

Article

Comparison of 24 h Surface Ozone Forecast for Poland: CAMS Models vs. Simple Statistical Models with Limited Number of Input Parameters

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Abstract: Surface ozone is usually measured in national networks, including the monitoring of gaseous components important for determining air quality and the short-term forecast of surface ozone. Here we consider the option of forecasting surface ozone based on measurements of only surface ozone and several weather parameters. This low-cost configuration can increase the number of locations that provide short-term surface ozone forecast important to local communities. 24 h prediction of the 1-h averaged concentration of surface ozone were presented for rural (Belsk, 20.79° E, 51.84° N) and suburban site (Racibórz, 18.19° E, 50.08° N) in Poland for the period 2018–2021 via simple statistical models dealing with a limited number of predictors. Multiple linear regression (MLR) and artificial neural network (ANN) models were examined separately for each season of the year using temperature, relative humidity, an hour of the day, and 1-day lagged surface ozone values. The performance of ANN (with $R^2 = 0.81$ in Racibórz versus $R^2 = 0.75$ at Belsk) was slightly better than the MLR model (with $R^2 = 0.78$ in Racibórz versus $R^2 = 0.71$ at Belsk). These statistical models were compared with advanced chemical–transport models provided by the Copernicus Atmosphere Monitoring Service. Despite the simplicity of the statistical models, they showed better performance in all seasons, with the exception of winter.

Keywords: surface ozone; forecast; statistical models; chemistry–transport models; air quality



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1. Introduction

Surface ozone (O_3) is a secondary photochemical pollutant at the ground level of the atmosphere [1]. The primary source of surface O_3 is photochemical production, including nitrogen oxides (NO_x), carbon monoxide (CO), and volatile organic compounds (VOC) [2–4]. The other sources are the downward transport of stratospheric ozone into the troposphere [5,6] and the long-range transport of surface O_3 from distant polluted areas [7]. The dominant sink of surface O_3 are processes of photochemical destruction and the mechanism of dry deposition on different surfaces [8]. Surface O_3 shows non-linear dependence on the concentration of its precursors [9]. It could be classified into two chemical regimes, NO_x saturated, and NO_x limited, which are determined by the sensitivity of surface O_3 to anthropogenic precursors [10]. Surface O_3 can decrease as NO_x decreases under NO_x saturated regime or as NO_x increases under NO_x limited regime. The increase of VOC generally leads to an increase of surface O_3 regardless of the kind of regime. The main sources of NO_x and VOC are traffic and biogenic emissions, respectively. Hence, the surface O_3 concentrations can vary significantly between rural and urban locations. Many studies have shown higher surface O_3 concentrations in rural areas compared to urban areas [11–13]. The chemistry of NO_x , VOC, and O_3 in the troposphere and their relationship is well known and extensively discussed in the literature [9,14].

Surface O₃ plays an important role in the atmosphere. It is an important greenhouse gas with a radiative forcing of $0.40 \pm 0.20 \text{ W/m}^2$ [15] and a major component of photochemical smog [16]. High levels of surface O₃ have an adverse effect on human health and vegetation [17–19]. Ozone photolysis processes play an important role in the troposphere as a source of hydroxyl radicals (OH)—a dominant atmospheric oxidant [20].

Surface O₃ formation and transport are strongly influenced by meteorological conditions. Temperature affects the rate of chemical reactions, the lifetime of polyacrylonitrile (PAN) compounds (functioning as a reservoir of NO_x) as well as affects the emission of VOC [21,22]. Solar radiation initiates photochemical processes [23]. An increase in relative humidity promotes the formation of clouds [24] and affects the stomatal conductivity of the leaves. In response to the increase in humidity, the stomata open, which increases the absorption of surface O₃ in the processes of dry deposition [25,26]. A detailed description of the connection between particular meteorological parameters has been broadly documented in the literature [1,27–29].

Surface O₃ can be predicted with the use of statistical and deterministic methods [30]. The ability of both methods to predict the surface O₃ variability as a result of changes in precursor emissions and ambient meteorological conditions is very important, especially nowadays, in a changing climate. Quantifying surface O₃ response to meteorological changes is a particular challenge [31]. The prediction of surface O₃ is further complicated by its nature as a secondary pollutant [32].

Chemistry–transport models (CTM) are commonly used to forecast surface O₃ variability [33,34]. However, their use is limited because they require huge computational resources and suffer from a large bias resulting from the coarse resolution [35], especially in urban areas with changing chemistry, varied topography, and uncertainty of emission inventory [36]. Therefore, statistical models, e.g., multiple linear regression (MLR) and artificial neural network (ANN), can be an additional tool supporting surface O₃ prediction.

