorological data as input, and online models that allow coupling and integration of chemistry with some of the physical components to various degrees (Baklanov et al. 2014). Differences between offline and online modelling approaches can be fairly small or significant, depending on the level of the model complexity and simulated variables (Zhang, 2008). The large number and complex interactions between meteorology and chemistry in the atmosphere influence the ability of the model to represent observed situations (Kong et al. 2014). Due to assumptions, parametrizations and simplifications of processes, the models themselves are subject to large uncertainties (Manders et al. 2012), which have been reflected in some regional differences in the magnitude of surface ozone response to projected climate change (Andersson and Engardt, 2010). Thus, model biases when compared to observations still remain a concern, especially in terms of the response of air quality under future climate (Fiore et al. 2009, Rasmussen et al. 2012). Comparisons between model outputs and measurements of available observational dataset assess the reliability of air quality models, and they are essential to quantify the models ability to reproduce observations.

The EURODELTA project was initiated by the Task Force on Measurement and Modelling and the Joint Research Centre of the European Commission to provide a benchmark for the EMEP model in order to assess its relevance for policy support (Colette et al.2017a). These multi-model exercises contribute to further improving modelling techniques and understanding the associated uncertainties in the models performance. Previous exercises have evaluated the performance of chemistry transport models for future European air quality (e.g. van Lon et al. 2007, Thunis et al. 2008). Recently, Bessagnet et al. (2016) presented an intercomparison and evaluation of chemistry transport model performance with a joint analysis of some meteorological fields. They highlighted the limitations of models to simulate meteorological variables, such as wind speed and planetary boundary layer height. Particularly, in the case of ozone, they showed the importance of boundary conditions on model calculations. Within this framework, the ongoing Eurodelta-Trends (EDT) exercise (Colette et al. 2017a) builds upon this tradition and focuses on the context of air quality trends modelling. This exercise has been designed to better understand the evolution of air pollution and its drivers over the last two decades (1990-2010) by the use of state-of-the-art air quality models. The EDT project will allow the evaluation of the skill of regional air quality models and quantification of the role of the different key driving factors of surface ozone, such as emissions changes, long-range transport and meteorological variability. One of the main goals of the EDT project is to assess the efficiency of mitigation strategies for improving air quality (more details can be found in Colette et al. 2017a).

Quantification and isolation of the effects of meteorology on ozone is a challenge, due to the complex interrelation between ozone, meteorology, emissions and chemistry (Solberg et al. 2015). There is a large number of representative studies in the literature that have established the relationship between surface ozone concentrations and meteorological variables using statistical modelling techniques (e.g. Bloomfield et al. 1996, Chaloukau et al 2003, Barrero et al. 2005, Ordóñez et al., 2005, Camalier et al., 2007, Seo et al., 2014, Porter et al. 2015, Otero et al., 2016). Most of these works examined the impact of meteorology on ozone pollution levels through observational datasets. Only a few studies, to our knowledge, examined the statistical relationship between surface ozone and meteorological parameters from models.

Davis et al. (2011) developed regression models to analyse the observed and modelled relationship between meteorology and surface ozone across the Eastern of U.S. They found that the Community Multiscale Air Quality (CMAQ) model did not capture the effect of temperature and relative humidity on daily maximum 8-h ozone and it generally underestimated the observed sensitivities to both meteorological variables, especially in the northeast. Rasmussen et al. (2012) examined the ozone-temperature relationship in a coupled chemistry-climate model and they found that the model underestimated the effect of temperature on ozone over the Mid-Atlantic. Lemaire et al. (2016) proposed a combined statistical and deterministic approach to assess the air quality response to projected climate change. Based on a data set from a deterministic climate and chemistry models, they identified the two major drivers of surface ozone over eight European regions, selected from a set of potential predictors that reached the highest correlations with ozone. Afterwards they built statistical models consisting of generalized linear models, which could be used to predict air quality.

Given that meteorology plays an essential role for surface ozone concentrations, it might be a considerable source of uncertainties in model outputs. The present study, thus, aims to provide a simple method to examine the influence of meteorological variability on modelled surface ozone concentrations over Europe. Specifically, our analysis focuses on the ozone season (April to September) over the years 2000-2010. The choice of this period is mainly motivated by the availability of the observational dataset from Schnell et al. (2014, 2015) (see section 2.1). Within the EDT framework, a recent report has presented the main findings on the long-term evolution of air quality (Colette et al. 2017b). Part of these results was obtained from the analysis of the 1990s (1990-2000) and 2000s (2000-2010) separately. Consistently, we decided to focus on the second decade, for which the interpolated dataset of observed on maximum daily 8-hourly mean ozone (MDA8 O3) used in this study was available. Similarly to Otero et al. (2016), we apply a multiple linear regression approach to examine the meteorological influence MDA8 O3. Statistical models are developed separately for observational datasets and air quality models, with the primary focus on examining the relationship between MDA8 O3 and potential meteorological drivers in the air quality models and comparing these with the corresponding relationships determined from observed data. Therefore, this study offers a method of model evaluation capable of understanding the discrepancies between air quality models and observations in terms of representing the relationship to meteorological input variability.

The present paper is structured as follows. Section 2 describes the observational data as well as the air quality models studied here. The methodology and the design of the statistical models are introduced in section 3. Section 4 discusses the results and the summary and conclusions are discussed in section 5.

2. Data

2.1. Observations

This study uses gridded MDA8 O3 concentrations created with an objective-mapping algorithm developed by Schnell et al. (2014). They applied a new interpolation technique over hourly observations of stations from the European Monitoring and Evaluation Programme (EMEP) and the European Environment Agency's air quality database (AirBase) to calculate surface ozone averaged over 1º by 1º grid cells. Recently, Otero et al. (2016) used this dataset for examining the influence of synoptic and local meteorological conditions over Europe. This interpolated product offers a possibility to establish a direct comparison between observations and CTMs. However, it must be acknowledged that for some areas with a low number of stations (i.e. the southeastern or northeastern European regions) the values interpolated into the 1x1 degree grid cells may not be representative of such large scales. A complete description of this process can be found in Schnell et al. (2014, 2015). The gridded dataset covers a total of 15-years (1998-2012), but here we use a common period of 11-years for both observations and CTMs (2000-2010).

This study investigates the observed influence of meteorological variables on MDA8 O3, based on the ERA-Interim reanalysis product provided by the European Centre for Medium-Range Weather Forecasts (ECMWF) at 1ºx1º resolution (Dee et al. 2011). Meteorological reanalyses products are essentially model simulations constrained by observations and they have been widely validated against independent observations. Daily mean values are calculated as the mean of the four available time steps at 00, 06, 12, and 18UTC for 10m wind speed components (u and v) and 2m relative humidity. Maximum temperature is approximated by the daily maximum of those time steps, while daily mean surface solar radiation is obtained from the 3-hourly values provided for the forecast fields.

2.2. **Chemistry Transport Models (CTMs)**

A set of state-of-the-art air quality models participating in the EDT exercise is used here: LOTOS-EUROS (Schaap et al., 2008, Manders et al. 2017), EMEP/MSC-W (Simpson et al., 2012), CHIMERE (Mailer et al., 2017), MATCH (Robertson et al., 1999), MINNI (Mircea et al., 2016) and WRF-Chem (Grell et al. 2005, Mar et al. 2016). The domain of the CTMs extends from 17ºW to 39.8ºE and from 32ºN to 70ºN and it follows a regular latitude-longitude projection of 0.25x0.4 respectively. The main features of the CTM setup are largely constrained by the EDT experimental protocol (e.g. meteorology, boundary conditions, emissions, resolution, see Colette et al. 2017a for further details). For instance, the boundary conditions were defined from climatology of observational data for most of the experiments of the EDT exercise (included the data used here). However, the representation of physical and chemical processes and the vertical distribution differ in the CTMs, as well as the vertical distribution of model layers (including altitude of the top layer and derivation of surface concentration at 3m height in the case of EMEP, LOTOS-EUROS and MATCH). Moreover, there were no specific constrains imposed on biogenic emissions (including soil NO emissions), which are represented by most of the models using an online module (Colette et al. 2017a). Since we aim here to compare the modelled relationship between meteorology and surface ozone, prescribing common features in the CTMs is particularly an advantage to identify potential sources of discrepancies.

