



Ozone modelling and mapping for risk assessment: An overview of different approaches for human and ecosystems health

Alessandra De Marco^{a,*}, Hector Garcia-Gomez^b, Alessio Collalti^c, Yusef Omid Khaniabadi^d, Zhaozhong Feng^e, Chiara Proietti^f, Pierre Sicard^g, Marcello Vitale^h, Alessandro Anav^a, Elena Paolettiⁱ

^a ENEA, CR Casaccia, Via Anguillarese, Rome, Italy

^b CIEMAT, Avda. Complutense, 40, Madrid, Spain

^c Forest Modelling Lab., ISAFOM-CNR, Via Madonna Alta, Perugia, Italy

^d Department of Environmental Health Engineering, Industrial Medical and Health, Petroleum Industry Health Organization (PIHO), Ahvaz, Iran

^e Key Laboratory of Agro-meteorology of Jiangsu Province, School of Applied Meteorology, Nanjing University of Information Science & Technology, Nanjing, 210044, China

^f ISPRA/BIENTE, Via Vitaliano Brancati, Rome, Italy

^g ARGANS, Route Du Pin Montard, Biot, France

^h Sapienza University of Rome, Piazzale Aldo Moro, Rome, Italy

ⁱ IRET-CNR, Via Madonna Del Piano, Sesto Fiorentino, Florence, Italy

ARTICLE INFO

Keywords:

Tropospheric ozone
Modelling and mapping
Chemical transport model
Geostatistics
Ensemble models

ABSTRACT

Tropospheric ozone (O_3) is one of the most concerned air pollutants due to its widespread impacts on land vegetated ecosystems and human health. Ozone is also the third greenhouse gas for radiative forcing. Consequently, it should be carefully and continuously monitored to estimate its potential adverse impacts especially in those regions where concentrations are high. Continuous large-scale O_3 concentrations measurement is crucial but may be unfeasible because of economic and practical limitations; therefore, quantifying the real impact of O_3 over large areas is currently an open challenge. Thus, one of the final objectives of O_3 modelling is to reproduce maps of continuous concentrations (both spatially and temporally) and risk assessment for human and ecosystem health. We here reviewed the most relevant approaches used for O_3 modelling and mapping starting from the simplest geo-statistical approaches and increasing in complexity up to simulations embedded into the global/regional circulation models and pro and cons of each mode are highlighted. The analysis showed that a simpler approach (mostly statistical models) is suitable for mapping O_3 concentrations at the local scale, where enough O_3 concentration data are available. The associated error in mapping can be reduced by using more complex methodologies, based on co-variables. The models available at the regional or global level are used depending on the needed resolution and the domain where they are applied to. Increasing the resolution corresponds to an increase in the prediction but only up to a certain limit. However, with any approach, the ensemble models should be preferred.

1. Introduction

Because of its widespread presence in urban and rural environments, air pollution is a serious threat for any life-form and especially for animal and plant health (Lelieveld et al., 2015; Sicard et al., 2016a). The increasing pollutant emissions in many regions of the world are perceived as the second biggest environmental concern by citizens, after climate change (EEA, 2019). This perception results in an increasing level of

attention for media and citizens. This growing public engagement, which includes ongoing citizen science initiatives supporting air quality monitoring (EEA, 2019) and initiatives to increase public awareness and behavioural changes around air pollution challenges, has led to growing expectations for measures aiming at preventing severe risk for human health. Tropospheric ozone (O_3) is one of the most important atmospheric pollutants in terms of detrimental effects on human (Cohen et al., 2017; Sicard et al., 2021a) and ecosystems health (Li et al., 2018;

* Corresponding author.

E-mail address: alessandra.demarco@enea.it (A. De Marco).

<https://doi.org/10.1016/j.envres.2022.113048>

Received 14 September 2021; Received in revised form 7 December 2021; Accepted 25 February 2022

Available online 4 March 2022

0013-9351/© 2022 Elsevier Inc. All rights reserved.

Feng et al., 2019), as well as on biodiversity conservation (Agathokleous et al., 2020).

Ground-level O₃ is a secondary pollutant formed by its precursors (nitrogen oxides, NO_x; Volatile Organic Compounds, VOCs; and methane) in the presence of sunlight; its concentrations are influenced by anthropogenic and natural emissions, chemical, physical, and biological processes (Lamarque et al., 2013). Local and remote pollution sources, atmospheric chemical processes, long-range transport (Huang et al., 2018; Jonson et al., 2018) and stratospheric influx (Knowland et al., 2017) all affect tropospheric O₃ concentrations. In addition to anthropogenic sources, natural processes such as El Niño-Southern Oscillation (ENSO) conditions influence tropospheric O₃ production (Rowlinson et al., 2019). Increments in surface O₃ concentrations contribute to changes in air quality (Sicard et al., 2020; Sicard, 2021), human health (Cohen et al., 2017), forest growth and vitality (Proietti et al., 2016; Feng et al., 2019) and agricultural productivity (Van Dingenen et al., 2009). Tropospheric O₃ contributes to increasing global warming both directly, due to its radiative effects (Checa-Garcia et al., 2018), and indirectly, by affecting photosynthesis and ultimately reducing the land carbon sink capacity (Sitch et al., 2008).

Air quality conditions require, as the first and essential step, reliable estimates of air pollutants concentrations. Different O₃ measurement techniques have been recently reviewed by Saitanis et al. (2020), showing that air quality monitoring stations cannot cover all the territory, due to economic and technical limitations. Indeed, monitoring networks are often spatially heterogeneous with limited geographic coverage, for instance in China (Sicard et al., 2021b) or in the United States (Bravo et al., 2012). Identifying the environmental factors that influence air pollutant levels over these areas is thus necessary to establish new locations for extending the network representativeness. Due to the impossibility to directly measure O₃ concentrations in all areas, the modelling approach is a useful and suitable tool to indirectly obtain information on O₃ concentrations over large regions. Researchers and technicians use models as integrative tools for risk assessment of O₃ pollution and policy evaluation in several ways. In the first place, models are used to estimate surface O₃ concentrations. Furthermore, modelling activities are needed to estimate the risk posed by these O₃ levels to ecosystems or human health. Finally, modelling is essential for forecasting both O₃ levels and their effects under the future scenarios of air pollution and climate change. Modelling ground-level O₃ has thus been one of the notable topics in the last decades among the air pollution community (Simpson et al., 2012).

The impact of air pollution can be indirectly estimated through epidemiological studies, the so-called “risk assessment”, for both human and ecosystem health (Braun et al., 2017). Regarding human health, the risk assessment represents the number of cases of health endpoints attributable to exposure to air pollutants at any scale (World Health Organization, 2013). These results, together with information about mortality and estimated risk, can be efficiently represented on geographical maps to highlight the distribution and extent of the threat, and to identify objectives and priorities for any prevention, remediation, or mitigation actions (Briggs, 2008). Regarding ecosystem health, the generation of reliable O₃ maps is needed for risk assessment and is a challenging process (Sicard et al., 2016b). Starting from several measurements over a large area, numerous approaches are used to map O₃ pollution and make predictions of the impacts because of O₃ pollution and have been reported in the literature (e.g., De Marco, 2008; Li et al., 2014). Although the O₃ formation and the dispersion of its precursors in the troposphere are intricate, researchers have made significant efforts to simplify this complex behaviour and to understand the characteristics of their distribution over time.

Overall, the approach to O₃ modelling can be formally grouped into two broad families defined as: *statistical*, which can be broken down further into “pure” statistical and geostatistical ones; and *deterministic*, e.g. chemistry transport models. Each of these two different inherently different approaches refers to variable spatial and temporal scale, with

different data needs and pros and cons as highlighted in the assessment of the model performance paragraph.

The main aims of this review paper are: i) to describe the current state-of-the-art knowledge used in tropospheric O₃ modelling and mapping; ii) to discuss whether different approaches differ (or look similar) each other and identifying pros and cons for each approach; and iii) to stimulate and outline important directions for further research in O₃ modelling for the near future. Overall, the information collected here can be used and serving as a guideline and handbook for those approaching to study ozone and to its modelling and helping in finding the best approach for a particular purpose.

2. Statistical approach

2.1. Statistical models

Traditional statistical approaches include multiple linear regressions (Abdul-Wahab et al., 2005), multiple linear regressions combined with principal component analysis (Tan et al., 2016), and atmospheric dispersion models at city scale (Pineda Rojas et al., 2016). The multiple linear regression method was widely used because of the convenience of establishing a direct relation between O₃ and the variables associated with its behaviour, through a rather simple and explicit equation (Barbero et al., 2006). On the other hand, the non-linear relationship between O₃ and its contributing factors makes the linear models unfit (De Marco et al., 2013). Multiple linear regressions also suffer from the risk of data collinearity and limitation to obtain the best fit and therefore need large datasets of local variables (Awang et al., 2015). Furthermore, the complexity of O₃ formation, combined with the uncertainty in the measurement of most of the involved parameters, makes the modelling process intricate (Lamarque et al., 2013).

In rural areas, where the geographical distribution of monitoring stations is heterogeneous, geostatistical models are of great value (Sicard et al., 2013). Starting from a set of monitoring stations, a hybrid regression-interpolation approach was proposed, i.e., local regression followed by kriging of residuals (Sicard et al., 2016b). Land-Use Regression and ordinary kriging comprise the most used geostatistical approach for O₃ prediction (Jerrett et al., 2004) and are useful to develop optimal O₃ maps. Each geostatistical model has its inherent uncertainty due to the complexity of the atmospheric environment (Adam-Poupard et al., 2014).

2.2. Geostatistical models

The geostatistical approach assumes that the phenomena occurring in natural conditions are spatially dependent and/or somehow correlated. Samples taken at nearby locations are expected to have more similar values than samples taken farther apart, based on the assumption that everything is related to everything else (Tobler, 1970). It was reported that Tobler's first law of geography is the core of spatial interpolation and geostatistical analysis (Miller, 2004). Spatially correlated values not only facilitate optimal and continuous mapping of the pollution in the entire area but also provide valuable information about the air quality of that area (De Marco, 2008). The final objective of the spatial interpolation is to predict the air pollution concentrations over a defined region by estimating the concentrations at unmeasured locations based on known measurements in specific sites. The simplest geostatistical methodology is the Inverse Distance Weighting (IDW), which produces a prediction as a weighted average of monitor data with weight based on inverse distance to the unsampled location. Berman et al. (2015) applied this methodology to map ozone concentration in the US, but its methodology was outperformed by other more accurate, such kriging. IDW is particularly critical because it is based on spatial autocorrelation. Indeed, IDW assigns more weight to nearby points than to distant points (Myers, 1991), thus requiring spatial autocorrelation.