A number of works have compared MLR and ANN methods for surface O₃ prediction starting from the early 1990s. Yi and Prybutok [37] developed ANN, linear regression model, and Box-Jenkins ARIMA to predict the surface O₃ maximum between 1993–1994 in Dallas. Comrie [38] investigated the potential of MLR and ANN to predict daily surface O₃ concentration between 1991 and 1995 for eight cities around the United States. Spellman [39] used MLR and ANN models to predict spring–summer surface O₃ (from May to September) in the period 1993–1996 for five different sites (remote, rural, and urban center) in the UK. Gardner and Dorling [40] used MLR, regression tree, and ANN models to predict hourly surface O₃ values in the period 1994–1997 for five sites (rural and urban) in the UK. Sousa et al. [41] examined MLR and ANN models to predict next-day hourly surface O₃ concentration values in Oporto (Northern Portugal). Capilla [42] used MLR and ANN models to predict surface O₃ for 1, 8, and 24 h in advance in an urban area of Valencia (Spain). Yu et al. [43] used MLR and ANN models to predict the maximum concentration of surface ozone. In all studies mentioned above, the ANN methods gave better results; however, in most cases, improvement was marginal.

In recent years, there have been many papers using more advanced machine learning methods. Freeman et al. [44] predicted an 8-h averaged concentration of surface O₃ using deep learning techniques such as Long Short-term Memory (LSTM) and Recurrent Neural Network (RNN). Ko et al. [45] forecasted the hourly concentration of surface O₃ for the upcoming 24 h using ANN and bidirectional LSTM models with a limited number of input data (surface O₃, temperature, relative humidity, and height of the planetary boundary layer). Oufdou et al. [46] compared the results of parametric (the Least Absolute Shrinkage and Selection Operator (LASSO) and Saddle Point Least Squares (SPLS) method) and non-parametric (Bagging, Classification and Regression Trees (CART) and Random Forest (RF)) methods to forecast daily surface O₃ in Morocco. Jia et al. [47] used a sequence-to-sequence deep learning model to predict surface O₃ for the next 6 h over the Yangtze River Delta in China. Juarez et al. [48] employed eight machine learning approaches (linear regression,

Support Vector Machines (SVM), K-Nearest Neighbors (KNN) algorithm, RF, Decision Trees, LSTM, AdaBoost, XGBoost) to forecast surface O₃ for the next 24 h in Delhi.

The main objective of the work was a 24 h forecast of the hourly averaged surface O₃ with steps every 3 h from 0:00 GMT for rural and suburban areas in Poland. We choose a simple statistical approach (MLR and ANN) that is adapted to the case with a limited number of predictors available for these locations. Two sets of predictors are examined, i.e., the meteorological data (temperature and relative humidity) plus an hour of the day, and the set comprising in addition also 1-day lagged surface O₃, and 3 h lagged temperature and relative humidity. Section 2 presents the observing sites, examined data, and models' details. Performances of all examined models are shown in Section 3. Discussion and conclusions are in Section 4.

2. Materials and Methods

2.1. Site Description

Concurrent measurements of surface O₃ concentrations (ppb) and meteorological parameters: temperature (°C), and relative humidity (%) were carried out in the Belsk observatory and Racibórz observatory from September 2018 to September 2021 (Figure 1, Table 1).



Figure 1. Location of the stations considered in the study. (source: nationsonline.org).

Table 1. Characteristics of the stations.

Station Name	Altitude (m a.s.l.)	Latitude	Longitude	Station Type
Belsk	176	51.837° N	20.792° E	rural
Racibórz	193	50.083° N	18.192° E	suburban

The first measuring station, Belsk, represents rural background conditions. It is located in the central part of Poland in typical rural areas, 50 km south of Warsaw at the Central Geophysical Observatory Belsk. It is situated in the direct neighborhood of the

Modrzewina nature reserve, far away from potential sources of anthropogenic pollution. The station is surrounded by coniferous forest and agricultural-horticultural lands. Belsk station is included in the National Air Quality Monitoring Network managed by the Main Inspectorate for Environmental Protection.

The second measuring station, Racibórz, represents suburban background conditions. It is located in the southern part of Poland, about 5 km from the Czech Republic border. It is situated on the southwestern outskirts of the city, in the immediate vicinity of single-family housing and agricultural areas from the west side and National Road No. 45 (about 150 m from the station) and typical urban infrastructure from the east site.

The selection of these locations, which represent rural and suburban conditions, makes it possible to conduct comparative statistical analysis for places with different chemical regimes.

2.2. Meteorological Conditions

In this work, only two meteorological parameters are considered, including temperature [°C] and relative humidity [%]. The monthly variation of both parameters for Racibórz (a) and Belsk (b) stations are presented in Figure 2.