Only one of the participating CTMs included online coupled chemistry/meteorology (WRF-Chem), while all the rest of the models used are offline. The CTMs were forced by regional climate model simulations using boundary conditions from the ERA-Interim global reanalysis (Dee et al., 2011). Most of these offline CTMs used the same meteorological input data, with a few exceptions. Three of them (EMEP, CHIMERE and MINNI) used input meteorology from the Weather Research and Forecast Model (WRF) (Skamarock et al. 2008). LOTOS-EUROS and MATCH used the input meteorology produced by RACMO2 (van Meijgaard, 2012) and HIRLAM (Dahlgren et al. 2016), respectively. Unlike the rest of the regional climate models, RACMO2 used in the EDT exercise excluded nudging towards ERA-Interim, which might have some impact in the meteorological fields generated by RACMO2. As mentioned, WRF-Chem couples the meteorology simulations online with chemistry. The meteorology used to drive WRF-Chem (initial and lateral boundary conditions and the application of limited four-dimensional data assimilation; see Colette et al GMD 2017a) is the same WRF meteorology from Skamarock et al. (2008) used as input for the EMEP, CHIMERE, and MINNI runs. Table 1 summarises the CTMs and the corresponding sources of

Atmospheric Chemistry and Physics Discussions

meteorological input data used here. It is important to highlight that though WRF-Chem is not strictly a CTM, in order to avoid confusion with the statistical models developed in this study, we refer to all the air quality models considered (offline and online models) as CTMs hereafter. As with the observations, CTMs and their meteorological counterpart were interpolated to a common grid with 1º x 1º horizontal resolution. The use of a coarser resolution could have an impact in some regions with a complex orography where airflow is usually controlled by mesoscale phenomena (e.g. see-breeze and mountain-valley winds) or in regions characterized by high emissions densities (Schaap et al., 2015, Gan et al. 2016). In such cases the use of a finer grid could be beneficial to capture the variability of local processes.

A set of meteorological parameters was selected from the meteorological input data for the regression analyses. Similarly to the procedure with ERA-Interim, daily means are obtained from the available time steps every 3 hours in the case of WRF and RACMO2, and every 6 hours for HIRLAM for the following variables: 10m wind speed components, 2m relative humidity and surface solar radiation. Maximum temperature is also approximated by the daily maximum of those time steps.

3. **Multiple Linear regression model**

Summertime usually brings favourable conditions for high tropospheric ozone concentrations, such as air stagnation due to high-pressure systems, warmer temperatures, higher UV radiation, and lower cloud cover (Dawson et al. 2007). As stated above, the impact of meteorology on ozone concentration has been addressed through a wide variety of statistical methods in the literature. This study attempts to better understand how CTMs represent the influence of meteorology on ozone. To this aim, we use a multiple linear regression approach that can provide useful information of sensitivities in the distribution of ozone concentration as a whole (Porter et al., 2015).

A total of five meteorological predictors (Table 2) are selected based on the existing literature that has shown their strong influence on ozone pollution. (e.g. Bloomfield et al. 1996, Barrero et al. 2005, Camalier et al. 2007, Dawson et al. 2007, Rasmussen et al. 2012, Davis et al. 2011, Doherty et al., 2013, Otero et al. 2016). Moreover, it has been shown that the occurrence of air pollution episodes might increase when the pollution levels of the previous day are higher than normal (Ziomas et al. 1995). Then, apart from the meteorological predictors, we add the effect of the lag of ozone (MDA8 from the previous day) in order to examine the role of ozone persistence. Additionally, we include harmonic functions that capture the effect of seasonality as in Rust et al. al (2009) and Otero et al. (2016), which is referred as “day” in the MLRs (see Table 2).

For this study, we divide the European domain into 10 regions: England (EN), Inflow (IN), Iberian Peninsula (IP), France (FR), Mid-Europe (ME), Scandinavia (SC), North Italy (NI), Mediterranean (MD), Balkans (BA) and Eastern Europe (EA). These regions are based on those defined in the recent ETC/ACM Technical Paper (Colette et al. 2017b). For our study, we further subdivide the original Mediterranean region (MD) into a region covering the Balkans (BA), due to the strong influence of the ozone persistence on MDA8 O3 over this particular region as noted previously in Otero et al. (2016). Figure 1 shows the spatial coverage of each region and Table 3 lists their coordinates. As shown Otero et al. (2016), the relative importance of predictors in the MLRs shows distinct seasonal patterns. Then, multiple linear regression models (MLR, hereafter) are developed for each region for two seasons: springtime (April-May-June, AMJ) and summertime (July-August-September, JAS). These seasons differ from the meteorological definition, but cover the period when surface ozone typically reaches its highest concentrations (i.e. April-September). Since the observations did not cover exactly the whole European domain as CTMs, we applied an observational-mask to use the same number of grid-cells for CTMs and observations. Data used to estimate parameters of the MLR were spatially averaged over each region. Thus, we compare MLRs developed separately for CTMs and observations at each region and season. The observational dataset contains the gridded MDA8O3 and the meteorology input from ERA-Interim, while the dataset for the CTMs contains the MDA8O3 from each one of them along with the corresponding meteorological input (e.g. LOTOS and RACMO2, CHIMERE and WRF) (see table 1).

A MLR is built to describe the relationship between MDA8 O3 (predictand) and a set of covariates (or predictors) describing seasonality, ozone persistence and the influence of meteorological fields (table 2). A data series $y_{t,}$ t= 1,..N (e.g. observations or CTM simulations) for a given region and season is conceived as a Gaussian random variable Y_t with varying mean μ_t and homogeneous variance σ^2. The mean μ_t is described as a linear function of the covariates, i.e.

$$Y_t \sim \mathcal{N}(\mu_t, \sigma^2),$$
$$\mu_t = \beta_0 + \beta_{sin} sin\left(\frac{2\pi}{365.25} d_t\right) + \beta_{cos} cos\left(\frac{2\pi}{365.25} d_t\right) + \beta_{lag} y_{t-1} + \sum_{K=1}^{K} \beta_k\, x_{t,k} \quad (1)$$

with t indexing daily values and d_t referring to the day in the year associated with the index t. β_0 is a constant offset, β_{sin} and β_{cos} are the first order coefficient of a Fourier series (e.g. Rust et al. 2009, 2013, Fischer et al. 2017), β_{lag} describes the persistence with respect to the previous day concentration y_{t-1}; if t is the first day in the late summer season (JAS, July 1^{st}), y_{t-1} is the concentration of June 30^{th}. Further regression coefficients β_k describe the linear relation to potential meteorological drivers (see table 2). For covariates standardized to unit variance, the regression coefficients (β) are standardised coefficients giving the change in the predictand with the covariate in units of covariate standard deviation.

Following the same strategy as used in Otero et al. (2016), the MLRs are developed through several common steps: 1) starting with the full set of potentially useful components in the predictor, a stepwise backward regression using the Akaike Information Criterion (AIC) as a selection criterion removes successively those components in the predictor, which contribute least to the model performance; and 2) a multi-collinearity index known as variance inflation factor (VIF, Maindonald and Braun 2006) is used to detect multi-collinearity problems in the predictor (i.e. high correlations between two or more components in the predictor). Components with a VIF above 10 are left out of the predictor (Kutner et al 2004).

The statistical performance of each MLR (built separately from observations and CTMs) is assessed through the adjusted coefficient (R^2) and the root mean square error (RMSE). The R^2 estimates the fraction of total variability described by the MLR and the RMSE gives the average deviation between model and observation obtained in the MLR. We also examine the relative importance of the individual components in the predictor. According to the method proposed by Lindeman et al (1980), the relative importance of each predictor is estimated by its contribution to the R^2 coefficient (Grömping 2007). We assess the sensitivities of ozone to the predictors through the standardised coefficients obtained from the regression. These coefficients indicate the changes in the ozone response to the changes in the predictors, in terms of standard deviation. Thus, for every standard deviation unit increase (decrease) of a specific predictor, the predictand (MDA8 O3) will increase (decrease) the amount indicated by its coefficient in standard deviation units,. The use of standardised coefficients allows us to establish a direct comparison in the influence of individual predictors. The effect of seasonality introduced by the harmonic functions (namely, "day", table 2) is kept in the MLRs (Eq. 1) for its usefulness in improving the power of the regression analysis, however further explanation about the effect of the predictors focuses on the rest of the variables.

4. **Results and discussion**

4.1. CTM performance by region

We compare the seasonal cycle of observations and CTMs through the time series of daily averaged values of MDAO8 O3 from observations and CTMs for the whole period (i.e. April-September, 2000-2010) spatially averaged over each region. Furthermore, correlation coefficients between both CTMs and observations at each region and season are used to quantify the CTM performance.