Kriging is one of the first geostatistical methods used in mining and

geological engineering since the 1950s (Chang, 2008). Since then, it has been used in air quality studies (e.g., De Marco, 2008; Adam-Poupart et al., 2014; Sicard et al., 2016b; Feng et al., 2019), with accurate predictions and estimates (Fraczek et al., 2001). The main advantage of using kriging in spatial interpolation relies on its ability to calculate the uncertainty of prediction which is useful in decision making. A kriging interpolation model predicts surfaces better than other geostatistical models when data are checked for outliers and errors. If the data follow a normal distribution, kriging is to date the best-unbiased method of predicting a surface (Kethireddy et al., 2014), even though the spatial prediction does not necessarily require the data to be normally distributed. Technological and scientific advances led to the development of geospatial platforms in which certain tools and extensions allow studying the spatial-temporal changes of geo-environmental phenomena. It was reported that geostatistical analysis can assess potential environmental hazards by interpolating the possible flow and direction of air pollution, biohazard releases, and any potentially harmful waste that may be introduced into an area (Kethireddy et al., 2014).

An extensive analysis of different O₃ interpolation techniques (from Inverse Distance Weighting to Ordinary Kriging) was performed by Hůnová et al. (2012) by estimating uncertainties linked to the interpolation as root-mean-square error (RMSE) in Czech forests. The most suitable methodology was the ordinary kriging recommended as the optimal approach out of the eleven spatial interpolation techniques examined. The estimation of RMSE was done for both O₃ concentrations and AOT40 (Accumulated hourly Ozone over Threshold of 40 ppb) and was ranging between 10% and 20%, respectively (Hůnová et al., 2012). Another example of geostatistical methodologies used to map O₃ was applied by Fraczek et al. (2001) in the Sierra Nevada (United States) and Carpathian (Central Europe) Mountains. In particular, kriging and co-kriging were compared. The latter was performed using two additional variables related to O₃ concentrations, elevation, and maximum air temperature. The use of the additional variables was able to supply the low intensity of O₃ data in the Carpathian Mountains. Sufficient numbers of monitoring sites, spatially homogeneous distributed across the territory, were found to be a key factor for model accuracy and reliability (Fraczek et al., 2001; Sicard et al., 2016b).

Among the different kriging options, Universal kriging, was observed to give better results than Ordinary kriging in US ozone concentrations mapping, allowing to assess the significance of environmental covariates for both inference and prediction of O₃ concentrations (Berman et al., 2015). Between the concerns of kriging, it is depending on spatial autocorrelation as IDW. Indeed, a critical component of kriging is the semivariogram. A useful semivariogram cannot be developed without the presence of spatial autocorrelation; the degree of spatial autocorrelation determines how successful spatial interpolation will be (Griffith and Layne, 1999).

Kriging performance can be improved using co-variable related to ozone concentrations in the co-kriging interpolation. Co-kriging allows to better estimate primary variable if the distribution of a secondary correlated variable is sampled more intensely than the primary variable. The most used co-variable is the Digital Elevation Model (DEM), taking into account topographic effects (Sicard et al., 2013). The authors applied this methodology in Mediterranean basin to background ozone stations. The co-kriging was able to compensate for the lack of sufficient sampling in some areas. The RMSSE was always close to 1, with 1 highlighting no variability in prediction and thus no uncertainty for the whole domain.

Land-Use Regression models.

More advanced exposure estimation techniques include Land-Use Regression (LUR) models. For instance, LUR models are used to predict air pollutant concentrations at unmonitored sites based on regression models of geo-referenced covariates that predict observed data in monitoring sites (Beelen et al., 2009). LUR modelling employs statistical methods to combine data from air pollution measurements with data from Geographic Information Systems to explain spatial concentration

variations (Hoek et al., 2008). A LUR model can characterize the spatial variability of air pollutants considering other information, such as roadside dispersion profiles. The model performance is limited by the number and the spatial distribution of sampling sites (Basagana et al., 2012; Wang et al., 2012). Kerckhoffs et al. (2015) applied LUR to predict O₃ levels in the Netherlands. They found that O₃ levels were highly correlated with NO and moderately with fine particles. They built a LUR model including small-scale traffic, large-scale address density, urban green and a regional indicator that was able to explain 71% of the spatial variation in summer average O₃ concentrations.

2.3. Machine Learning algorithms

Spatial linear LUR is commonly used for long-term modelling of air pollution in support of exposure assessment. However, Machine Learning methods, with spatio-temporal modelling, provide more accurate exposure metrics than LUR in modelling human exposures for epidemiological studies (Ren et al., 2020). Ren et al. (2020) and Requia et al. (2020) have compared different Machine Learning algorithms to model the relationship between dependent variables and predictor variables to fill in the missing values, in order to estimate the daily maximum 8-h mean O₃ concentrations at high spatial resolution (1 × 1 km grid cell) across the United States: linear regression models (i.e., Multiple Linear Regression, Ridge regression, Elastic Net regularization, Principal Component Regression, Partial Least Squares Regression) and non-linear modelling options (i.e., Lazy Learning, k-Nearest Neighbors, Kernel Trick, Support Vector Regression, Artificial Neural Networks, Artificial Neural Networks, Deep Neural Networks, Decision Trees, Regression Trees, Random Forest, and Extreme Gradient Boosting).

The non-linear Machine Learning methods led to higher accuracy of predictions compared to linear LUR i.e., 10–40% decrease of predicted RMSE (Ren et al., 2020). By applying three Machine Learning algorithms (neural network, random forest, and gradient boosting) Requia et al. (2020) obtained high model performance ($r^2 = 0.86–0.90$), and the best performance was observed during summer ($r^2 = 0.88$) in the United States. The performance of the Machine Learning algorithms depends on the location and O₃ concentration, therefore it recommended to apply a hybrid model instead of a single model (Ren et al., 2020).

2.4. Deterministic approach

Chemical transport models.

Because O₃ is a highly reactive trace gas, estimates of its contribution to climate forcing must rely on global chemistry-transport models (Derwent, 2020). Atmospheric chemical transport models (CTMs) are used to simulate the formation, removal and transport of O₃ (Lamarque et al., 2013) into the troposphere. These models were formulated to quantify the impact of air pollutant emissions on the chemical composition of the atmosphere and corresponding consequences on the environment (Gupta and Mohan, 2015). The reliability of the models increases with increasing temporal and spatial resolution of input data, such as emission inventory (Karlický et al., 2017). The key limitations of CTMs include the requirements of high computational resources and data, and good knowledge about the atmospheric processes and source of air pollution (Tong et al., 2011). Furthermore, CTMs tend to underestimate the magnitude of fluctuations on shorter temporary scales with the possibility of overestimating during periods of extensive cloud cover (Pal et al., 2014). Many studies have used computer numerical models implemented at regional (or even global) scales to supplement the missing information from in-situ measurements (Sicard et al., 2021b). In the past decades, the importance of these numerical models has been increasingly recognized and numerous air dispersion or air quality models were developed at various spatial scales to assist in understanding, controlling, and forecasting air pollution (Miranda et al., 2015). CTMs are numerical models that simulate over a given region the atmospheric chemistry taking into account four main processes: i)

assessment of natural and anthropogenic emissions ii) atmospheric transport, iii) chemical production/destruction and iv) losses to surface by dry deposition. They are widely used to estimate the concentration of gases in the atmosphere at different temporal and spatial scales and have been successfully applied to air pollution research and air quality management at a regional scale worldwide (e.g., Reis et al., 2005; Haase et al., 2014; De Marco et al., 2020).

CTMs have been used in China, covering whole country or specific regions (Hu et al., 2015; Li et al., 2018; Quennehen, 2008). However, the representation of air quality and meteorology over Asia is still challenging because of complex physical and meteorological conditions of this area, characterized by the monsoon system and large uncertainty in the anthropogenic emissions (Sicard et al., 2021b). Nevertheless, CTMs are widely used to study air quality over Asia. For instance, Hu et al. (2015) applied the Community Multi-scale Air Quality (CMAQ) and Weather Research Forecasting (WRF) modelling system to predict air pollutant concentrations for the whole of China. The results showed an over-estimation of 1-h or 8-h O₃ average, due probably to the coarse horizontal resolution (36 km). A modified WRF/CMAQ experiment was performed to simulate O₃ in winter (December 2014–February 2015) and summer (June–August 2015) for the entire Sichuan Basin (Qiao et al., 2019). The 1-h and 8-h O₃ averages were both greatly over-predicted in winter, but the model performance was acceptable in summer when the photochemical production of O₃ since anthropogenic emissions should be strongest in the basin (Qiao et al., 2019). The WRF-CMAQ model was used in India with a different spatial resolution for emissions and meteorological inputs (e.g., 36 km) to assess source and species sensitivities of ground-level O₃ concentrations (Sharma et al., 2016). In the framework of the Hemispheric Transport of Air Pollution (HTAP) phase 2 experiment, simulations of O₃ and its precursors were conducted using the updated version-2 (HTAP-v2) emission inventory and the offline global chemistry transport model MOZART-4 (Surendran et al., 2015). Comparison between model simulations and surface/balloon-borne observations at several sites showed reasonable model performance, but some disagreement in O₃ concentration and seasonal variation over South Asia was still evident (Surendran et al., 2015). The WRF model, coupled with Chemistry (i.e., WRF-Chem) was used to simulate the spatial and seasonal variability of main physical and chemical variables over Asia for the year 2015 at 8-km horizontal resolution and to estimate O₃ impacts on Asian forests (De Marco et al., 2020). Overall, WRF-Chem reproduced well the spatial and seasonal variability of tropospheric O₃ content, with limited over-estimation during the warm season (3–7%) and larger over-prediction (11–13%) during the cold period (Sicard et al., 2021b). Emissions of NO_x, methane, carbon monoxide and isoprene had the potential to contribute in a major way to model output uncertainties (Derwent, 2020).

In Europe, CTMs are used with resolution ranging between 12 and 25 km for operational European wide applications (e.g.; Mues et al., 2014; Anav et al., 2016), 4–10 km for application to a single country (e.g. Vieno et al., 2010; Baldasano et al., 2011; Hendriks et al., 2013) and reaching 1 km for some European regions (Pay et al., 2014). As an increase in horizontal model resolution will quadratic or cubically increase the computational costs and poses additional challenges concerning high-resolution input data and model formulation, it is important to reach a cost-effective compromise (an “optimum resolution”) in the trade-off between the model performance and computational cost. Projected changes in ground-level O₃ vary considerably among models (Wild et al., 2012). Several studies have evaluated the impact of spatial model resolution on O₃ production (e.g., Tie et al., 2010; Lauwaet et al., 2013) as well as O₃ precursors (Walaszek et al., 2018). In general, high-resolution simulations may provide a much better separation between regions defined by high concentrations of biogenic volatile organic compounds and high NO_x levels (Pugh et al., 2013). Tie et al. (2010) performed an experiment over United States to assess the impact of model resolution on simulated air quality; they used

a domain of 36, 12, and 4 km² respectively, finding that the 36-km² resolution leads to an under-prediction of daily maximum 8-h O₃ averages, and an over-prediction of daily minimum 8-h O₃ averages (Tie et al., 2010). Other studies support the finding that modelled O₃ formation systematically increases with the resolution for regional and global scale applications (Wild and Prather, 2006). Evaluations of global, hemispheric, and regional CTMs show that regional models typically perform better (van Loon and Coauthors, 2007; Simpson et al., 2014).