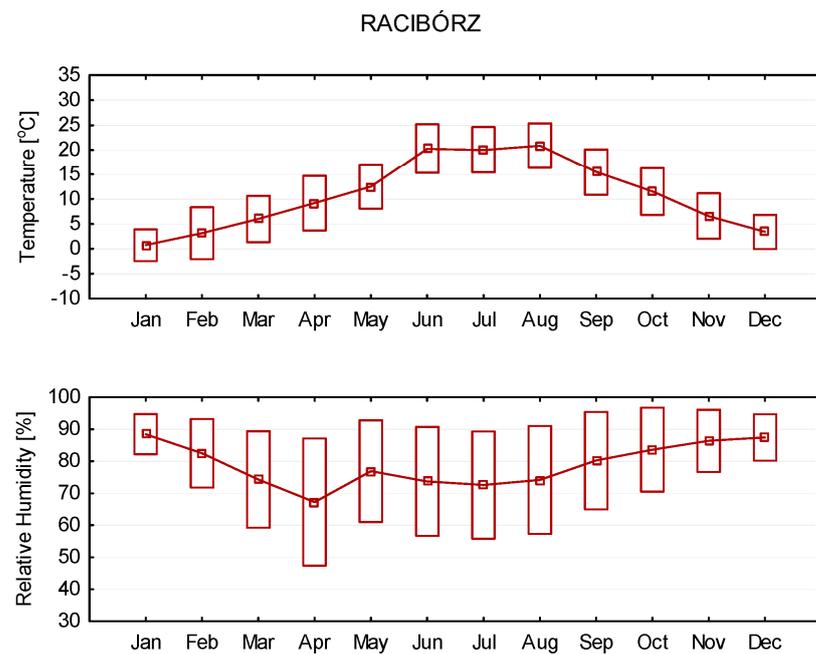
At both locations, a characteristic annual cycle of temperature with a maximum during summer and a minimum during winter was noted. Generally, higher values of temperature were observed in Racibórz station. The differences for individual months ranged from 1.5 °C in February to 0.4 °C in November. The highest values of the monthly mean temperature at both stations were noted in August (20.9 °C—Racibórz, and 20.2 °C—Belsk) while the lowest in January (0.7 °C—Racibórz and −0.3 °C—Belsk). The annual cycle of relative humidity is characterized by spring-summer minimum and winter maximum. The higher values for most of the year were recorded in Racibórz. The highest monthly mean relative humidity was observed in January (88%—Racibórz) and in November (91%—Belsk), while the lowest values were found in April (67%—Racibórz and 60%—Belsk).

2.3. Data Description

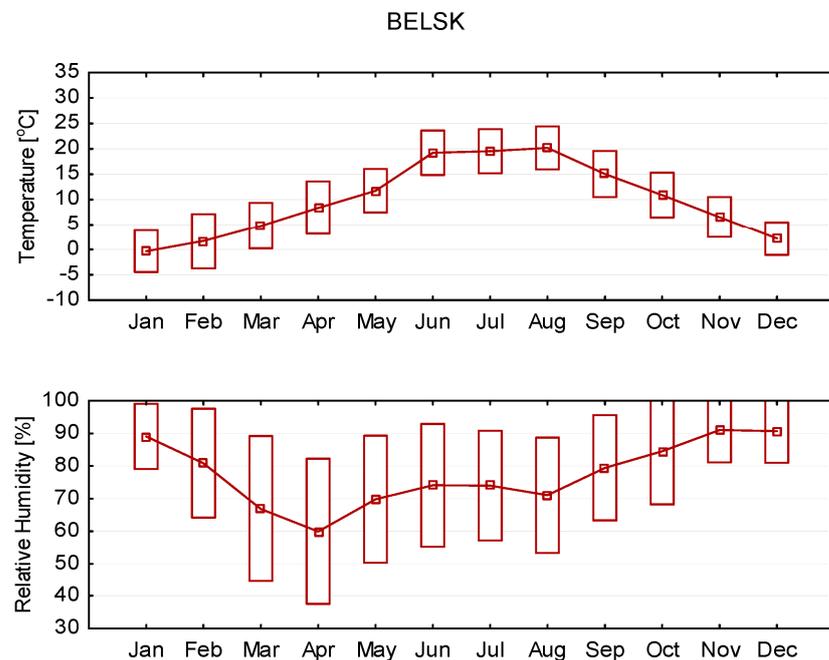
2.3.1. Ground-Based Stations

Hourly-averaged meteorological parameters at Belsk were provided by the Department of Physics of the Atmosphere, Institute of Geophysics, Polish Academy of Sciences. Hourly-averaged surface O₃ concentrations were obtained from the Main Inspectorate for Environmental Protection. In Racibórz, measurements of meteorological parameters were performed by the Institute of Environmental Engineering of the Polish Academy of Sciences. The air pollution concentrations (including surface O₃) were obtained from the Department of Physics of the Atmosphere, Institute of Geophysics, Polish Academy of Sciences.