4.1.1. Seasonal cycle of MDA8 O3

We examine the ozone seasonal cycle represented by both the observational and modelled dataset. Figure 2 depicts daily averages during 2000-2010 of MDA8 O3 at each region for the CTMs and observations. In general, all CTMs are biased high compared with observations. CTM results are visually closer to observations in the northwestern regions (i.e. IN, EN and FR), while the spread becomes larger over the southern and southeastern regions (i.e. BA, NI, MD). The IN, EN and SC regions show the highest observed concentrations in the starting months (AMJ), which is not generally well captured by most of the CTMs, and they show a more flat timeline (e.g. LOTOS, MATCH, CHIMERE or WRF-Chem). For example, in the SC region, some of the CTMs underestimate the ozone concentrations in AMJ (i.e. WRF-Chem, CHIMERE and MINNI). The rest of the regions show the highest observed concentrations in JAS, which is generally overestimated by the CTMs. Models show discrepancies when compared to each other and to observations, and in some regions we find substantial differences. Larger discrepancies are found in the southern regions, such as IP, MD and BA, where the models show a considerable spread. There, the CTMs are not able to capture the variability of MDA8 O3 and they exhibit a different behaviour when compared to each other. For instance, the EMEP model shows a peak of ozone levels in April, while CHIMERE and MINNI show a peak in July. Overall LOTOS shows a relatively constant positive bias in all regions, more evident in the MD and NI regions. WRF-Chem tends to underestimate the ozone concentrations at the start of the seasonal period in some regions (e.g. SC, ME, EN, or EA).

CTM assessments have been presented in early EURODELTA exercises, although with a different set up for different purposes, which makes it difficult to establish a direct comparison on the performance of the models. For instance, Colette et al. (2017b) reported systematic differences among some models (i.e. CHIMERE, EMEP and LOTOS) when examining the long-term mean ozone concentration during the whole period of 1990-2010. Bessagnet et al. (2016) showed that most of the models in their study, (e.g. CHIMERE, LOTOS, or MINNI among others) overestimated the ozone concentrations in the selected study period. Specifically, they found a larger spread during nighttime than daytime, which was suggested to be related to the vertical mixing, given that most of the models shared the same meteorology but different vertical resolution and boundary conditions.

4.1.2. Correlation coefficients between modelled and observed time series

The correlation coefficients between the observed and modelled values of MDA8 O3 at each region and in each season are shown in Fig. 3. Overall, MDA8 O3 from the CTMs is better correlated with observations in JAS than in AMJ in the regions ME, NI, EA and EN. As expected from inspection of the average time series (Fig. 2), the lowest correlations between models and observations are found in BA, especially in AMJ for all models. In particular, EMEP is negatively correlated with observations over this region. As mentioned above, the larger discrepancies between CTMs and observations found over BA might be attributed to a low density of observation sites from which the interpolated dataset is derived, resulting in a lower quality or higher uncertainties of such product (Schnell et al. 2014). The highest correlations in AMJ are obtained at the following regions: ME; FR; NI; and EN for most of the models, except for EMEP for which the highest correlation with observations was found in IN and SC. The WRF-Chem model also shows a different behaviour in terms of the correlation coefficient with higher values in NI, MD and IP, and very low and negative correlations (-0.02) in SC. In general, the models that are most closely correlated with observations are MATCH, MINNI and CHIMERE, while LOTOS and WRF-Chem show the lowest correlations. In the case of LOTOS, it could be partially due to the use of a different set-up of the RACMO2 model, without nudging towards ERA-Interim (section 2.2). These correlations reflect the patterns represented by the seasonal cycle described above.

4.2. MLR performance

Figures 4 and 5 depict the statistical performance of each MLR in terms of R^2 and RMSE (respectively) at the different regions for both seasons, AMJ and JAS. The R^2 values indicate that all MLRs models (based on both observations and CTMs) are able to explain more than 60% of the MDA8 O3 variance in all regions. Overall, the MLRs show a stronger fit in JAS than in AMJ in most of the regions, with the exception of SC and IN that, in general show lower values of R^2 in JAS than in AMJ (Fig. 4). The MLRs appear to perform better in certain regions such as NI, ME, FR or EA, while the poorest statistical performance is found in IN and EN. The results obtained from the CTM-based MLRs show a similar performance to the observation-based MLRs in most of the regions. The lowest RMSE values for most of the MLR are found in SC ranging between 1 and 3 ppb, while EN shows the largest RMSE values, especially for the MLR built from WRF-Chem (Fig. 5). The MLRs from MATCH and CHIMERE show the lowest RMSE values (1-3ppb) suggesting the best statistical fit from a predictive point of view.

Both R^2 and RMSE metrics indicate that the statistical performance of MLRs for observations and CTMs show distinct variations between seasons and regions. Overall, better performances are found in JAS and in some regions (i.e. ME, NI, or FR) where MLRs are able to describe more than the 80% of the variance in CTMs and observations. This could be attributed to the major role of meteorology in summer influencing local photochemistry processes of ozone production, while in spring long range transport plays a stronger role (Monks, 2000, Tarasova et al. 2007). As it includes the bias, the RMSE reveals more differences among the MLRs when compared to each other (e.g. larger errors for WRF-Chem or LOTOS when compared to MATCH or CHIMERE). However, it is interesting that in general all MLRs show a similar tendency when evaluating the statistical performance, which indicate that observations-based and CTMs-based MLRs present a similar statistical performance for modelling MDA8 O3. The ability of the CTMs to reproduce the influence of meteorological drivers on MDA8 O3 is discussed in more detail below.

4.3. Effects of drivers of ozone concentrations

The analysis of the influence of the predictors in the MLRs reveals distinctive regional patterns in both observation-based and CTM-based MLRs. In agreement with Otero et al. (2016), here we also find that the regions geographically located towards the interior (including central, western and eastern regions) appear to be more sensitive to the meteorological predictors, especially in JAS. On the contrary, a minor meteorological contribution is found in the regions over the northernmost and southernmost edges, implying that non-local processes play a stronger role. Considering such similarities, in the following, the regions: EN, FR, ME, NI and EA are referred as the internal regions, while the rest of the regions: IN, SC, IP, MD and BA, are referred as the external regions (see Fig. 1).

4.3.1 Relative importance

Figure 6 depicts the relative importance of the predictors for the observation-based and CTM-based MLRs in the internal regions (Fig. 1). Here, a larger meteorological influence (i.e., the predictors other than LO3 and day) can be seen in JAS compared to AMJ in all of these regions. In general, the dominant meteorological drivers from the observation-based MLRs in these internal regions are RH and Tx. The contribution of RH is evident in AMJ (e.g. ME, or EA), while Tx is clearly dominant in JAS. SSRD is also a key driver of MDA8 O3 and generally, the wind factors (W10m and Wdir) appear to have a minor contribution.

Despite the CTM-based MLRs being able to capture the meteorological predictors, we observe discrepancies among the internal regions when compared to the observation-based MLR. The inter-model differences in terms of the relative importance of predictors are greater in AMJ than in JAS. For instance, the contribution of the LO3 is overestimated by most of CTMs, specifically WRF-Chem that shows a larger sensitivity to LO3 in both seasons over all of these regions. Similarly, EMEP also shows a larger contribution of LO3 than the rest of the CTMs, particularly in AMJ. Substantial differences are found in the influence of RH when comparing the observation-based and the CTMs-based models. The CTMs do not capture the relative importance of the RH well, especially in AMJ. In general, the CTMs driven by WRF meteorology show a slightly larger contribution of RH in most of the cases, although we notice that there are also some differences among the models that share the same meteorology. CTMs do capture the relative importance of Tx in all regions, but overall they overestimate it, as they also show for SSRD. Here, we find discrepancies when comparing the contribution of predictors in the statistical models from CTMs driven by the same meteorology (e.g. EMEP and WRF-Chem when compared to CHIMERE and MINNI). The largest differences among the CTMs are found for WRF-Chem, which tends to underestimate the contribution of the meteorological drivers in most of the regions. Interestingly, as mentions in Section 2, this is the only online coupled model participating in EDT.