In Europe, long-term O₃ simulations from seven regional air quality models (i.e., the Unified EMEP model, LOTOS-EUROS, CHIMERE, RCG, MATCH, DEHM, and TM5) were inter-compared and compared to O₃ measurements within the framework of the EuroDelta experiment (van Loon and Coauthors, 2007; Colette et al., 2011). This study clearly showed that increasing model resolution is advantageous for European scale applications and that moving from a resolution of 50 km in favour of a resolution between 10 and 20 km is practical and worthwhile. With increasing resolution of the meteorological model and emission inventories, and adjustment of CTM process descriptions and parameterizations to this higher resolution, an improved performance of CTMs model is expected (Schaap et al., 2015). The performance of the different models to simulate O₃ fields is compared and in general the models reproduce the main features of the O₃ diurnal cycle, even if over-estimating daytime O₃. LOTOS-EUROS and RCG have a more pronounced diurnal cycle variation than observations, in contrast with TM5. CHIMERE has a large positive bias, which can be explained by a systematic bias in boundary conditions.

Regional chemistry-climate models at coarse horizontal resolution (e.g., 36–50 km) are often unable to resolve the local features influencing the chemical transformation and poorly reproduce the ground observations (Schaap et al., 2015). On the other hand, a weakness linked to regional models is their high time and resources consumption. Indeed, the run of a single model requires from weeks to months to have a final output.

In recent years, researchers have focused their attention on advanced models like ensemble models, which showed better performance than standard single CTMs (Gong & Ordieres-Meré, 2016). Singh et al. (2013) used the ensemble trees to predict air quality, applying meteorological parameters as estimators. The methodology to assess the model performance was based on classification and regression.

Recently a new approach was developed to integrate CTM predictions and measures, the so-called Regionalized Air Quality Model Performance approach, using the Bayesian Maximum Entropy framework (DeLang et al., 2021). Thus, estimates are produced that put priority on observations and take advantage of air quality model predictions based on how well they reproduce the observed values. Spatial fields generated from this approach provide an observation and CTM informed representation of O₃ across space/time that is more accurate and precise than relying only on observation data. This was especially true for locations away from monitoring stations.

2.5. Chemistry-climate models

In the climate models, physical atmospheric processes are calculated by solving equations that describe fluid flow and radiative transfer, which can not only respond to changes in greenhouse gas concentrations, solar output, or other forcing but also generate their internal meteorological variability (Flato et al., 2014). Chemistry-climate models, or composition-climate models (CCMs), represent the most complex models in this family, where the chemically driven changes in radiatively active gases and aerosols (e.g. O₃, methane, sulfates) influence the model radiation scheme, thus chemistry directly influences climate through its direct and indirect effects (O'Connor et al., 2015). The use of CCMs with tropospheric chemistry and aerosols is a relatively recent development (Morgenstern et al., 2017), whereas coupling of upper atmosphere chemistry to climate has a much longer history due to

the increased importance of chemically active compounds for heating rates in the stratosphere (Morgenstern et al., 2017). A less complex model than the CCM is the chemistry CTM (Chemical Transport Model), where the chemistry is affected by the climate changes from the radiative and dynamical parts of the model but the chemically driven changes in radiatively active gases and aerosols do not subsequently affect climate. This type of model was the first step in coupling tropospheric chemistry to physical climate models (Roelofs and Lelieveld, 1997), and it is still occasionally used (Lamarque et al., 2013).

2.6. Chemical reanalyses and ensemble approaches

Applications of chemical ensembles include comprehensive spatio-temporal evaluation of independent models, such as those developed in the framework of the Atmospheric Chemistry and Climate Model Intercomparison Project (ACCMIP; Yang et al., 2012) and CCMi (Morgenstern et al., 2018). In their study the ACCMIP ensemble O₃ simulations were evaluated using a chemical reanalysis, complementing the use of individual measurements for such a purpose. The chemical reanalyses can also be used as an input to meteorological reanalyses, as for radiation calculations (Dee et al., 2011), and can provide boundary conditions to regional-scale models and to analyze particular pollution events such as those associated with heatwaves or large-scale forest fires (Huijnen et al., 2012). Finally, they can be used as a reference to identify to what extent particular periods and regions deviate from climatology, as provided by the reanalysis, for instance as also discussed in the series of the “State of the Climate” (Flemming and Innes, 2018).

The global chemistry models developed under the ACCMIP project were used by Sicard et al. (2017) to determine the impacts of O₃ on forests productivity at the global level, in four climate scenarios RCPs. ACCMIP models were widely validated and used to evaluate projected changes in atmospheric chemistry and air quality under different emission and climate assumptions (Lamarque et al., 2010; Voulgarakis et al., 2013). Lamarque et al. (2013) provided the main characteristics of 16 models and details for the ACCMIP simulations. The length of historical and RCP simulations varies between models, but for all models, the historical runs cover a period centred around 2000, while the time slice of RCPs is centred around 2050 and 2100.

Changes in emissions from one region can impact air quality over others, also affecting air-pollution-related health impacts due to inter-continental transport (Zhang et al., 2017). In the framework of the Task Force on Hemispheric Transport of Air Pollution (TF-HTAP), Anenberg et al. (2009) found that reduction of foreign O₃ precursor emissions can contribute to more than 50% of the avoided deaths by simultaneously reducing both domestic and foreign precursor emissions. A reduction in emissions in North America and Europe results in largest impacts as reduction of O₃-related premature deaths in downwind regions as compared to within the source region (Anenberg et al., 2009).

For most O₃ indicators, the ensemble average identified “ensemble model”, almost always exhibits a superior skill compared to any individual model, even though it has a too weak variability. The spread of ensemble-model values is fairly representative of the uncertainty of summertime O₃ daily maxima, as the occurrence of the observation within the model values range has a rather flat distribution, when the bias is removed. For a given day, the probability distribution of occurrence of the observation is well represented by the distribution of the simulated values.

2.7. Assessing model performance

Statistical models are associated with a relative simplicity of the approaches suggested, even though they are associated with high level of uncertainties (LRM) and high RMSE (IDW, Kriging). Methodology with increasing level of complexity, such as co-Kriging, LUR and Machine Learning, showed lower RMSE, but on the other hand have much more information as input data requested. All the statistical models

requires measured data, and have as output continuous layers of pollutant concentration over a specific domain. This request imply that the RMSE is lower when the distance between measurement sites is lower, decreasing in this way the uncertainties of the modelling approaches.

The deterministic models are generally characterized by lower level of accuracy and higher accuracy, showing different level of complexity, that is increasing from Global model to Regional models. These type of models require high number of input data, such as emission inventories, and need pollutant dispersion module and meteorological model. On the same time they request high computation time and high storage room.

Validation of the model performance from ground observations is, so far, still a problem due to the scarcity of monitored information (Sicard et al., 2021b). Recently, few authors have validated regional model data with in-situ, balloon-borne observations, and satellite observations (e.g., Im et al., 2015; Surendran et al., 2015; Ghim et al., 2017; Crippa et al., 2019; Sicard et al., 2021b). The model performance can be evaluated over different seasons by using the Pearson's correlation coefficient (r), mean bias (MB), the fractional bias (FB), and the Root-Mean-Square Error (RMSE). These statistics are successfully used in several studies for evaluating the performance of regional air quality models (e.g., Im et al., 2015; Ghim et al., 2017; Crippa et al., 2019; Sicard et al., 2021b). In case of in-situ data, we have to extract model results at the lowest model layer, and we calculate the performance statistics for each station. The Pearson's coefficient allows estimating the spatial agreement between model and observations. For physical parameters, the MB provides the absolute bias of the model, with negative and positive values indicating respectively underestimation and overestimation by the model while the FB (in %) is used for the chemical variables, as in this case the absolute bias would be hard to interpret. The cross validation (e.g., 10-fold cross validation) is usually used. Here, we first divide the monitoring sites into 10 splits, and then we train the model with 90% of the data and predicted the O₃ concentration at the remaining 10% of the sites. Then, the RMSE is commonly used to measure the differences between modelled values and the observations.

We have summarized all pros and cons of the different approaches in Fig. 1, where in the same time we estimated the performance of each approach on the base of its accuracy, spatial resolution, complexity, temporal resolution, statistical vs. deterministic nature and data need. We gave a score to each of these parameters ranging between 0 and 1 and at the end we have estimated the performance of the model on the basis of the area of the obtained graphs. Higher is the area, higher is the performance of the model.

3. Ozone risk assessment

3.1. Models for human health

Acute exposures are characterized by high O₃ concentrations for a relatively short-time period, within hours or days, while chronic exposures involve lower O₃ concentrations persisting, or recurring, over a longer period (Grulke et al., 2007; World Health Organization, 2008; Sicard et al., 2016b). To protect population, it was considered that the 8-h guideline would protect against acute elevated 1-h O₃ exposures (World Health Organization, 2008). The current O₃ human health metrics (SOMO35, i.e., the annual Sum Of daily maximum 8-h Means Over 35 ppb, and the number of exceedances of daily maximum 8-h values greater than 60 ppb) consider only acute health effects (e.g., lung inflammation), and do not account for possible chronic effects at long-term O₃ exposure levels below 35 ppb (World Health Organization, 2013).

In cities, PM_{2.5} and ground-level O₃ have potentially the most significant adverse effects on human health associated with respiratory and cardiovascular diseases and mortality, compared to other air pollutants (World Health Organization, 2013; Cohen et al., 2017). The Global Burden of Disease (GBD) Study reported 4.1 million disability-adjusted



Fig. 1. Performance of the different approaches. A score was assigned on the basis of the characteristics of the suggested approach in terms of accuracy, spatial resolution, complexity, temporal resolution, statistical vs. deterministic nature and data need. The higher is the area the higher is supposed to be the model performance and its applicability.

life years (DALYs) in 2015 attributable to O₃ exposure (Forouzanfar et al., 2016) that is estimated to provoke more than 0.7 million deaths per year worldwide (Anenberg et al., 2010). Short-term effects induced by the oxidative stress of this pollutant on the respiratory system are well-established, particularly in people with pre-existing obstructive chronic pulmonary diseases (COPD) (Nuvolone et al., 2018). The World health organization (World Health Organization, 2013), the European Council (Directive, 2008/50/EC), the Environmental Protection Agency (US Federal Register, 2015) have set Ambient Air Quality Standards for the protection of human health (Table 2). For ground-level O₃, China adopted in 2012 the Ambient Air Quality Standard of 80 ppb as maximum daily 8-h running average (Ministry of Environmental Protection, 2012) (Table 1).