Surface O₃ concentrations were monitored by Thermo Scientific 49i (Belsk) and Environment 42 (Racibórz) ozone analyzers, with the use of the UV absorption method and reference to the norm PN-EN 14625. In both stations, the surface O₃ monitors were regularly calibrated with a certified standard photometer and certified gas mixtures. Detailed checks of the surface O₃ data, i.e., verification and validation, as well as analysis of the deviations of the concentrations measured at nearby stations with the same category (rural or suburban), to ensure adequate data quality were performed. Meteorological parameters were measured using Vaisala Milos m520 and Lufft WS510-UMB (Belsk), and Meteo Davis Vantage Pro 2 (Racibórz). The 1 h averages of surface O₃ and meteorological parameters constitute the basis for further statistical calculations, which were done using the Statistica 12 package.



(a)



(b)

Figure 2. Monthly averaged values of temperature [°C] and relative humidity [%] in Racibórz (a) and Belsk (b) for the period 2018–2021. Points display the mean value; the box shows the range: mean \pm 1 standard deviation.

2.3.2. CAMS

The Copernicus Atmosphere Monitoring Service (CAMS) is a service implemented by the European Center for Medium-Range Weather Forecasts (ECMWF) that provides

continuous data and information on atmospheric composition. CAMS produces global forecasts for atmospheric composition twice a day. The initial conditions of each forecast are obtained by combining a previous forecast with current satellite observations through a process called data assimilation. This best estimate of the state of the atmosphere at the initial forecast time step called the analysis, provides estimates of the concentration of atmospheric pollutants at sites where no direct observations are available. Surface O₃ forecasts were downloaded from CAMS European air quality forecasts dataset. This dataset provides daily air quality analyses and forecasts for Europe.

CAMS produces specific daily air quality analyses for the European domain at high spatial resolution (0.1 degrees, approx. 10 km). In parallel, air quality forecasts are produced once a day for the next four days. Both the analysis and the forecast are available at hourly time steps at seven height levels, including the surface level. For this study, a set of the following air quality models were used: *Chimere*, *Emep*, *Ensemble*, *Mocage*, *Match*, *Lotos*, and *Euradim*. A detailed description of selected chemistry-transport models is available in Colette et al. [49].

2.4. Models

MLR and ANN (with multiple the perceptron (MLP) approach) were used to predict surface O₃ concentration using basic meteorological parameters (temperature and relative humidity) as explaining variables. Hour of the day and surface O₃ concentration in the previous day (24 h back) was also attached to the input list. Time of the day can be a useful predictor, especially in urban environments where vehicular emissions are strongly dependent on the time of day [50]. Additionally, the most important meteorological predictors (e.g., temperature, solar radiation) are characterized by a distinct daily course with the maximum during noon hours and minimum during night. Predictors used in the models have a 3 h time resolution since 00:00 UTC. Both models were developed separately for Belsk and Racibórz for each season of the year: spring (March–April–May), summer (June–July–August), autumn (September–October–November), and winter (December–January–February). MLR and ANN models were chosen because they are tailored to the limited number of predictors available at the locations. These models can predict short-term surface ozone variability in many places equipped only with an ozone meter and a simple weather station.

2.4.1. Multiple Regression Analysis

MLR is one of the most common tools used in surface O₃ prediction. It is based on the relationship between the O₃ concentration, and a set of predictors (usually including meteorological and chemical drivers) obtained by the least-squares method [51–53]. In this work, the forward stepwise regression method was used. It consists of the next (stepwise) adding a new variable included in the model to the predictor list, which at a given step has the most significant influence on the dependent variable.

2.4.2. Artificial Neural Network

In recent years ANN, especially the MLP approach, has become an efficient alternative to traditional statistical techniques. A great advantage of ANN is the ability to model the highly non-linear relationships between predictors and predictand variables. The ANN system consists of a system of neurons interconnected by weights. The neurons are divided into input, hidden, and output layers. Using a training set consisting of series of input and related output data, it is possible to learn the network. During the process of learning, the training data are repeatedly presented to MLP, and weights are adjusted until the appropriate input-output matching is obtained and the resulting error of estimation is minimal. ANN is based on the non-linear transformation of input data to approximate output value. A comprehensive description of ANN is in Gardner and Dorling [54] and Spellman [39] and in the literature contained therein.

Comparative analysis of both methods could be helpful in indicating the dependency of the surface O₃ concentration on selected explanatory variables. If the performance of the ANN model is comparable with the MLR model, it can be stated that the relationship between input and output variables is almost linear. When the performance of ANN outperforms MLR, it will indicate possible interactions between variables [40].

3. Results

3.1. Diurnal and Seasonal Cycles of Surface O₃ Concentration

Surface O₃ concentration in the suburban and rural regions has been analyzed statistically in terms of daily and annual variability in the period from September 2018 to September 2021. The box plots presented in Figure 3 summarize the hourly surface O₃ variations in Racibórz and Belsk.