Figure 7 presents the relative importance of individual predictors in the MLRs developed at the external regions (Fig. 1) for both seasons. The observation-based MLRs show that the main driving factor is LO3 in AMJ, while the effect of meteorological drivers becomes stronger in JAS. RH presents a larger contribution in some regions (e.g. IN, IP or SC) in AMJ and Tx in JAS (e.g. IN, IP, SC and BA). The contribution of wind components, Wdir and W10m, is mainly reflected in both seasons in the western regions (i.e. IN and IP) and in MD, respectively.

Overall, all CTMs show this tendency, although there are substantial differences when comparing the individual drivers' contribution in the observation-based and CTM-based MLRs, particularly in AMJ (Fig. 7). CTMs do not capture the contribution of LO3 reflected by the observation-based MLRs. As in the previous analysis (section 4.1) the largest discrepancies are found in BA, where observation-based MLR shows that most of the variability of ozone would be explained by LO3. On the contrary the CTM-based MLRs underestimate the contribution of LO3 and overestimate the meteorological effect in terms of larger contribution of Tx, SSRD and RH (e.g. LOTOS, CHIMERE and MINNI). The contribution of RH is underestimated by the CTMs in most of the regions, (except in BA). On the contrary, the relative importance of SSRD is overestimated in some regions (e.g. IP, IN or MD) and Tx (IN, SC), in particular for the CTMs driven by WRF. Overall, CTMs show the observed contribution of W10m and Wdir in both seasons, although with some inconsistences among the regions and CTMs.

Our results indicate that the relative importance of meteorological factors is stronger in the internal regions (Fig.6) than in the external regions (Fig.7), which could be partially attributed to a larger variability of most of the meteorological fields in internal regions (Fig. S1). The external regions are also more likely to be influenced by the lateral boundary conditions applied by each CTM. In addition, in some external regions (e.g. IP or MD), as mentioned in section 2, the use of a coarser grid in some regions might be insufficient to capture mesoscale processes, such as land-sea breezes, which also control MDA8 O3 concentrations (Millán et al. 2002). Moreover, we observe that meteorology becomes more important in summer, when local photochemistry processes are dominant. In general, CTMs show this tendency, but limitations to reproduce the effect of some meteorological drivers are found. Specifically, while CTMs tend to overestimate the contribution of Tx, and SSRD, they underestimate the relative importance of RH, which is also reflected in the correlations coefficients between predictand the predictors (Figs. S2, S3).

4.3.2 Sensitivity of ozone to the drivers

We assess the sensitivities of MDA8 O3 to the drivers through their standardised coefficients obtained in the MLR (Section 3). These coefficients provide further information about the changes of MDA8 O3 due to effect of each driver. Figures 8 and 9 depict the values of the main driving factors obtained in the MLR for the internal and the external regions (respectively): LO3, Tx and RH. Similarly to those patterns described by the relative importance of drivers, we observe that the ozone response to LO3 is stronger in AMJ than in JAS: the corresponding standardised coefficients are always positive and generally higher in AMJ. The observed sensitivities to LO3 are smaller in the internal regions (Fig. 8), being particularly dominant in the external regions (Fig. 9). Overall, most of the CTMs reflect a similar tendency. However, there are evident differences among observations and CTMs when comparing the values of the standardised coefficients, specifically in some regions such as BA or MD. When comparing the ozone responses of the CTMs to LO3, we observe that in most of the regions MATCH and MINNI show values closest to observations, while WRF-Chem shows a large sensitivity to LO3.

Correlations between MDA8 O3 and Tx are strong, especially in the internal regions in JAS (Fig. S2). Overall, we show that the CTMs appear to capture the observed effect of Tx better in JAS than in AMJ in most of the regions. The highest sensitivities to Tx are found in some internal regions such as ME, NI, FR and EN, which is also shown in the CTMs. However, we see that most of the CTMs tend to overestimate the effect of Tx. Moreover, distinct sensitivities to Tx are shown by models that share the same meteorology (i.e. CHIMERE, EMEP, MINNI and WRF-Chem). In particular, the MINNI and CHIMERE models show higher Tx sensitivities when compared to the rest of the CTMs. While MINNI model presents the highest sensitivities to Tx in spring, specifically in EN and FR, EMEP shows smaller values and it underestimates the correlations between Tx and MDA8 O3 (Figs. S2, S3).

The slope of the ozone-temperature relationship ($m_{O3\text{-}T}$) has been used in several studies to assess the ozone climate penalty (eg. Bloomer et al., 2009, Steiner et al., 2010, Rasmussen et al., 2012, Brown-Steiner et al. 2015) in the context of future air quality. Thus, we additionally analyse the relationship ozone-temperature in order to provide insight into the ability of CTMs to reproduce the observed $m_{O3\text{-}T}$. Similarly as in previous work (Brown-Steiner et al. 2015), the slopes are obtained from a simple linear regression using only Tx (without the influence from other predictors) and they are used to quantify such relationship in both seasons, AMJ and JAS.

Figures 10 and 11 illustrate the $m_{O3\text{-}T}$ for the internal and the external regions respectively. The observed $m_{O3\text{-}T}$ is larger in JAS than in AMJ. In AMJ, it ranges between -0.45 and 1.15 ppbK^{-1} with the largest values found in ME, NI and MD. In JAS, the observed climate penalty is of the order of 1-2.7 ppbK^{-1} with the largest values in EN, FR, ME, NI, and MD. CTMs show a better agreement with observations in JAS than in AMJ. CTMs tend to overestimate the climate penalty in AMJ in most of the regions, with some exceptions, such as EMEP and MATCH that systematically underestimate the slopes. Also, CTMs are generally better in simulating the observed $m_{O3\text{-}T}$ in the internal regions compared to the $m_{O3\text{-}T}$ in the external regions, where in general CTMs appear to overestimate the climate penalty in both seasons. Using this metric, we identify some regions particularly sensitive to temperature, with larger values of $m_{O3\text{-}T}$ (e.g. EN, ME, FR, NI or MD). Through a multi-model assessment, Colette et al. (2015) showed a significant summertime climate penalty in southern, western and central European regions (e.g. EA, IP, FR, ME or MD) in the majority of the future climate scenarios used. Our study shows that most of the CTMs confirm the observed climate penalty in JAS in such regions in the near present, although we found that most of the CTMs overestimate the climate penalty in AMJ, especially in the external regions.

We see a stronger effect of RH in AMJ than in JAS in the observations compared with the CTMs (Figs. 8 and 9), with the greatest impact in the internal regions (e.g. EA, ME, NI, FR and EN). The CTMs show this tendency slightly in some regions (e.g. ME, FR or EN), but differences become evident when compared to the observed values and overall they underestimate the effect of RH. As mentioned, CTMs underestimate the strength of the relationship between ozone-RH (Figs. S2, S3). This general lack of sensitivity to RH could also partially explain the tendency for all CTMs to show a high bias in simulated ozone compared with observations (Fig. 2). Among the possible reasons for this inconsistency, we hypothesize that it can be related to the fact that ozone removal processes can be associated to higher relative humidity levels during thunderstorm activity on hot moist days, which might not be well captured by CTMs. Furthermore, the documented impacts of ozone dry deposition suggest that it may also play a role in explaining the problems that CTMs show to reproduce the observed relationship ozone-relative humidity.

High SSRD levels favour photochemical ozone formation and it is usually positively correlated to ozone. In this case, CTMs also present some limitations to capture this effect and they overestimated the sensitivities of ozone to SSRD (Figs. S4, S5). For example, the observations show lower and surprisingly negative effect of SSRD. Although the correlations between SSRD and ozone are positive (see Fig. S2, S3), the presence of other predictors in the regression may reverse the sign of the estimated coefficient. The CTMs show a stronger sensitivity of ozone to SSRD and they overestimate its influence on surface ozone. Similarly, the sensitivities to Wdir and W10m are also overestimated by the CTMs, especially in AMJ (Figs. S4, S5).

Our analysis suggests that CTMs present more limitations to reproduce the influence of meteorological drivers to MDA8 O3 concentrations in the external regions than in the internal regions, particularly in AMJ. Moreover, we find the largest discrepancies in BA, where models show the poorest seasonal performance and correlation coefficients (Figs. 2 and 3, respectively), probably due a low quality of the observational dataset.