For the estimation of health effect, different methods or models are used. The more common methods for assessing the short-term effects of air pollution on human health is time-series analysis. The time-series analysis method is a simple and descriptive-statistical approach for O₃ modelling (Tian et al., 2020; Javanmardi et al., 2018). Time-series analyses showed that O₃ is associated with an increased risk of premature mortality, but currently, statistical models (including meta-analysis regression) are being developed to establish indicators of risk mortality or hospital admission from short-term O₃ exposure (e.g. maximum daily 8-h mean concentration). Li et al. (2020) used two stages strategy to investigate the relationship between O₃ exposure and years of life lost (YLL). For this, city-specific associations were calculated by generalized

Table 1

Air quality standards for ozone in terms of target values for the protection of human health (World Health Organization, 2013; Directive, 2008/50/EC; US Federal Register, 2015; Ministry of Environmental Protection, 2012).

Guideline	WHO	EU	US	China
Maximum daily 8-h mean (ppb)	50 ppb	60 ppb	75 ppb	80 ppb

Table 2

Relative Risk for health outcomes, and people at risk (e.g., all ages or > 30 years-old), for 10 µg m⁻³ increase in daily maximum 8-h ozone mean concentrations with 95% confidence intervals (lag 0–1 days).

Outcome - Region	RR (95% CI) per 10 µg/m ³	Ref.
Mortality		
All-causes (all ages) - Europe	1.003 (1.001–1.004)	(WHO, 2013)
All-natural causes (>30 years) - France	1.009 (1.004–1.014)	Sicard et al. (2019)
All-cause mortality, summer (all ages)– United States	1.007 (1.004–1.011)	Bell et al. (2005)
Cardiovascular diseases (all ages) - Europe	1.005 (1.002–1.007)	Gryparis et al. (2004)
Cardiovascular diseases (>30 years)- Europe	1.004 (1.003–1.005)	(WHO, 2013)
Respiratory diseases (all ages) - Europe	1.013 (1.007–1.015)	Gryparis et al. (2004)
Respiratory diseases (>30 years)- Europe	1.014 (1.005–1.024)	Héroux et al. (2015)
Daily Hospital Admissions		
Chronic Obstructive Pulmonary Disease (all ages) - Europe	1.009 (1.004–1.013)	(WHO, 2013)
Cardiovascular diseases (all ages) - Europe	1.009 (1.005–1.013)	Héroux et al. (2015)
Respiratory diseases (all ages)- Europe	1.004 (1.001–1.008)	Héroux et al. (2015)
Respiratory diseases (15–64 years old) - Europe	1.001 (0.991–1.012)	(WHO, 2008)
Respiratory diseases (≥65 years old) - Europe	1.005 (0.998–1.012)	(WHO, 2008)
Myocardial infarction (ozone <70 ppb)– United States	0.998 (0.996–1.000)	Yazdi et al. (2019)
Pneumonia (ozone <70 ppb) – United States	1.030 (1.028–1.032)	Yazdi et al. (2019)

additive models (GAM). The family function of GAM is the Gaussian model (Guo et al., 2013). The daily observed YLL (95% CI) was estimated by the following equation (1), and their sum divided by total non-accidental mortality was additional life gained per deceased people.

$$\sum_{t=1}^{1826} (YLL_t) \times ([O_3]_t - Target) \times \beta \quad (1)$$

where YLL_t and $[O_3]_t$ are respectively the daily number of lost life years and the O_3 concentration at the day t . Target and β are the concentration target of ozone and the national average relative change of YLL per $1 \mu\text{g m}^{-3}$ increase of ozone, respectively (Li et al., 2020).

These statistical models relate mortality or hospital admission to data on air pollution, and weather, correcting by age, gender, socioeconomic indicators, race/ethnicity, etc. (Zanobetti and Schwartz, 2008). For estimation of mortality and hospital admissions due to O_3 exposure some models need inputs such as baseline incidence (BI), relative risk (RR), specified population and 1-h or 8-h concentrations of O_3 . The BI use epidemiological models to estimate the occurrence of events in different population subsets like the evidence of events for patients with risk factors compared with those without risk factors (Nelson et al., 2015). Relative risk is the possibility of developing a disease following exposure to a pollutant. The RR is the attributable health risk related to people who have defined exposures and so it can be calculated by the equation (2).

$$RR = \frac{\text{Probability of a health effect when exposed to air pollution}}{\text{Probability of a health effect when not exposed}} \quad (2)$$

The estimation of different diseases and mortality due to O_3 exposure is based on BI and RR, calculated from meta-analysis and/or epidemiological studies for hospital admissions and mortality due to cardiovascular and respiratory diseases (World Health Organization, 2013). Table 2 shows the different RR in the studies of ozone exposure and its effects on human health.

Several models have been used to investigate the effects of O_3 exposure on human health (Sicard et al., 2019; Yang et al., 2012; Jerrett et al., 2009; Gryparis et al., 2004). For instance, the AirQ software elaborated by the WHO Regional Office for Europe is widely used worldwide e.g., in Asia (Yang et al., 2020), Iran (Khaniabadi et al., 2018; Amoatey et al., 2019), and Europe (De Marco et al., 2009; Sicard et al., 2019; Khaniabadi and Sicard, 2021). In this AirQ model the BI and RR are used as input for estimation of mortality and hospital admissions. The attributable proportion AP, defined as the fraction of health consequences in a population exposed to ozone, is calculated as follows:

$$AP = \frac{\sum \{ [RR(c) - 1] \times P(c) \}}{\sum [RR(c) \times P(c)]} \quad (3)$$

Where $RR(c)$ is the relative risk of a certain effect on health in category

"c" (e.g., residential or industrial) of exposure that it is taken from the exposure-response functions from published epidemiological studies, being $P(c)$ the number of individuals in the under exposure population. Table 3 shows some results of studies, published in the last decade, using AirQ model for estimating mortality due to O_3 exposure in different countries. Almost all papers investigated cardiovascular and respiratory-related diseases with the RR suggested in Table 2.

The O_3 concentrations increased in most cities worldwide (on average: $+0.31 \text{ ppb year}^{-1}$ since 1990s), in particular $+0.33 \text{ ppb year}^{-1}$ in North America, $+0.68 \text{ ppb year}^{-1}$ in East Asia and $+0.27 \text{ ppb year}^{-1}$ in Europe between 2005 and 2014 (Sicard, 2021). Between 2000 and 2017, the annual O_3 -related number of premature deaths increased ($+0.55$ deaths per 10^6 inhabitants) in the EU-28 cities (Sicard et al., 2021a). Knowlton et al. (2004) assessed changes in O_3 -related mortality in the 2050s compared with the 1990s using the coupled GCM/MM5/CMAQ models in the United States, and in the New York state. They found that climate change could increase regional summer O_3 -related mortality by a median of 4.5% in the 2050s compared with the 1990s, without including the population growth, reaching a median of 59.9% when the increase in population at risk was considered.

4. Models for plant ecosystems

To protect vegetation, the current exposure index AOT40 assumes O_3 concentrations below 40 ppb, and do not account for possible chronic effects (Sicard et al., 2016b).

To provide accurate impact metrics to protect human health and vegetation from adverse effects of O_3 , accurate hourly O_3 concentrations are needed, and the models must reproduce well the spatial and seasonal O_3 variability even for lower concentrations e.g., in cities. The performance statistics have to be based on hourly data year-round.

Apart from complementing atmospheric chemistry measurements and evaluating potential threats to human health, modelling activities are also applying to estimate the risk posed by these O_3 levels to ecosystems, particularly to vegetation. The adverse effects of O_3 on plants were first identified in the 1950s (Ashmore, 2005). Ozone can reduce agricultural yield, mainly by the appearance of visible injury that reduces market value and the reduction of the yields due to decreased photosynthetic rates and accelerating leaf senescence (Feng et al., 2019; González-Fernández et al., 2016; Monga et al., 2015; Pleijel et al., 2019). There is also evidence of lower growth of tree species, reductions of the nutritional quality of pastures, reduction in the reproductive capacity of plants, and biodiversity changes in the species composition of pastures (Agathokleous et al., 2020; Alonso et al., 2014; Ashmore, 2005; Büker et al., 2015; Li et al., 2018; Sanz et al., 2016).

The methodology for vegetation risk assessment was developed in the framework of the United Nations Economic Commission for Europe (UNECE) Convention on Long-range Transboundary Air Pollution (CLRTAP). Experimental studies in which vegetation is exposed to

Table 3

Number of cases attributed to exposure to ozone (O_3) for mortality for all natural causes, cardiovascular diseases, and respiratory diseases, using AirQ software (95% Confidence Interval).

Reference	Location	Time period	Annual mean conc. ($\mu\text{g}/\text{m}^3$)	Ozone-related premature deaths		
				All-causes	Cardiovascular diseases	Respiratory diseases
Rovira et al. (2020)	Catalonia, Spain	2017	59.8	–	–	9 (3–15)
Bonyadi et al. (2020)	Shirza, Iran	2017	51.6	122 (8–202)	85 (34–119)	45 (25–72)
Du et al. (2019)	Jinhua, China	2019	84.5	–	–	–
Amoatey et al. (2019)	Ahvaz, Iran	2015	79.2	128 (85–171)	156 (0–233)	41 (21–61)
Sicard et al. (2019)	Marseille, France	2015	55.0	169 (76,261)	65 (12–117)	20 (10–32)
Asl et al. (2018)	Hamadan, Iran	2014–2015	73.0	52 (35–86)	36.5 (15–50)	19.1 (11–22)
Sicard et al. (2019)	Rome, Italy	2015	41.5	614 (372–853)	69 (51–86)	37 (14–59)
Khaniabadi et al. (2018)	Kermanshah, Iran	2014–2015	83.2	–	83 (0–123)	32 (13–53)
Hadei et al. (2013)	Tehran, Iran	2015–2016	42.1	341 (228–565)	272 (122–419)	123 (68–142)
Jeong (2013)	Suwon, Korea	2011	43.0	43 (29–71)	16 (6–22)	14 (7–16)

different concentrations of ozone are used to obtain a relationship between concentration of pollutants in the air and their effects on plants (CLRTAP, 2017). When just the concentration (exposure) is used to establish this relationship, the atmospheric chemistry simulations alone are sufficient to assess the risk that O₃ poses to vegetation at regional scale, testing the modelled concentrations against established O₃-level thresholds. This is a very useful approach for large scales since it is possible to apply for most vegetation types (Sicard et al., 2019). However, in the framework of the CLRTAP, vegetation risk assessment is preferably performed by calculating the exceeded dose of O₃ absorbed by the plant stomata over an experimentally set threshold, the so-called phytotoxic ozone dose (POD) (CLRTAP, 2017). For POD, two steps are required: a CTM accounting for the surface concentrations and a parameterization which allow to estimate the vegetation absorption of O₃ (occurring through plant stomata).