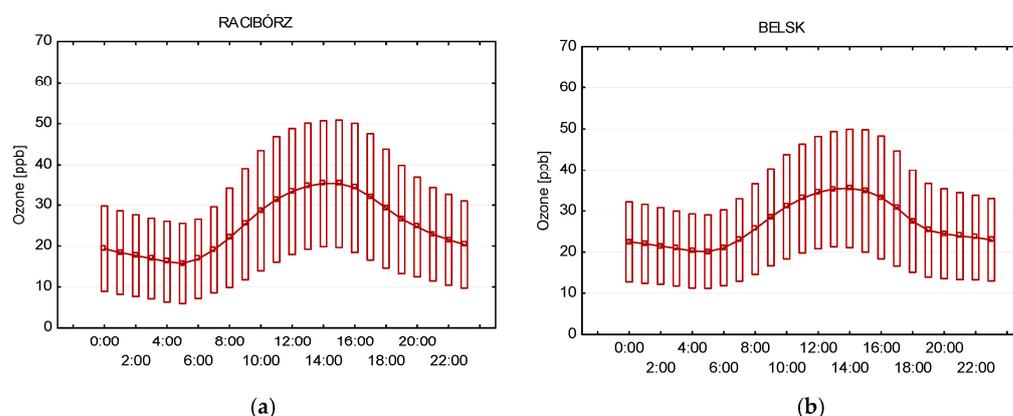


Figure 3. Mean daily course of surface O₃ from observations for the period from 2018 to 2021 in Racibórz (a) and at Belsk (b). The point shows the mean value, and the box displays the range: mean ± 1 standard deviation.

At both stations, a characteristic daily course of surface O₃ was recorded with maxima during the afternoon hours and minima in the early morning, just before sunrise. From 06:00, there was a constant increase in surface O₃ lasting until early afternoon (14:00), which is attributed to photochemical processes of ozone formation (involving VOC and NO_x species) and vertical transport from upper layers of the atmosphere that develops during a day by convective activity in the atmospheric boundary layer [55]. Between 13:00 and 15:00, the highest values of surface O₃ were equal to 33.3 ppb and 34.5 ppb for Belsk and Racibórz, respectively. There has been a continuous slow decline since then until 05:00, when the daily minimum has been reached. Lowering surface O₃ levels during evening and night is attributed to the reduction of photochemical processes and processes of O₃ titration ($O_3 + NO \rightarrow NO_2 + O_2$) [56,57].

The differences between rural and suburban surface O₃ are as follows:

- The average surface O₃ concentration is slightly higher at the rural station (25.1 ppb) than at the suburban (24.2 ppb). It is attributed to limited sinks of surface O₃ in rural areas (especially lower NO_x level results in less surface O₃ destruction through titration processes).
- The cycle of diurnal variability of surface O₃ is weaker (has lower diurnal amplitude) at the rural station. The highest difference between surface O₃ concentration in Racibórz and Belsk was noted at 05:00 (~3.6 ppb). Lower concentrations in the suburban station during the night and morning hours are an indicator of the presence of fresh NO in urban areas [58]. Higher diurnal surface O₃ maxima also indicate a high concentration of surface O₃ precursors (NO_x, VOC) at the site. The maximum of 1 h averaged surface O₃ concentration was equal to 91.2 ppb in Racibórz (19 June 2021) while 80.9 ppb at Belsk (1 July 2019).

Figure 4 presents the monthly averaged surface O₃ concentration at urban and rural stations. At both stations, a characteristic annual cycle with a spring-summer maximum and autumn minimum was recorded. The maximum was noted in April (38.3 ppb) at Belsk while in Racibórz in June (35.8 ppb). The existence of a maximum peak in April (Belsk) is probably related to the vertical transport of air from the upper atmosphere [59]. The existence of a broad spring-summer maximum (Racibórz) from April to August seems to be associated with the photochemical surface O₃ formation by processes involving NO_x and VOC under the influence of solar radiation [43,50]. The annual minimum at each station was noted in November (~13 ppb).