Furthermore, LO3 is the main driver over most of the external regions and explains a large proportion to the total variability of MDA8 O3, while meteorological factors play a smaller influence. Lemaire et al. (2016) found a very low performance (based on R^2) over the British Isles, Scandinavia and the Mediterranean using a different statistical approach that only included two meteorological drivers. They attributed this low skill to the large influence over those regions of long-range transport of air pollution (Lemaire et al. 2016). Our results confirm the small influence of the meteorological drivers over those regions and the strong influence of the ozone persistence. Moreover, in the case of the external regions of northern Europe, it could also be explained due to the dominance of transport processes such as the stratospheric-tropospheric exchange or long-range transport from the European continent, rather than local meteorology, particularly in AMJ (Monks, 2000, Tang et al. 2009, Andersson et al. 2009).

Previous work pointed out that local sources of NOx and biogenic VOC (ozone precursors) are important factors of summertime ozone pollution in the Mediterranean basin (Richards et al. 2013). Moreover, some studies suggested that the local vertical recirculation and accumulation of pollutants play an important role in ozone pollution episodes in this region: during the nighttime the air masses are held offshore by land-sea breeze, creating reservoirs of pollutants that are brought the following day (Millán et al. 20002, Jiménez et al. 2006, Querol et al. 2017). All of these factors (e.g. local emissions as well as local and large-scale processes) control the ozone variability, which might explain the smaller influence of local meteorological factors shown in this study over the Mediterranean basin when compared to meteorological influence in the internal regions. Thus, we may hypothesize that the strong impact of LO3 observed in the external regions over southern Europe (i.e. IP, MD, BA) could be partially due to the role of vertical accumulation and recirculation of air masses along the Mediterranean coasts as a result of the mesoscale phenomena, which is enhanced by the complex terrains that surround the Basin. Other important factor for the strong impact of LO3 observed is the slow dry deposition of ozone on water that would favour the ozone persistence in southern Europe.

Overall we conclude that CTMs capture the effect of meteorological drivers better in the internal regions (EN, FR, ME, NI and EA), where the influence of local meteorological conditions is stronger. The major effect of meteorological parameters found in the internal European regions might be also attributed to the fact that overall the variability of meteorological conditions is larger in those regions (Fig. S1). We also find differences among the CTMs driven by the same meteorology. As mentioned in the introduction, Bessagnet el al. (2016) suggested that the spread in the model results could partly explained by the differences in the vertical diffusion coefficient and the planetary boundary layer, differently diagnosed in each of the CTMs. Our results also indicate that even though models share the same meteorology (considering the prescribed requirements defined by the EDT exercise) they show discrepancies when compared to each other, which could be attributed other sources of uncertainties (such as physical and chemical internal process in the CTMs). The NMVOC and NO_x emissions from the biosphere are critical in the ozone formation. Since biogenic emissions were not specifically prescribed, which have a strong dependence on temperature and solar radiation, discrepancies in the CTMs performances, (e.g. different sensitivities to Tx) might be expected. Furthermore, we notice that the CTMs do not reproduce consistently the regional ozone-temperature relationship, which is a key factor when assessing the impacts of climate change on future air quality.

5. Summary and conclusions

The present study evaluates the capability of a set of Chemical Transport Models (CTMs) to represent the regional relationship between daily maximum 8-hour average ozone (MDA8 O3) and meteorology over Europe. Our results show systematic differences between the CTMs in reproducing the seasonal cycle when compared to observations. In general, they tend to overestimate the MDA8 O3 in most of the regions. In the western and northern regions (i.e. Inflow, England and Scandinavia), some models did not capture the high ozone levels in spring (e.g. CHIMERE, MINNI and WRF-Chem), while in other southern regions (e.g. Iberian Peninsula, Mediterranean and Balkans) they overestimated the ozone levels in summer (e.g. LOTOS, CHIMERE). Of the CTMs, MATCH and MINNI were the most successful in capturing the observed seasonal cycle of ozone in most regions. All CTMs revealed limitations to reproduce the variability of ozone over the Balkans region, with a general overestimation of the ozone concentrations, considerably larger during the warmer months (July, August). As reflected in the results, a limitation of the interpolated observational product used here is that in some regions (e.g. southern Europe) it has a lower quality due to a reduced number of stations (section 2.1).

The MLRs performed similarly for most of the CTMs and observations, describing more than 60 % of the total variance of MDA8 O3. Overall, the MLRs perform better in JAS than in AMJ, and the highest percentages of described variance were found in Mid Europe and North Italy. This could be attributed to local photochemical processes being more important in JAS, and is consistent with a stronger influence of long-range transport in AMJ.

The effects of predictors revealed spatial and seasonal patterns, in terms of their relative importance in the MLRs. Particularly, we noticed a larger local meteorological influence in the regions located towards the interior, here termed as the internal regions (i.e. England, France, Mid-Europe, North Italy and East-Europe). A minor local meteorological contribution was found in the rest of the regions, referred as the external regions (i.e. Inflow, Iberian Peninsula, Scandinavia, Mediterranean and Balkans). The CTMs are in better agreement with the observations in the internal regions than in the external regions, where they were not as successful in reproducing the effects of the ozone drivers. Overall, the different behaviour in the MLRs developed in the external regions could be attributed to (i) a larger influence of dynamical processes rather than local meteorological processes (e.g. long range transport in the northern regions) (ii) a stronger impact of the boundary conditions (iii) the use of a coarser grid that might be insufficient to capture mesoscale processes that also influence MDA8 O3 (e.g. sea-land breezes in the southern regions).

We found substantial differences in the sensitivities of MDA8 O3 to the different meteorological factors among the CTMs, even when they used the same meteorology. As Bessagnet et al. (2016) point out, the differences amongst CTMs could be partly attributed to some other diagnosed model variables (e.g. vertical diffusion coefficient and boundary layer height, as well as vertical model resolution). To assess the effect of such potential sources of uncertainties, further investigations would be required. Moreover, variations in the sensitivity of ozone to meteorological parameters could depend on differences in the chemical and photolysis mechanisms and the implementation of various physics schemes, all of which differ between the CTMs (see Colette et al. 2017a). Specifically, the discrepancies found in the sensitivities of MDA8 O3 to maximum temperature might be also attributed to biogenic emissions not prescribed in the models. This was particularly reflected in the analysis of the slopes ozone-temperature ($m_{O3\text{-}T}$) to assess the climate penalty, which differed between CTMs and regions when compared to the observations in both seasons. Most of the CTMs confirm the observed climate penalty in JAS, but with larger discrepancies in the external regions than in the internal regions. Furthermore, CTMs tend to overestimate the climate penalty in AMJ (particularly in the external regions).

Our results have shown that CTMs tend to overestimate the influence of maximum temperature and surface solar radiation in most of the regions, both strongly associated with ozone production. None of the CTMs captured the strength of the observed relationship between ozone and relative humidity appropriately, underestimating the effect of relative humidity, a key factor in the ozone removal processes. We speculate that ozone dry deposition schemes used by the CTMs in this study may not adequately represent the relationship between humidity and stomatal conductance, thus underestimating the ozone sink due to stomatal uptake. Further sensitivity analyses would be recommended for testing the impact of the current dry deposition schemes in the CTMs.

Data availability

The data are available upon request from the corresponding author.

Acknowledgments

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List of Tables:

CTM	Meteorology	Coupling
LOTOS-EUROS	RACMO2	Off-line
MATCH	HIRLAM	Off-line
EMEP	WRF	Off-line
CHIMERE		Off-line
MINNI		Off-line
WRF-Chem		On-line

Table 1. List of the chemistry-transport models used in the study, their corresponding meteorological driver and chemistry/meteorology coupling.

Predictor	Definition
LO3	Lag of O3 (24 h)
Tx	Maximum temperature
RH	Relative humidity
SSRD	Surface solar radiation
Wdir	Wind direction
W10m	Wind speed
day	$\sin(2\pi d_t/365.25)$, $\cos(2\pi d_t/365.25)$

Table 2. List of the predictors used in the multiple linear regression analysis: meteorological parameters, lag of O3 (24h, previous day) and the seasonal cycle components.

Region	Acronym	Coordinates (longitude, latitude)
England	EN	5W-2E, 50N-55N
Inflow	IN	10W-5W, 50N-60N, and 5W-2E, 55N-60N
Iberian Peninsula	IP	10W-3E, 36N-44N
France	FR	5W-5E, 44N-50N
Mid-Europe	ME	2E-16E, 48N-55N
Scandinavia	SC	5E-16E, 55N-70N
North Italy	NI	5E-16E, 44N-48N
Balkans	BA	18E-28E, 38N-44N
Mediterranean	MD	3E-18E, 36N-44N
Eastern Europe	EA	16E-30E, 44N-55N

Table 3. List of the regions with the short name and the coordinates.