Resistance-analogue models are commonly applied to estimate ozone transfer from the atmosphere to vegetation. One of the most used models to estimate ozone uptake by plants is the DO₃SE model (Deposition of O₃ for Stomatal Exchange; Jarvis, 1976; Büker et al., 2012), a multiplicative algorithm. DO₃SE is currently included within the European Monitoring and Evaluation Programme (EMEP; Simpson et al., 2012) photo-oxidant CTM, which simulations are used in the framework of CLRTAP to inform the European strategies for pollutant emission control (Simpson et al., 2007). However, for using this method, the threshold for different plant species or vegetation types must be defined, as well as the species-specific parameterization of the DO₃SE model. De Marco et al. (2020) applied a CTM over Asia, to assess the O₃ risk for forests, comparing both metrics to estimate potential ozone damage: exposure- and flux-based. Using POD allowed including in this analysis some limiting conditions of plant activity, such as soil water content, which is key for risk assessment in a context of climate change. In Europe, the application of the DO₃SE model to calculate POD in the context of climate change allowed to also consider the implications of a changing ozone concentration profile in future scenarios (Hayes et al., 2019).

The above-exposed methodologies are empirical approaches to model O₃ effects that can be completed with other empirical plant-response functions and applied to different environmental conditions (De Vries et al., 2017). However, new modelling approaches based on mathematical simulations of the processes behind the pollutant effects are currently being developed (Kinose et al., 2020; Schaubberger et al., 2019). These process-based models are considered very reliable tools for simulating the effects of O₃ on biological dynamics on novel conditions including air pollution and climate scenarios (Evans, 2012) that can complement the current approach.

5. Conclusive remarks and future directions

Due to the impossibility to measure surface O₃ concentrations in large regions, for economic and practical reasons, the use of modelling is very important and highly suggested methodology to define the risk assessment for ecosystems and human health. In general, the geostatistical approach is relatively simple, requiring low informatics and storage resources. It is strongly limited by the availability of data on the study area, but this limit can be minimized by the use of the co-kriging methodology, where other variables, spatially and temporally correlated with O₃ concentration, can be used. Many different types of models are available to map appropriately tropospheric O₃ starting from the simple geostatistical model to more complex CTM. The choice of a specific model instead of another one depends on the available data and on the final objective of the investigation. Indeed, O₃ risk assessment can be obtained at global, regional or local scale using different resolution levels. Increasing the resolution level can increase the uncertainties level, but a moderate resolution improvement can improve the information released. While geostatistical model use is not the time or computation resources needed, they can be considered as “quick”, but

the ozone distribution in areas not covered by measurements is highly uncertain with ordinary methodology and less uncertain when co-variables are used.

Author contributions

ADM designed the structure, MV and CP authored first draft of the geostatistical approach, HGG authored the first draft related to plant risk assessment, YOK and PS authored the part related to human health risk assessment, ADM, AC, ZZ, PS and EP critically revised the manuscript. All authors revised the manuscript for important intellectual content and approved the final version for submission.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

This article was prepared within the International Union of Forest Research Organizations (IUFRO) Research Group 8.04.00 ‘Air Pollution and Climate Change’ and under the Working Party 8.04.04 ‘Modelling and risk-assessment’.

The manuscript is supported by the LIFE project AIRFRESH LIFE19-ENV_FR_000086 and by the National Natural Science Foundation of China (grant number 42061160479).

References

- Abdul-Wahab, S.A., Bakheit, C.S., Al-Alawi, S.M., 2005. Principal component and multiple regression analysis in the modelling of ground-level ozone and factors affecting its concentrations. *Environ. Model. Software* 20, 1263–1271.
- Adam-Poupard, A., Brand, A., Fournier, M., Jerrett, M., Smargiassi, A., 2014. Spatiotemporal modelling of ozone levels in Quebec (Canada): a comparison of kriging, land-use regression (LUR), and combined Bayesian maximum entropy-LUR approaches. *Environ. Health Perspect.* 122, 970–976.
- Agathokleous, E., Feng, Z., Oksanen, E., Sicard, P., Wang, Q., et al., 2020. Ozone affects plant, insect, and soil microbial communities: a threat to terrestrial ecosystems and biodiversity. *Sci. Adv.* 6, eabc1176.
- Alonso, R., Elvira, S., González-Fernández, I., Calvete, H., García-Gómez, H., Bermejo, V., 2014. Drought stress does not protect *Quercus ilex* L. from ozone effects: results from a comparative study of two subspecies differing in ozone sensitivity. *Plant Biol.* 16, 375–384.
- Amoatey, P., Takdastan, A., Sicard, P., Hopke, P.K., Baawain, M., Omidvarborna, H., et al., 2019. Short and long-term impacts of ambient ozone on health in Ahvaz, Iran. *Human and Ecological Risk Assessment.* Int. J. 25 (5), 1336–1351.
- Anav, A., De Marco, A., Proietti, C., Alessandri, A., Dell’Aquila, A., et al., 2016. Comparing concentration-based (AOT40) and stomatal uptake (PODY) metrics for ozone risk assessment to European forests. *Global Change Biol.* 22, 1608–1627.
- Anenberg, S.C., West, J.J., Fiore, A.M., Jaffe, D.A., Prather, M.J., Bergmann, D., Cuvelier, K., Dentener, F.J., Duncan, B.N., Gauss, M., Hess, P., Jonson, J.E., Lupa, A., MacKenzie, I.A., Marmar, E., Park, R.J., Sanderson, M.G., Schultz, M., Shindell, D.T., Szopa, S., Vivanco, M.G., Wild, O., Zeng, G., 2009. *Environ. Sci. Technol.* 43 (17), 6482–6487.
- Anenberg, S.C., Horowitz, L.W., Tong, D.Q., West, J.J., 2010. An estimate of the global burden of anthropogenic ozone and fine particulate matter on premature human mortality using atmospheric modelling. *Environ. Health Perspect.* 118, 1189–1195.
- Ashmore, M.R., 2005. Assessing the future global impacts of ozone on vegetation. *Plant Cell Environ.* 28, 949–964.
- Asl, F.B., Leili, M., Vaziri, Y., Arian, S.S., Cristaldi, A., Conti, G.O., et al., 2018. Health impacts quantification of ambient air pollutants using AirQ model approach in Hamadan, Iran. *Environ. Res.* 161, 114–121.
- Awang, N.R., Ramli, N.A., Yahaya, A.S., Elbayoumi, M., 2015. Multivariate methods to predict ground level ozone during daytime, nighttime, and critical conversion time in urban areas. *Atmos. Pollut. Res.* 6, 726–734.
- Baldasano, M., Pay, M.T., Jorba, O., Gassó, S., Jiménez-Guerrero, P., 2011. An annual assessment of air quality with the CALIOPE modelling system over Spain. *Sci. Total Environ.* 409, 2163–2178.
- Barrero, M.A., Grimalt, J.O., Cantón, L., 2006. Prediction of daily ozone concentration maxima in the urban atmosphere. *Chemometr. Intell. Lab. Syst.* 80, 67–76.
- Basagana, X., Rivera, M., Aguilera, I., Agis, D., Bouso, L., et al., 2012. Effect of the number of measurement sites on land use regression models in estimating local air pollution. *Atmos. Environ.* 54, 634–642.