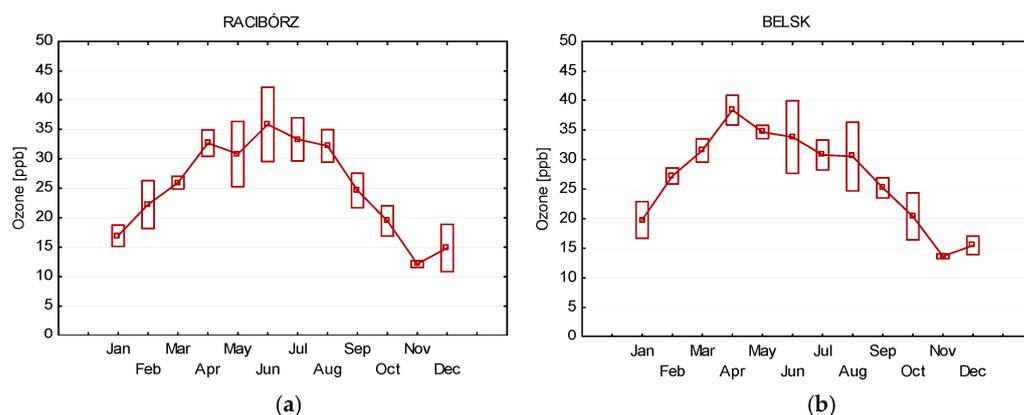


Figure 4. Monthly average surface O₃ concentrations in Racibórz (a) and at Belsk (b) for the period September 2018–September 2021. The point displays the mean value; the box shows the range: mean \pm 1 standard deviation.

The rural-suburban surface O₃ differences were examined for individual hours and months. Results show that the differences (rural minus suburban) are much higher during night and morning hours (Figure 5a) and during winter-spring months (Figure 5b). During the afternoons and evenings (from 15:00 to 20:00), greater surface O₃ is noted in Racibórz station, similarly as during summer months (from June to August) which indicates the greater photochemical potential of surface O₃ formation.

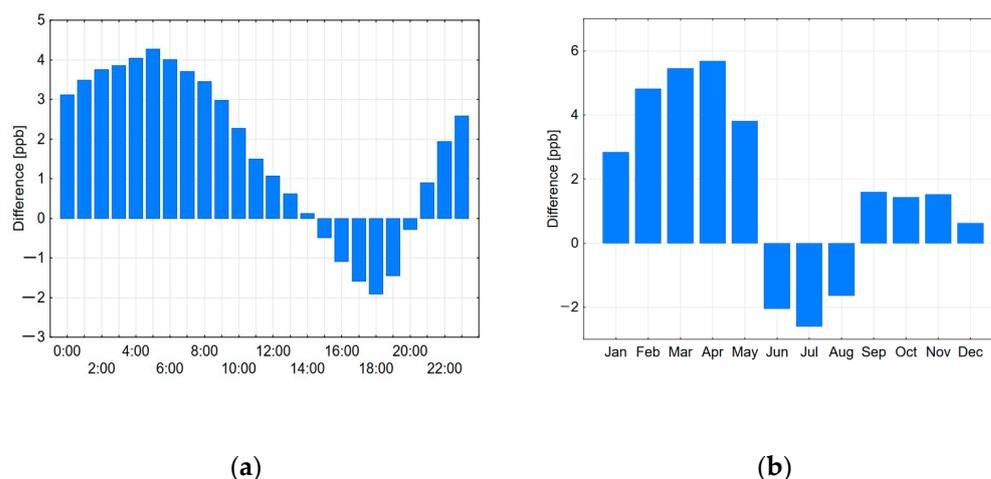


Figure 5. The differences between surface O₃ measured at Belsk and Racibórz (ppb), from 2018 to 2021, for diurnal (a) and monthly (b) scales.

The fit of the hourly and monthly surface O₃ values to a normal distribution was performed using the Shapiro-Wilk test (significance level: $\alpha = 0.05$). The test was applied separately for all data from September 2018 to September 2021 separately for each hour

during the day. The same test was performed for daily averaged values separately for each month (January–December) in the period 2018–2021. As the analyzed data were not normally distributed, the nonparametric U Mann-Whitney test was applied to find out whether the differences in surface O₃ concentrations between hours and months were statistically significant.

The difference between surface O₃ concentration in Belsk and Racibórz was statistically significant at a 95% confidence level for all hours, with the exception of hours between 13:00 and 16:00 and 20:00 and for months from January to May and for July.

3.2. Seasonal Cycle of Surface O₃ Concentration from CAMS Simulations

Figure 6 presents averaged daily variations of surface O₃ from the measurements and CAMS forecasts for both stations for the period September 2018–September 2021. For each season, seven simulations: *Chimere*, *Emep*, *Ensemble*, *Mocage*, *Match*, *Lotos*, and *Euradim* were shown for both sites. Comparative analysis was performed separately for each location.

The mean differences between the CAMS forecasts and measured surface O₃ are presented in Figure 7. All simulations show overestimation, especially during autumn and winter. In Belsk, the over- and under-estimations were slightly lower. Small under-estimations were noted during spring and winter for *Emep*, *Match*, and *Euradim* (up to 2.6 ppb). The simulations show differences not only in comparison with measurements but also when comparing CAMS pairs. More details on the CAMS-observation differences will be given in Section 3.3.

In order to determine whether the differences between CAMS forecast, and observations were statistically significant, the non-parametric U Manna-Whitney test was performed. The test was carried out using all hourly averaged data for individual seasons from 2018 to 2021 for each location. In almost all cases (with the exception of the spring season at Belsk for *Emep*), the differences between CAMS forecasts and observed surface O₃ data were statistically significant.