Atmos. Chem. Phys. Discuss., https://doi.org/10.5194/acp-2017-787
Manuscript under review for journal Atmos. Chem. Phys.
Discussion started: 19 April 2018

List of Figures:

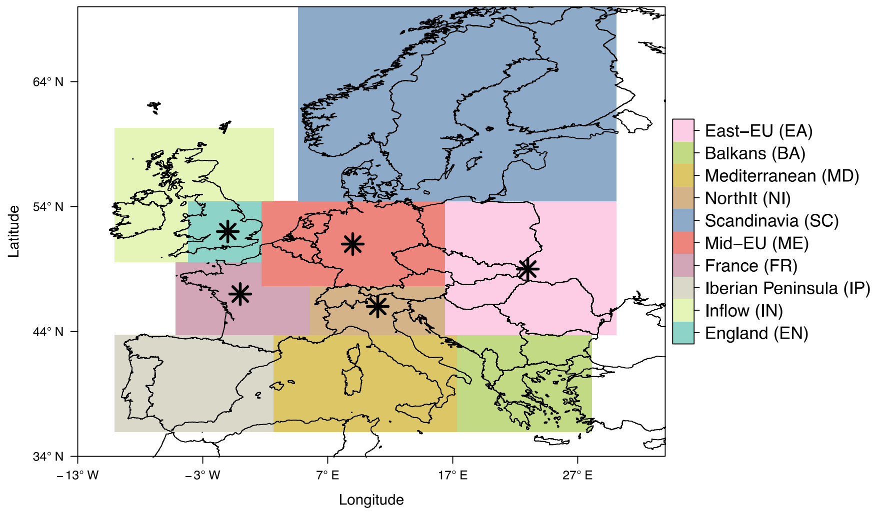

Figure 1. Map of the regions considered in the study. Regions indicated with a black star are referred to the internal regions in the text. The rest of regions are referred to the external regions of the European domain.

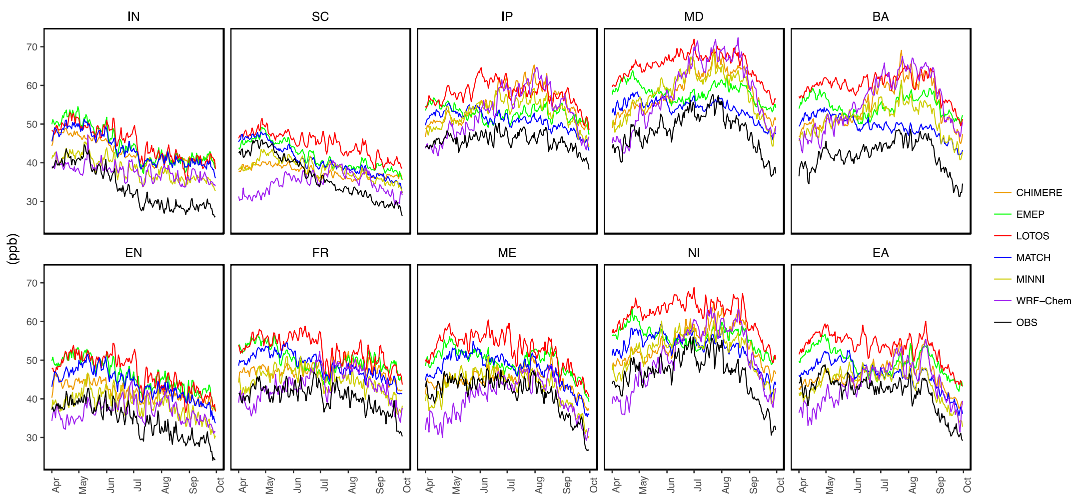

Figure 2. Time series of daily averages of MDA8 O3 during the ozone season (April-September) for the period of study (2000-2010) at each subregion.

Atmos. Chem. Phys. Discuss., https://doi.org/10.5194/acp-2017-787
Manuscript under review for journal Atmos. Chem. Phys.
Discussion started: 19 April 2018

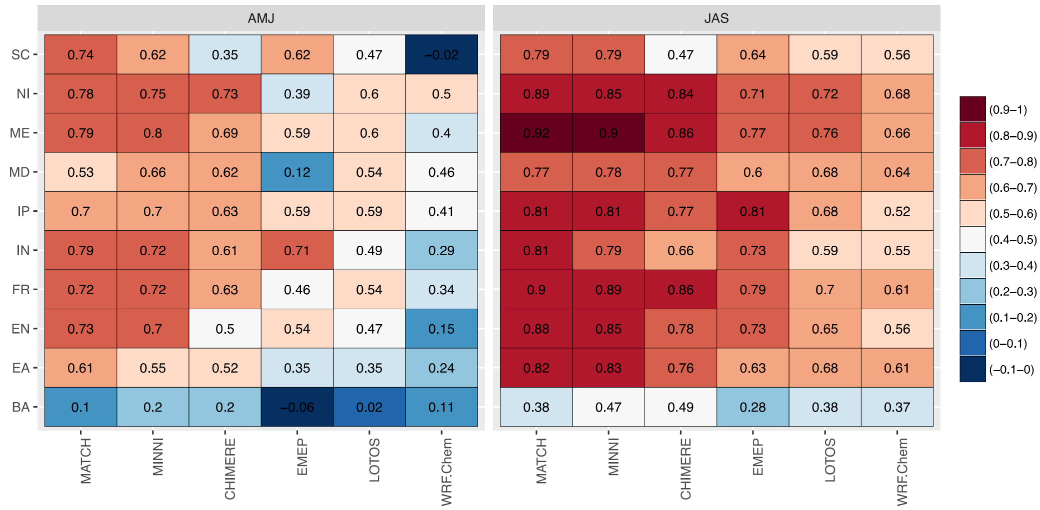

Figure 3. Correlation coefficients between observed and modelled MDA8 O3 for spring (AMJ) and summer (JAS) for the period of study (2000-2010) at each region (rows) and models (columns, ordered by highest correlation values).

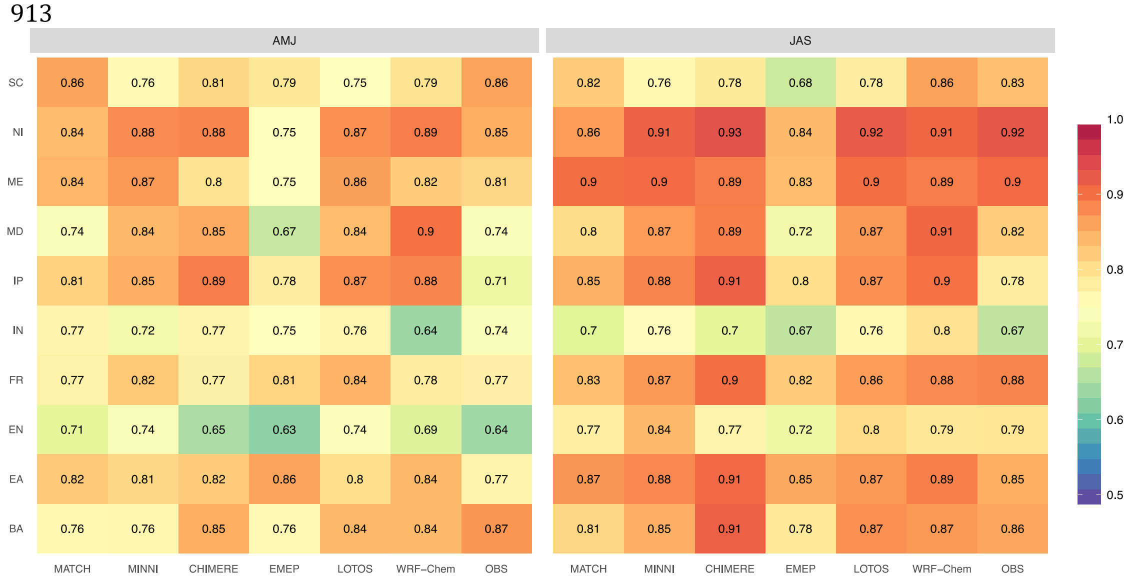

Figure 4. Coefficients of determination (R^2) for each CTM-based (ordered as in Fig.3) and observation-based MLR in spring (AMJ) and summer (JAS).