- Beelen, R., Hoek, G., Pebesma, E., Vienneau, D., de Hoogh, K., Briggs, D.J., 2009. Mapping of background air pollution at fine spatial scale across the European Union. *Sci. Total Environ.* 407, 1852–1867.
- Bell, M.L., Dominici, F., Samet, J.M., 2005. A meta-analysis of time-series studies of ozone and mortality with comparison to the national morbidity, mortality, and air pollution study. *Epidemiology* 16 (4), 436.
- Berman, J.D., Breyse, P.N., White, R.H., Waugh, D.W., Curriero, F.C., 2015. Evaluating methods for spatial mapping: applications for estimating ozone concentrations across the contiguous United States. *Environ. Technol. Innovat.* 3, 1–10.
- Bonyadi, Z., Arfaeinia, H., Ramavandi, B., Omidvar, M., Asadi, R., 2020. Quantification of mortality and morbidity attributed to the ambient air criteria pollutants in Shiraz city, Iran. *Chemosphere* 127233.
- Bravo, M.A., Fuentes, M., Zhang, Y., Burr, M.J., Bell, M.L., 2012. Comparison of exposure estimation methods for air pollutants: ambient monitoring data and regional air quality simulation. *Environ. Res.* 116, 1–10.
- Braun, S., Achermann, B., De Marco, A., Pleijel, H., Karlsson, P.E., Rihm, B., Schindler, C., Paoletti, E., 2017. Epidemiological analysis of ozone and nitrogen impacts on vegetation—critical evaluation and recommendations. *Sci. Total Environ.* 603, 785–792.
- Briggs, D.J., 2008. A framework for integrated environmental health impact assessment of systemic risks. *Environ. Health* 7, 61.
- Büker, P., Morrissey, T., Briolat, A., Falk, R., Simpson, D., et al., 2012. DO3SE modelling of soil moisture to determine ozone flux to forest trees. *Atmos. Chem. Phys.* 12, 5537–5562.
- Büker, P., Feng, Z., Uddling, J., Briolat, A., Alonso, R., et al., 2015. New flux based dose-response relationships for ozone for European forest tree species. *Environ. Pol.* 206, 163–174.
- Chang, K.T., 2008. Introduction to Geographic Information Systems, fourth ed. McGraw-Hill Publishers, New York, NY, USA, pp. 326–356. *Int. J. Environ. Res. Public Health* 2014, 11 1000 23.
- Checa-García, R., Hegglin, M.I., Kinnison, D., Plummer, D.A., Shine, K.P., 2018. Historical tropospheric and stratospheric ozone radiative forcing using the CMIP6 database. *Geophys. Res. Lett.* 45, 3264–3273.
- CLRTAP (Convention on Long-range Transboundary Air Pollution), 2017. Mapping critical levels for vegetation. In: *Manual on Methodologies and Criteria for Modelling and Mapping Critical Loads & Levels and Air Pollution Effects, Risks and Trends*. Umweltbundesamt, Dessau, Germany. Available on-line at: <http://www.icpmapping.org>.
- Cohen, A.J., Brauer, M., Burnett, R., Anderson, H.R., Frostad, J., Estep, K., et al., 2017. Estimates and 25-year trends of the global burden of disease attributable to ambient air pollution: an analysis of data from the Global Burden of Diseases Study 2015. *Lancet* 389, 1907–1918.
- Colette, A., Granier, Claire, Hodnebrog, Ø., Jakobs, H., Maurizi, A., et al., 2011. Air quality trends in Europe over the past decade: a first multi-model assessment. *Atmospheric Chemistry and Physics, European Geosciences Union* 11 (22), 11657–11678.
- Crippa, P., Sullivan, R.C., Thota, A., Pryor, S.C., 2019. Sensitivity of simulated aerosol properties over eastern North America to WRF-Chem parameterizations. *J. Geophys. Res. Atmos.* 124, 3365–3383.
- De Marco, A., 2008. Assessment of present and future risk to Italian forests and human health: modelling and mapping. *Environ. Pollut.* 12 (5), 1407–1412, 157.
- De Marco, A., Screpanti, Augusto, Paoletti, E., 2009. Geostatistics as a validation tool for setting ozone standards for durum wheat. *Environ. Pollut.* 158, 536–542.
- De Marco, A., Screpanti, A., Attorre, F., Proietti, C., Vitale, M., 2013. Ozone and nitrogen impact assessment on net primary productivity of tree species differently distributed in Italy. *Environ. Pollut.* 172, 250–263.
- De Marco, A., Anav, A., Sicard, P., Feng, Zhaozhong, Paoletti, E., 2020. High spatial resolution risk-assessment for Asian forests. *Environ. Res. Lett.* <https://doi.org/10.1088/1748-9326/abb501> (in press).
- De Vries, W., Posch, M., Simpson, D., Reinds, G.J., 2017. Modelling long-term impacts of changes in climate, nitrogen deposition and ozone exposure on carbon sequestration of European forest ecosystems. *Sci. Total Environ.* 605–606, 1097–1116.
- Dee, D.P., Uppala, S.M., Simmons, A.J., Berrisford, P., Poli, P., Kobayashi, S., Andrae, U., Balmaseda, M.A., Balsamo, G., Bauer, P., Bechtold, P., Beljaars, A.C.M., van de Berg, L., Bidlot, J., Bormann, N., Delsol, C., Dragani, R., Fuentes, M., Geer, A.J., Haimberger, L., Healy, S.B., Hersbach, H., Hólm, E.V., Isaksen, I., Kållberg, P., Köhler, M., Matricardi, M., McNally, A.P., Monge-Sanz, B.M., Morcrette, J.-J., Park, B.-K., Peubey, C., de Rosnay, P., Tavolato, C., Thépaut, J.-N., Vitart, F., 2011. The ERA-Interim reanalysis: configuration and performance of the data assimilation system. *Q. J. R. Meteorol. Soc.* 137, 553–597, 2011.
- DeLang, M.N., Becker, J.S., Chang, K., Serre, M.L., Cooper, O.R., Schultz, M.G., Schröder, S., Lu, X., Zhang, L., Deushi, M., Josse, B., Keller, C.A., Lamarque, J.F., Lin, M., Liu, J., Maréchal, V., Strode, S.A., Sudo, K., Tilmes, S., Zhang, L., Cleland, S. E., Collins, E.L., Brauer, M., West, J.J., 2021. Mapping yearly fine resolution global surface ozone through the bayesian maximum entropy data fusion of observations and model output for 1990–2017. *Environ. Sci. Technol.* 55 (8), 4389–4398, 2021.
- Derwent, R.G., 2020. Monte Carlo analyses of the uncertainties in the predictions from global tropospheric ozone models: tropospheric burdens and seasonal cycles. *Atmos. Environ.* 231, 117545.
- Du, W., Zhang, W., Hu, H., Zhang, M., He, Y., Li, Z., 2019. Associations between ambient air pollution and hospitalizations for acute exacerbation of chronic obstructive pulmonary disease in Jinhua. *Chemosphere* 2020, 128905.
- EEA, 2019. Air Quality in Europe — 2019 Report 1994–2019.
- Evans, M.R., 2012. Modelling ecological systems in a changing world. *Philos. Trans. R. Soc. B Biol. Sci.* 367, 181–190. <https://doi.org/10.1098/rstb.2011.0172>.
- Feng, Z., De Marco, A., Anav, A., Gualtieri, M., Sicard, P., Tian, H., Fornasier, F., Tao, F., Guo, A., Paoletti, E., 2019. Economic losses due to ozone impacts on human health, forest productivity and crop yield across China. *Environ. Int.* 131 (104966), 9.
- Fraczek, W., Bytnerowicz, Andrzej, Arbaugh, Michael J., 2001. Application of the ESRI geostatistical analyst for determining the adequacy and sample size requirements of ozone distribution models in the Carpathian and Sierra Nevada mountains. *Sci. World J.* 1, 969403, 19 pages.
- Flato, G., Marotzke, J., Abiodun, B., Braconnot, P., Chou, S.C., Collins, W., Cox, P., Driouech, F., Emori, S., Eyring, V., Forest, C., Gleckler, P., Guilyardi, E., Jakob, C., Kattsov, V., Reason, C., Rummukainen, M., 2014. Evaluation of climate models. In: *Climate Change 2013 – the Physical Science Basis: Working Group I Contribution to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*. Cambridge University Press, pp. 741–866.
- Flemming, J., Innes, A., 2018. Carbon monoxide [in “state of the climate in 2017”]. *Bull. Am. Meteorol. Soc.* 99, S59–S61.
- Forouzanfar, M.H., et al., 2016. Global, regional, and national comparative risk assessment of 79 behavioural, environmental and occupational, and metabolic risks or clusters of risks, 1990–2015: a systematic analysis for the Global Burden of Disease Study 2015. *Lancet* 388, 1659–1724. [https://doi.org/10.1016/S0140-6736\(15\)00128-2](https://doi.org/10.1016/S0140-6736(15)00128-2).
- Ghim, Y.S., Choi, Y., Kim, S., Bae, C.H., Park, J., Shin, H.J., 2017. Evaluation of model performance for forecasting fine particle concentrations in Korea. *Aerosol Air Qual. Res.* 17, 1856–1864.
- Gong, B., Ordieres-Meré, J., 2016. Prediction of daily maximum ozone threshold exceedances by preprocessing and ensemble artificial intelligence techniques: case study of Hong Kong. *Environ. Model. Software* 84, 290–303.
- González-Fernández, I., Elvira, S., Calatayud, V., Calvo, E., Aparicio, P., Sánchez, M., et al., 2016. Ozone effects on the physiology and marketable biomass of leafy vegetables under Mediterranean conditions: spinach (*Spinacia Oleracea* L.) and Swiss chard (*Beta Vulgaris* L. var. *cycla*). *Agric. Ecosyst. Environ.* 235, 215–228.
- Griffith, D.A., Layne, L.J., 1999. A Casebook for Spatial Statistical Data Analysis. Oxford University Press, New York.
- Grulke, N.E., Paoletti, E., Heath, R.L., 2007. Chronic vs. short-term acute O₃ exposure effects on nocturnal transpiration in two Californian oaks. *Sci. World J.* 134–140.
- Gryparis, A., Forsberg, B., Katsouyanni, K., Analitis, A., Touloumi, G., Schwartz, J., et al., 2004. Acute effects of ozone on mortality from the “air pollution and health: a European approach” project. *Am. J. Respir. Crit. Care Med.* 170 (10), 1080–1087.
- Guo, Y., Li, S., Tian, Z., Pan, X., Zhang, J., Williams, G., 2013. The burden of air pollution on years of life lost in Beijing, China, 2004–08: retrospective regression analysis of daily deaths. *Bmj* 347.
- Gupta, M., Mohan, M., 2015. Validation of WRF/Chem model and sensitivity of chemical mechanisms to ozone simulation over megacity Delhi. *Atmos. Environ.* 122, 220–229.
- Haase, D., Larondelle, N., Andersson, E., Artmann, M., Borgstrom, S., et al., 2014. A quantitative review of urban ecosystem service assessments: concepts, models, and implementation. *Ambio* 43, 413–433.
- Hadei, M., Hopke, P.K., Nazari, S.S.H., Yarahmadi, M., Shahsavani, A., Alipour, M.R., 2017. Estimation of mortality and hospital admissions attributed to criteria air pollutants in Tehran metropolis, Iran. *Aerosol Air Qual. Res.* 17 (10), 2474–2481, 2013–2016.
- Hayes, F., Mills, G., Alonso, R., González-Fernández, I., Coyle, M., Grünhage, L., et al., 2019. A site-specific analysis of the implications of a changing ozone profile and climate for stomatal ozone fluxes in Europe. *Water, Air, Soil Pollut.* 230 (1), 4.
- Hendriks, C., Kranenburg, R., Kuenen, J.J.P., Van Gijlswijk, R., Wichink Kruit, R., Segers, A.J., Denier van der Gon, H.A.C., Schaap, M., 2013. The origin of ambient particulate matter concentrations in The Netherlands. *Atmos. Environ.* 69, 289–303.
- Héroux, M.-E., Anderson, H.R., Atkinson, R., Brunekreef, B., Cohen, A., Forastiere, F., et al., 2015. Quantifying the health impacts of ambient air pollutants: recommendations of a WHO/Europe project. *Int. J. Publ. Health* 60 (5), 619–627.
- Hoek, G., Beelen, R., de Hoogh, K., Vienneau, D., Gulliver, J., et al., 2008. A review of land-use regression models to assess spatial variation of outdoor air pollution. *Atmos. Environ.* 42, 7561–7578.
- Hu, E.Z., Gao, F., Xin, Y., Jia, H.X., Li, K.H., Hu, J.J., Feng, Z.Z., 2015. Concentration- and flux-based ozone dose-response relationships for five poplar clones grown in North China. *Environ. Pollut.* 207, 21–30.
- Huang, J., Li, G., Xu, G., Qian, X., Zhao, Y., Pan, X., et al., 2018. The burden of ozone pollution on years of life lost from chronic obstructive pulmonary disease in a city of Yangtze River Delta, China. *Environ. Pollut.* 242, 1266–1273.
- Huijnen, V., Flemming, J., Kaiser, J.W., Inness, A., Leitão, J., Heil, A., Eskes, H.J., Schultz, M.G., Benedetti, A., Hadji-Lazarou, J., Dufour, G., Eremenko, M., 2012. Hindcast experiments of tropospheric composition during the summer 2010 fires over western Russia. *Atmos. Chem. Phys.* 12, 4341–4364.
- Hůnová, I., Horálek, J., Schreiberová, M., Zapletal, M., 2012. Ambient ozone exposure in Czech forests: a GIS-based approach to spatial distribution assessment. *Sci. World J.* 10, 2012, Article ID 123760.
- Im, U., Bianconi, R., Solazzo, E., Kioutsiouk, I., Badia, A., Balzarini, A., Baro, R., Bellasio, R., et al., 2015. Evaluation of operational online-coupled regional air quality models over Europe and North America in the context of AQMEII phase 2. Part I: ozone. *Atmos. Environ.* 115, 404–420.
- Jarvis, P.G., 1976. The interpretation of the variations in leaf water potential and stomatal conductance found in canopies in the field. *Philos. Trans. R. Soc. London, Ser. A* B 273, 593–610.
- Javanmardi, P., Morovati, P., Farhadi, M., Geravandi, S., Khaniabadi, Y.O., Angali, K.A., et al., 2018. Monitoring the impact of ambient ozone on human health using time