3.3. Quality of CAMS Forecasts

CAMS model performance is determined by standard measures of goodness of fit of the model to the measurements, including coefficient of determination (R²), mean bias error (MBE) [ppb], mean absolute error (MAE) [ppb], and root mean squared error (RMSE) [ppb] (Table 2). These measures (so-called comparative statistics) are given by Equations (1)–(4), respectively.

$$R^2 = \left(\frac{\frac{1}{n} \sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})}{SD_x SD_y} \right) \quad (1)$$

$$MBE = \frac{1}{n} \sum_{i=1}^n (y_i - x_i) \quad (2)$$

$$MAE = \frac{1}{n} \sum_{i=1}^n |y_i - x_i| \quad (3)$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - x_i)^2} \quad (4)$$

where: x_i —observed variable, y_i —predicted variable, \bar{x} —mean of x variable, \bar{y} —mean of y variable, SD_x —standard deviation of observed variable, SD_y —standard deviation of the predicted variable.

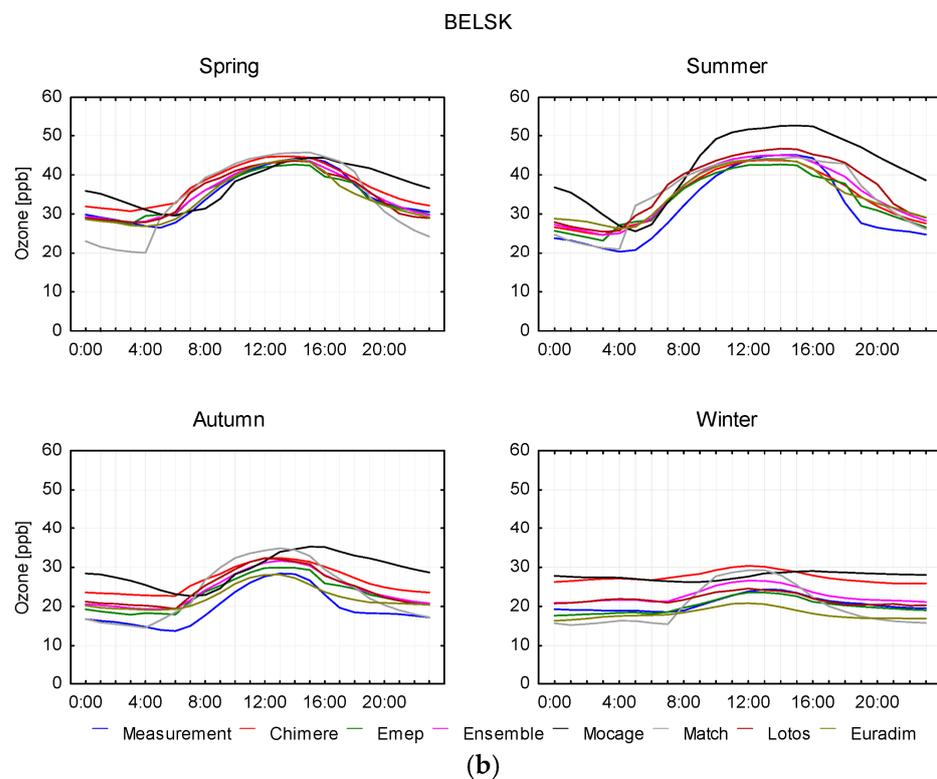
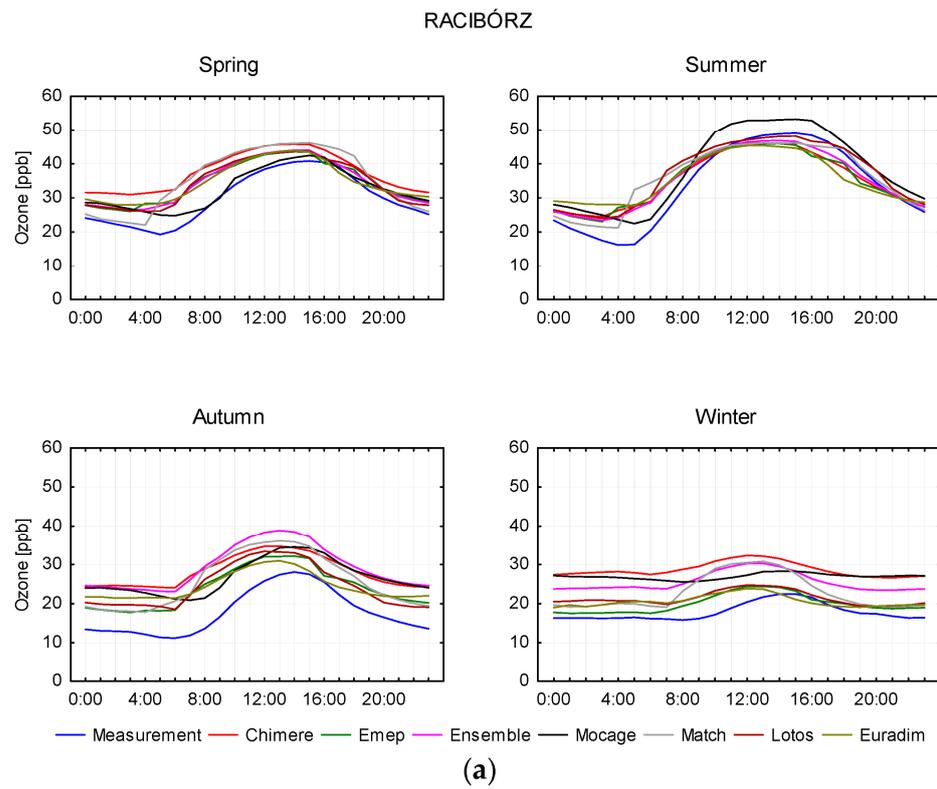