Atmos. Chem. Phys. Discuss., https://doi.org/10.5194/acp-2017-787
Manuscript under review for journal Atmos. Chem. Phys.
Discussion started: 19 April 2018

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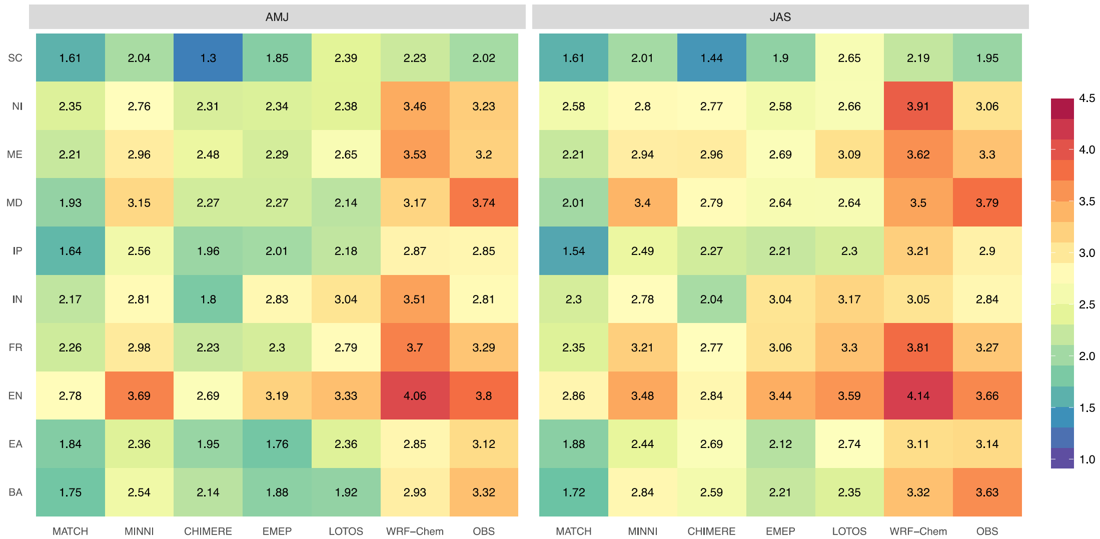

Figure 5. Root mean square errors (RMSE) for each CTM-based (ordered as in Fig.3) and observation-based MLR at each region, in spring (AMJ) and summer (JAS).

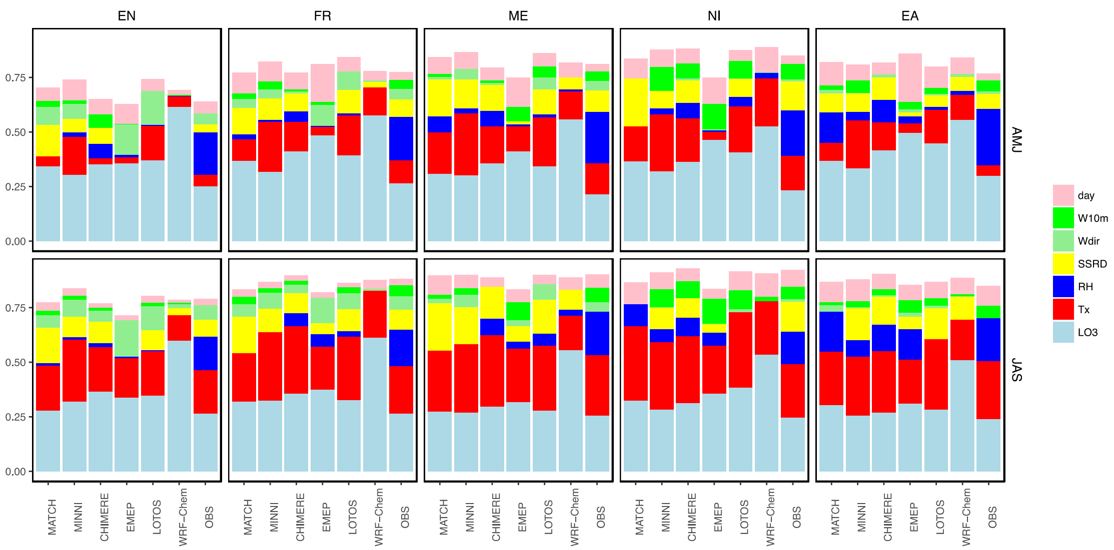

Figure 6. Proportion of each predictor to the total explained variance for each CTM-based (ordered as in Fig.3) and observation-based MLR in AMJ (top) and JAS (bottom) for the internal regions: England (EN), France (FR), Mid-Europe (ME), North Italy (NI) and East-Europe (EA).

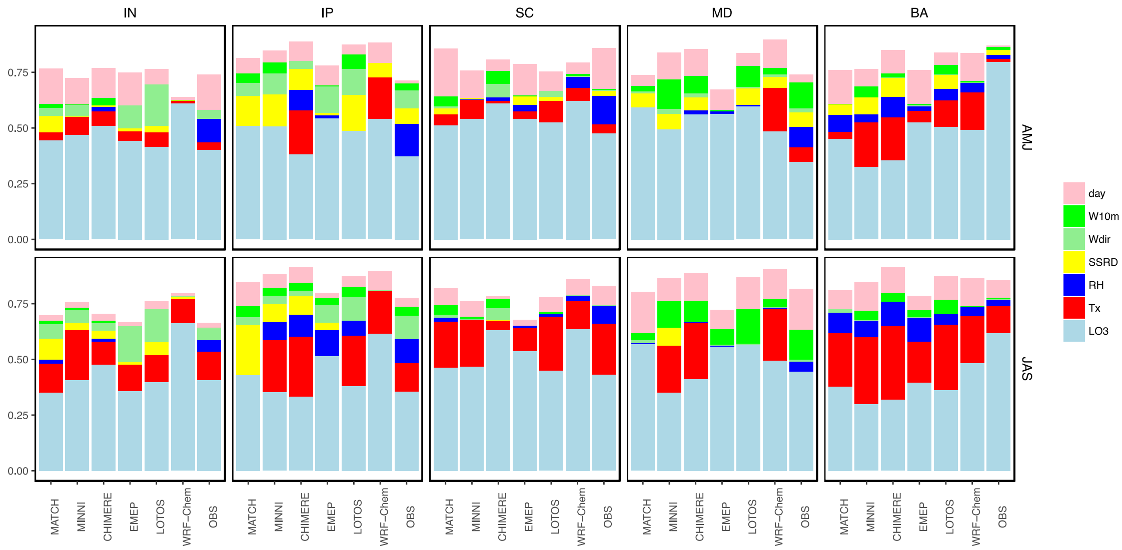

Figure 7. Proportion of each predictor to the total explained variance for each CTM-based (ordered as in Fig.3) and observation-based MLR in AMJ (top) and JAS (bottom) for the external regions: Inflow (IN), Iberian Peninsula (IP), Scandinavia (SC), Mediterranean (ME) and Balkans (BA).

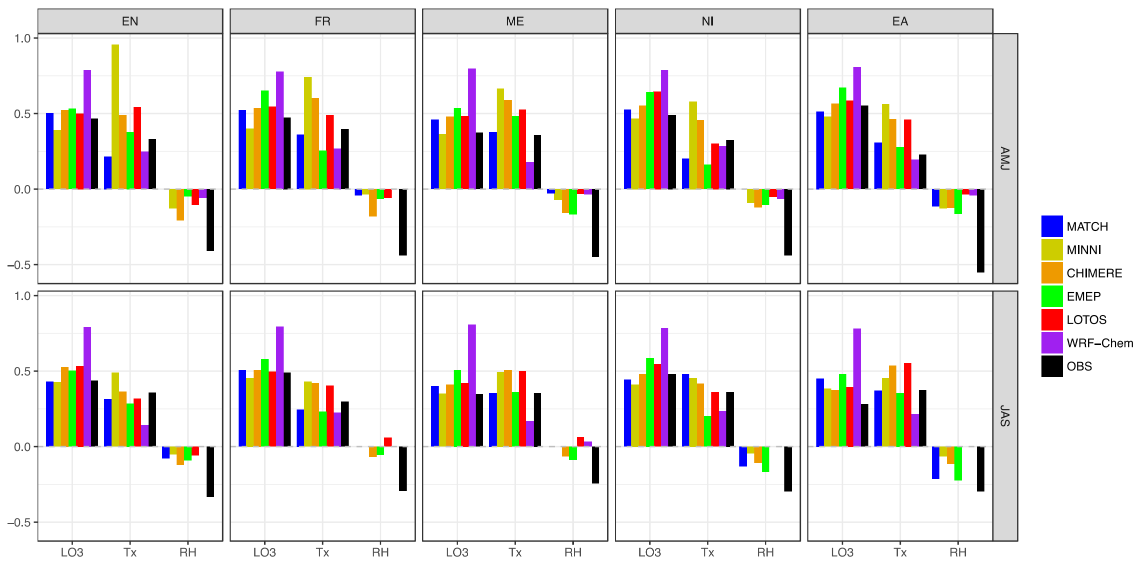

Figure 8. Standardised coefficients values of the main key-driving factors (LO3, Tx and RH) for each CTM-based (ordered as in Fig.3) and observation-based MLR in AMJ (top) and JAS (bottom) and for the internal regions: England (EN), France (FR), Mid-Europe (ME), North Italy (NI) and East-Europe (EA).