- series analysis and air quality model approaches. *Fresenius Environ. Bull.* 27 (1), 533–544.
- Jeong, S.J., 2013. The impact of air pollution on human health in Suwon City. *Asian journal of atmospheric environment* 7 (4), 227–233.
- Jerrett, M., Arain, A., Kanaroglou, P., Beckerman, B., Potoglou, D., et al., 2004. A review and evaluation of intraurban air pollution exposure models. *J. Expo. Anal. Environ. Epidemiol.* 15, 185.
- Jerrett, M., Burnett, R.T., Pope III, C.A., Ito, K., Thurston, G., Krewski, D., et al., 2009. Long-term ozone exposure and mortality. *N. Engl. J. Med.* 360 (11), 1085–1095.
- Jonson, J.E., Schulz, M., Emmons, L., Flemming, J., Henze, D., Sudo, K., Tronstad Lund, M., Lin, M., Benedictow, A., Koffi, B., Dentener, F., Keating, T., Kivi, R., Davila, Y., 2018. The effects of intercontinental emission sources on European air pollution levels. *Atmos. Chem. Phys.* 18, 13655–13672.
- Karlický, J., Huszár, P., Halenka, T., 2017. Validation of gas phase chemistry in the wrf-chem model over europe. *Adv. Sci. Res.* 14, 181–186.
- Kerckhoffs, J., Wang, M., Meliefste, K., Malmqvist, E., Fischer, P., Janssen, N.A.H., 2015. Rob. Beelen, Gerard Hoek A national fine spatial scale land-use regression model for ozone. *Environ. Res.* 140, 440–448.
- Kethireddy, S.R., Tchounwou, P.B., Ahmad, H.A., Yerramilli, A., Young, J.H., 2014. Geospatial interpolation and mapping of tropospheric ozone pollution using geostatistics. *Int. J. Environ. Res. Publ. Health* 11, 983–1000.
- Khaniabadi, Y.O., Sicard, P., 2021. A 10-year assessment of ambient fine particles and related health endpoints in a large Mediterranean city. *Chemosphere* 278, 130502.
- Khaniabadi, Y.O., Daryanoosh, M., Sicard, P., Takdastan, A., Hopke, P.K., Esmaili, S., et al., 2018. Chronic obstructive pulmonary diseases related to outdoor PM10, O3, SO2, and NO2 in a heavily polluted megacity of Iran. *Environ. Sci. Pollut. Control Ser.* 25 (18), 17726–17734.
- Kinose, Y., Fukamachi, Y., Okabe, S., Hiroshima, H., Watanabe, M., Izuta, T., 2020. Toward an impact assessment of ozone on plant carbon fixation using a process-based plant growth model: a case study of *Fagus crenata* grown under different soil nutrient levels. *Sci. Total Environ.* 716, 137008.
- Knowland, K.E., Ott, L.E., Duncan, B.N., Wargan, K., 2017. Stratospheric intrusion-influenced ozone air quality exceedances investigated in the NASAMERRA-2 reanalysis. *Geophys. Res. Lett.* 44 (10), 701, 691–10.
- Knowlton, K., Rosenthal, J.E., Hogrefe, C., Lynn, B., Gaffin, S., Goldberg, R., Rosenzweig, C., Civerolo, K., Ku, J.Y., Kinney, P.L., 2004. Assessing ozone-related health impacts under a changing climate. *Environ. Health Perspect.* 112 (15), 1557–1563.
- Lamarque, J.-F., Bond, T.C., Eyring, V., Granier, C., Heil, A., et al., 2010. Historical (1850–2000) gridded anthropogenic and biomass burning emissions of reactive gases and aerosols: methodology and application. *Atmos. Chem. Phys.* 10, 7017–7039.
- Lamarque, J.F., Shindell, D.T., Josse, B., Young, P.J., Cionni, I., et al., 2013. The Atmospheric Chemistry and Climate Model Intercomparison Project (ACCMIP): overview and description of models, simulations and climate diagnostics. *Geosci. Model Dev. (GMD)* 6, 179–206.
- Lauwaet, D., Viane, P., Brissou, E., van Noije, T., Strunk, A., Van Looy, S., Maiheu, B., Veldeman, N., Blyth, L., De Ridder, K., Janssen, S., 2013. Impact of nesting resolution jump on dynamical downscaling ozone concentrations over Belgium. *Atmos. Environ. Times* 67, 46–52.
- Lelieveld, J., Evans, J.S., Fnais, M., Giannadaki, D., Pozzer, A., 2015. The contribution of outdoor air pollution sources to premature mortality on a global scale. *Nature* 525, 367–371.
- Li, D., Bou-Zeid, E., Oppenheimer, M., 2014. The effectiveness of cool and green roofs as urban heat island mitigation strategies. *Environ. Res. Lett.* 9 (5), 055002.
- Li, P., De Marco, A., Feng, Z., Anav, A., Zhou, D., Paoletti, E., 2018. Nationwide ground-level ozone measurements in China suggest serious risks to forests. *Environ. Pollut.* 237, 803–813.
- Li, J., Yin, P., Wang, L., Zhang, X., Liu, J., Liu, Y., Zhou, M., 2020. Ambient ozone pollution and years of life lost: association, effect modification, and additional life gain from a nationwide analysis in China. *Environ. Int.* 141, 105771, 2020.
- MEP, Ministry of Environmental Protection, 2012. Government of China. Ambient Air Quality Standards (In Chinese). GB 3095–2012.
- Miller, H.J., 2004. Tobler's first law and spatial analysis. *Ann. Assoc. Am. Geogr.* 94, 284–289.
- Miranda, Silveira C., Ferreira, J., Monteiro, A., Lopes, D., Relvas, H., Borrego, C., Roebeling, P., 2015. Current air quality plans in Europe designed to support air quality management policies. *Atmos. Pollut. Res.* 6, 434–443.
- Monga, R., Marzuoli, R., Alonso, R., Bermejo, V., González-Fernández, I., Faoro, F., et al., 2015. Varietal screening of ozone sensitivity in Mediterranean durum wheat (*Triticum durum*, Desf.). *Atmos. Environ.* 110, 18–26.
- Morgenstern, O., et al., 2017. Review of the global models used within phase 1 of the chemistry-climate initiative (CCMI) Geosci. Model Dev 10, 639–671.
- Morgenstern, O., Stone, K.A., Schofield, R., Akiyoshi, H., Yamashita, Y., Kinnison, D.E., Garcia, R.R., Sudo, K., Plummer, D.A., Scinocca, J., Oman, L.D., Manyin, M.E., Zeng, G., Rozanov, E., Stenke, A., Revell, L.E., Pitari, G., Mancini, E., Di Genova, G., Visioni, D., Dhomse, S.S., Chipperfield, M.P., 2018. Ozone sensitivity to varying greenhouse gases and ozone-depleting substances in CCMI-1 simulations. *Atmos. Chem. Phys.* 18, 1091–1114.
- Mues, A., Kuenen, J.J.P., Hendriks, C., Manders, A., Segers, A., Scholz, Y., Hueglin, C., Builjtes, P., Schaap, M., 2014. Sensitivity of air pollution simulations with LOTOS-EUROS to temporal distribution of anthropogenic emissions. *Atmos. Chem. Phys.* 14, 939–955.
- Myers, D.E., 1991. Interpolation and estimation with spatially located data. *Chemometrics and Intelligent Laboratory Systems* 11, 209–228.
- Nelson, S.D., Malone, D., Lafleur, J., 2015. Calculating the baseline incidence in patients without risk factors: a strategy for economic evaluation. *Pharmacoeconomics* 33 (9), 887–892.
- Nuvolone, D., Petri, D., Voller, F., 2018. The effects of ozone on human health. *Environ. Sci. Pollut. Control Ser.* 25, 8074–8088.
- O'Connor, M.I., Holding, J.M., Kappel, C.V., Duarte, C.M., Brander, K., Brown, C.J., Bruno, J.F., Buckley, L., Burrows, M.T., Halpern, B.S., Kiessling, W., Moore, P., Pandolfi, J.M., Parmesan, C., Poloczanska, E.S., Schoeman, D.S., Sydeman, W.J., Richardson, A.J., 2015. Strengthening confidence in climate impact science. *Global Ecol. Biogeogr.* 24, 64–76.
- Pal, S., Lee, T.R., Phelps, S., De Wekker, S.F.J., 2014. Impact of atmospheric boundary layer depth variability and wind reversal on the diurnal variability of aerosol concentration at a valley site. *Sci. Total Environ.*
- Pay, M.T., Martínez, F., Guevara, M., Baldasano, J.M., 2014. Air quality forecasts at kilometer scale grid over Spanish complex terrains. *Geosci. Model. Dev.* 7, 1979–1999.
- Pineda Rojas, A.L., Venegas, L.E., Mazzeo, N.A., 2016. Uncertainty of modelled urban peak O3 concentrations and its sensitivity to input data perturbations based on the Monte Carlo analysis. *Atmos. Environ.* 141, 422–429.
- Pleijel, H., Broberg, M.C., Uddling, J., 2019. Ozone impact on wheat in Europe, Asia and North America—A comparison. *Sci. Total Environ.* 664, 908–914.
- Proietti, C., Anav, A., De Marco, A., Sicard, P., Vitale, M., 2016. A multi-sites analysis on the ozone effects on Gross Primary Production of European forests. *Sci. Total Environ.* 556, 1–11.
- Pugh, T.A.M., Ashworth, K., Wild, O., Hewitt, C.N., 2013. Effects of the spatial resolution of climate data on estimates of biogenic isoprene emissions. *Atmos. Environ. Times* 70, 1–6.
- Qiao, X., Guo, H., Wang, P., Tang, Y., Ying, Q., Zhao, X., Deng, W., Zhang, H., 2019. Fine particulate matter and ozone pollution in the 18 cities of the Sichuan Basin in southwestern China: model performance and characteristics. *Aerosol Air Qual. Res.* 19, 2308–2319.
- Quennehen, B., 2008. Multi-model evaluation of short-lived pollutant distributions over East Asia during summer. *Atmos. Chem. Phys.* 1680, 7324, 2015.
- Reis, S., Nitter, S., Friedrich, R., 2005. Innovative approaches in integrated assessment modelling of European air pollution control strategies - implications of dealing with multi-pollutant multi-effect problems. *Environ. Model. Softw.* 20 (12), 1524–1531.
- Ren, X., Mi, Z., Georgopoulos, P.G., 2020. Comparison of Machine Learning and Land Use Regression for fine scale spatiotemporal estimation of ambient air pollution: modeling ozone concentrations across the contiguous United States. *Environ. Int.* 142, 105827.
- Requia, W.J., Di, Q., SilvernR, F., KellyJ, T., KoutrakisP, MickleY, J., SulprizioM, P., AminiH, Shi, L., Schwartz, J., 2020. An ensemble learning approach for estimating high spatiotemporal resolution of ground-level ozone in the contiguous United States. *ES T (Environ. Sci. Technol.)* 11037–11047.
- Roelofs, G.J., Lelieveld, J., 1997. Model study of the influence of cross-tropopause O3 transports on tropospheric O3 levels. *Tellus B* 49 (1), 38–55.
- Rovira, J., Domingo, J.L., Schuhmacher, M., 2020. Air quality, health impacts and burden of disease due to air pollution (PM10, PM2.5, NO2 and O3): application of AirQ + model to the Camp de Tarragona County (Catalonia, Spain). *Sci. Total Environ.* 703, 135538.
- Rowlinson, M.J., Rap, A., Arnold, S.R., Pope, R.J., Chipperfield, M.P., et al., 2019. Impact of El Niño–Southern Oscillation on the interannual variability of methane and tropospheric ozone. *Atmos. Chem. Phys.* 19, 8669–8686.
- Saitanis, C., Sicard, P., De Marco, A., Feng, Z., Paoletti, E., Agathokleous, E., 2020. On the atmospheric ozone monitoring methodologies. *Current Opinion in Environmental Science & Health* 18, 40–46.
- Sanz, J., González-Fernández, I., Elvira, S., Muntifering, R., Alonso, R., Bermejo-Bermejo, V., 2016. Setting ozone critical levels for annual Mediterranean pasture species: combined analysis of open-top chamber experiments. *Sci. Total Environ.* 571, 670–679.
- Schaap, M., Cuvelier, C., Hendriks, C., Bessagnet, B., Baldasano, J., et al., 2015. Performance of European chemistry transport models as function of horizontal resolution. *Atmos. Environ.* 112, 90–105.
- Schauberger, B., Rolinski, S., Schaphoff, S., Müller, C., 2019. Global historical soybean and wheat yield loss estimates from ozone pollution considering water and temperature as modifying effects. *Agric. For. Meteorol.* 265, 1–15.
- Sharma, S., Chatani, S., Mahtta, R., Goel, A., Kumar, A., 2016. Sensitivity analysis of ground level ozone in India using WRF-CMAQ models. *Atmos. Environ. Times* 131, 29–40.
- Sicard, P., 2021. Ground-level ozone over time: an observation-based global overview. *Current Opinion in Environmental Science & Health* 19, 100226.
- Sicard, P., De Marco, A., Troussier, F., Renou, C., Vas, N., Paoletti, E., 2013. Decrease in surface ozone concentrations at Mediterranean remote sites and increase in the cities. *Atmos. Environ.* 79, 705–715.
- Sicard, P., Augustaitis, A., Belyazid, S., Calafapietra, C., De Marco, A., et al., 2016a. Global topics and novel approaches in the study of air pollution, climate change and forest ecosystems. *Environ. Pollut.* 213, 977–987.
- Sicard, P., Serra, R., Rossello, P., 2016b. Spatio-temporal trends of surface ozone concentrations and metrics in France. *Environ. Res.* 149, 122–144.
- Sicard, P., Anav, A., De Marco, A., Paoletti, E., 2017. Projected global ground-level ozone impacts on vegetation under different emission and climate scenarios. *Atmos. Chem. Phys.* 17, 12177–12196.
- Sicard, P., Khaniabadi, Y.O., Perez, S., Gualtieri, M., De Marco, A., 2019. Effect of O3, PM10 and PM2.5 on cardiovascular and respiratory diseases in cities of France, Iran and Italy. *Environ. Sci. Pollut. Control Ser.* 26 (31), 32645–32665.

- Sicard, P., Paoletti, E., Agathokleous, E., Araminienė, V., Proietti, C., Coulibaly, F., De Marco, A., 2020. Ozone weekend effect in cities: Deep insights for urban air pollution control. *Environ. Res.* 191, 110193.
- Sicard, P., Agathokleous, E., De Marco, A., Paoletti, E., Calatayud, V., 2021a. Urban population exposure to air pollution in Europe over the last decades. *Environ. Sci. Eur.* 28 <https://doi.org/10.21203/rs.3.rs-101275/v1>.
- Sicard, P., Crippa, P., De Marco, A., Castruccio, S., Giani, P., et al., 2021b. High spatial resolution WRF-chem model over Asia: physics and chemistry evaluation. *Atmos. Environ.* 224, 118004.
- Simpson, D., Ashmore, M.R., Emberson, L., Tuovinen, J.P., 2007. A comparison of two different approaches for mapping potential ozone damage to vegetation. A model study. *Environ. Pollut.* 146, 715–725.
- Simpson, D., Benedictow, A., Berge, H., Bergström, R., Emberson, L.D., et al., 2012. The EMEP MSC-W chemical transport model - technical description. *Atmos. Chem. Phys.* 12, 7825–7865.
- Simpson, D., Andersson, C., Christensen, J.H., Engardt, M., Geels, C., Nyiri, A., Posch, M., Soares, J., Sofiev, M., Wind, P., et al., 2014. Impacts of climate and emission changes on nitrogen deposition in Europe: a multi-model study. *Atmos. Chem. Phys.* 14 (13), 6995–7017.
- Singh, K.P., Gupta, S., Rai, P., 2013. Identifying pollution sources and predicting urban air quality using ensemble learning methods. *Atmos. Environ.* 80, 426–437.
- Sitch, S., Huntingford, C., Gedney, N., Levy, P.E., Lomas, M., Piao, S.L., Betts, R., Ciais, P., Cox, P., Friedlingstein, P., Jones, C.D., Prentice, I.C., Woodward, F.I., 2008. Evaluation of the terrestrial carbon cycle, future plant geography and climate-carbon cycle feedbacks using five Dynamic Global Vegetation Models (DGVMs). *Global Change Biol.* 14, 2015–2039.
- Surendran, D.E., Ghude, S.D., Beig, G., Emmons, L.K., Jena, C., et al., 2015. Air quality simulation over South Asia using hemispheric transport of air pollution version-2 (HTAP-v2) emission inventory and model for ozone and related chemical tracers (MOZART-4). *atmos. Environ. Times* 122, 357–372.
- Tan, K.C., San Lim, H., Jafri, M.Z.M., 2016. Prediction of column ozone concentrations using multiple regression analysis and principal component analysis techniques: a case study in peninsular Malaysia. *Atmos. Pollut. Res.* 7, 533–546.
- Tian, Y., Wu, Y., Liu, H., Si, Y., Wu, Y., Wang, X., et al., 2020. The impact of ambient ozone pollution on pneumonia: a nationwide time-series analysis. *Environ. Int.* 136, 105498.
- Tie, X., Brasseur, G., Ying, Z., 2010. Impact of model resolution on chemical ozone formation in Mexico City: application of the WRF-Chem model. *Atmos. Chem. Phys.* 10, 8983–8995. <https://doi.org/10.5194/acp-10-8983-2010>.
- Tobler, W.R., 1970. A computer movie simulating urban growth in Detroit region. *Econ. Geogr.* 46, 234–240.
- Tong, N.Y.O., Leung, D.Y.C., Liu, C.-H., 2011. A review on ozone evolution and its relationship with boundary layer characteristics in urban environments. *Water, Air, Soil Pollut.* 214, 13–36.
- Van Dingenen, R., Dentener, F.J., Raes, F., Krol, M.C., Emberson, L., Cofala, J., 2009. The global impact of ozone on agricultural crop yields under current and future air quality legislation. *Atmos. Environ. Times* 43, 604–618.
- van Loon, M., Coauthors, 2007. Evaluation of long-term ozone simulations from seven regional air quality models and their ensemble. *Atmos. Environ.* 41, 2083–2097.
- Vieno M., Dore A.J., Stevenson D.S., et al. Modelling surface ozone during the 2003 heat wave in the UK 2010. *Atmos. Chem. Phys.*, 10), pp. 7963-7978.
- Voulgarakis, A., Naik, V., Lamarque, J.F., Shindell, D.T., Young, P.J., et al., 2013. Analysis of present day and future OH and methane lifetime in the ACCMIP simulations. *Atmos. Chem. Phys.* 13, 2563–2587.
- Wataszek, K., Kryza, M., Werner, M., 2018. The role of precursor emissions on ground level ozone concentration during summer season in Poland. *J. Atmos. Chem.* 75, 181–204. <https://doi.org/10.1007/s10874-017-9371-y>.
- Wang, M., Beelen, R., Eeftens, M., Meliefste, K., Hoek, G., Brunekreef, B., 2012. Systematic evaluation of land use regression models for NO₂. *Environ. Sci. Technol.* 46 (8), 4481–4489.
- Wild, O., Prather, M.J., 2006. Global tropospheric ozone modeling: quantifying errors due to grid resolution. *J. Geophys. Res.* 111, D11305.
- Wild, O., Fiore, A.M., Shindell, D.T., Doherty, R.M., Collins, W.J., et al., 2012. Modelling future changes in surface ozone: a parameterized approach. *Atmos. Chem. Phys.* 12, 2037–2054.
- World Health Organization, 2008. Health Risks of Ozone from Long-Range Transboundary Air Pollution. WHO/Euro product, ISBN 978 92 890 42895.
- World Health Organization, 2013. Review of Evidence on Health Aspects of Air Pollution - REVIHAAP Project. World Health Organization, Regional Office for Europe, Copenhagen, Denmark (Technical Report).
- Yang, C., Yang, H., Guo, S., Wang, Z., Xu, X., Duan, X., et al., 2012. Alternative ozone metrics and daily mortality in suzhou: the China air pollution and health effects study (CAPES). *Sci. Total Environ.* 426, 83–89.
- Yang, Y., Qi, J., Ruan, Z., Yin, P., Zhang, S., Liu, J., et al., 2020. Changes in life expectancy of respiratory diseases from attaining daily PM_{2.5} standard in China: a nationwide observational study. *Innovation* 1, 100064.
- Yazdi, M.D., Wang, Y., Di, Q., Zanobetti, A., Schwartz, J., 2019. Long-term exposure to PM_{2.5} and ozone and hospital admissions of Medicare participants in the Southeast USA. *Environ. Int.* 130, 104879.
- Zanobetti, A., Schwartz, J., 2008. Mortality displacement in the association of ozone with mortality - an analysis of 48 cities in the United States. *Am. J. Respir. Crit. Care Med.* 177, 184–189.
- Zhang, Q., Jiang, X., Tong, D., et al., 2017. Transboundary health impacts of transported global air pollution and international trade. *Nature* 543, 705–709.