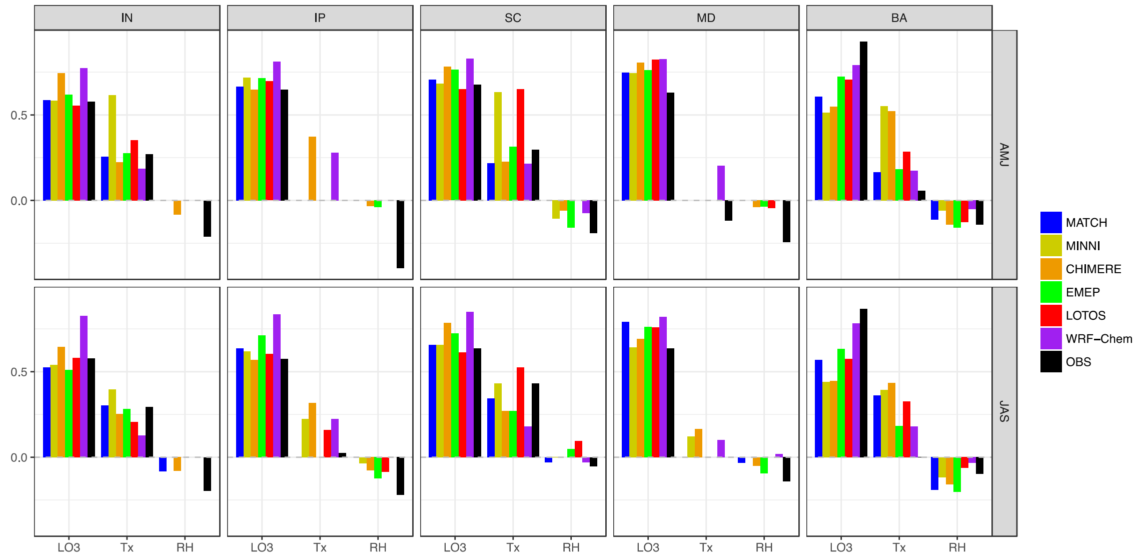

Figure 9. Standardised coefficients values of the main key-driving factors (LO3, Tx and RH) for each CTM-based (ordered as in Fig.3) and observation-based MLR in AMJ (top) and JAS (bottom) and for the external regions: Inflow (IN), Iberian Peninsula (IP), Scandinavia (SC), Mediterranean (ME) and Balkans (BA).

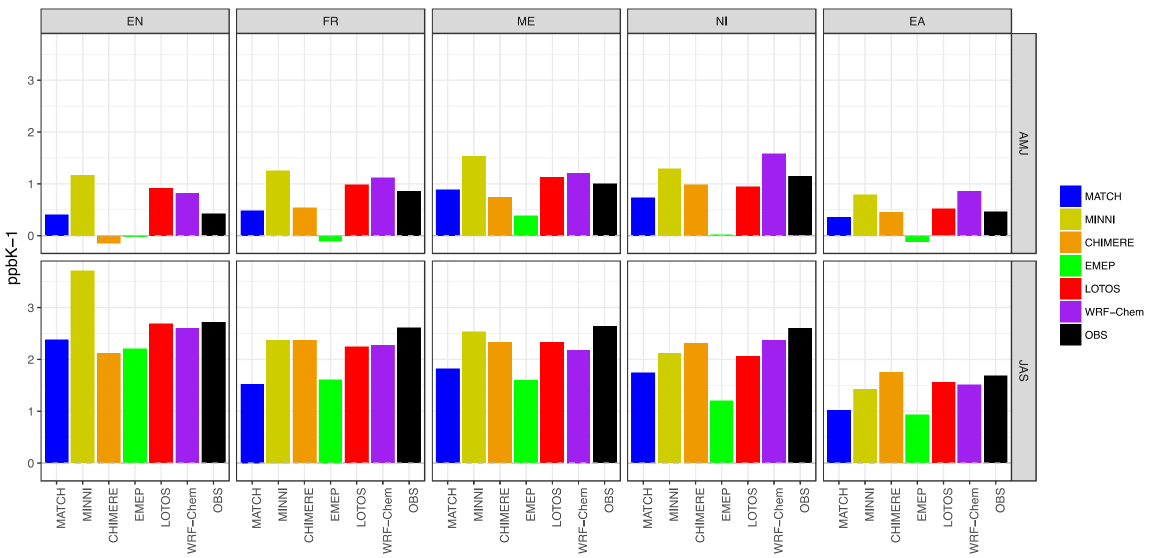

Figure 10. Slopes (m_{O3-T}; $ppbK^{-1}$) obtained from a simple linear regression to estimate the relationship ozone-temperature for each CTM-based (ordered as in Fig.3) and observation-based MLR in AMJ (top) and JAS (bottom) and for the internal regions: England (EN), France (FR), Mid-EU (ME), North Italy (NI), East-EU (EA).

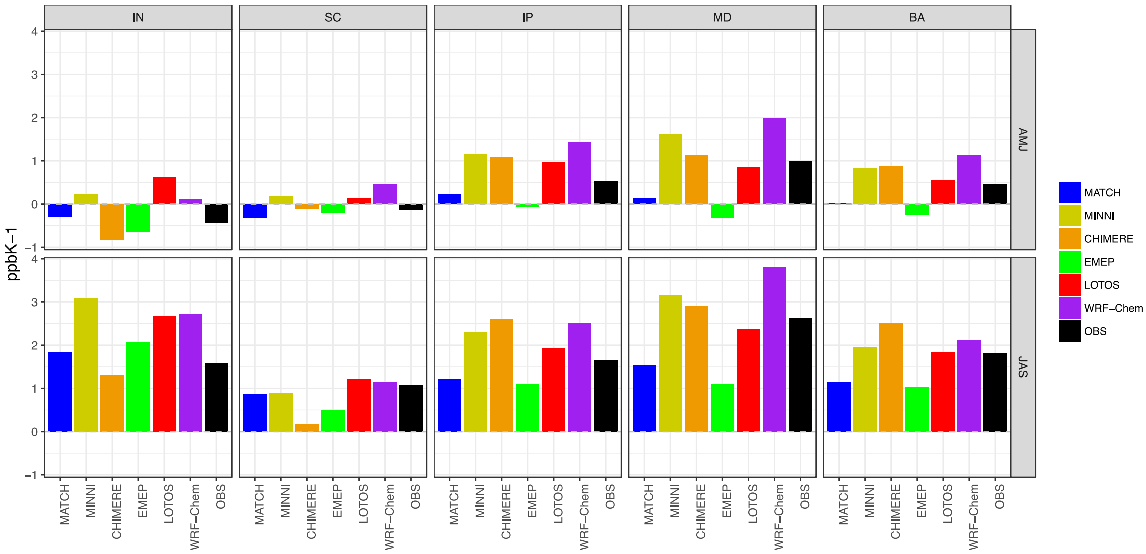

Figure 11. Slopes (m_{O3-T}; $ppbK^{-1}$) obtained from a simple linear regression to estimate the relationship ozone-temperature for each CTM-based (ordered as in Fig.3) and observation-based MLR in AMJ (top) and JAS (bottom) and for the external regions: Inflow (IN), Iberian Peninsula (IP), Scandinavia (SC), Mediterranean (ME) and Balkans (BA).

Atmos. Chem. Phys. Discuss., https://doi.org/10.5194/acp-2017-787
Manuscript under review for journal Atmos. Chem. Phys.
Discussion started: 19 April 2018

Atmospheric Chemistry and Physics Discussions

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