Figure 6. Time series of diurnal variation of surface O₃ concentration for each season at Racibórz (a) and Belsk (b) station for the period 2018–2021. Colors of lines: blue-measurement, red-Chimere, dark green-Emep, pink-Ensemble, black-Mocage, light grey-Match, brown-Lotos, light green-Euradim.

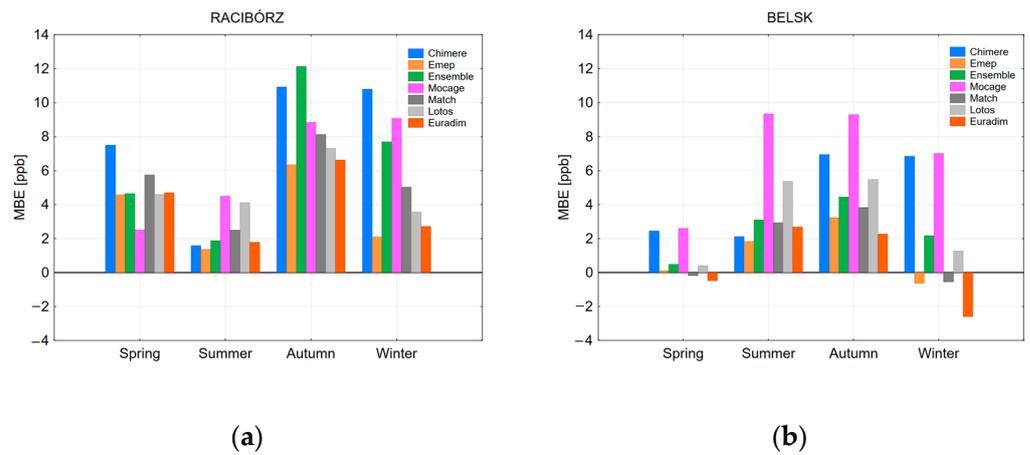


Figure 7. Mean bias error (see Equation (2) for definition), CAMS forecasts minus observed surface O₃, for the period 2018–2021, separately for each season for Racibórz (a) and Belsk (b) station.

Table 2. Summary of comparative statistics of surface O₃ concentrations between measured and CAMS forecasts. MBE, MAE and RMSE are in ppb.

Index	Racibórz							Belsk						
	CH	EM	EN	MO	MA	LO	EU	CH	EM	EN	MO	MA	LO	EU
Spring														
R ²	0.48	0.52	0.54	0.42	0.40	0.36	0.22	0.49	0.52	0.57	0.24	0.47	0.40	0.35
MBE	7.49	4.58	4.64	2.52	5.75	4.60	4.70	2.45	0.10	0.49	2.61	−0.18	0.41	−0.48
MAE	9.12	7.52	7.29	7.65	9.12	9.30	9.39	6.00	5.45	5.01	7.84	6.83	6.91	6.84
RMSE	11.46	9.63	9.42	9.83	11.59	11.77	12.30	7.71	7.18	6.71	10.16	8.69	9.03	8.99
Summer														
R ²	0.61	0.53	0.70	0.61	0.56	0.56	0.41	0.54	0.42	0.60	0.40	0.49	0.45	0.41
MBE	1.58	1.37	1.89	4.49	2.50	4.12	1.78	2.12	1.83	3.10	9.34	2.93	5.36	2.69
MAE	8.04	8.66	7.34	8.76	8.49	8.80	9.66	7.02	7.62	6.82	11.39	7.65	8.85	8.11
RMSE	10.01	10.83	9.21	10.95	10.66	11.14	12.12	9.04	9.70	8.84	14.25	9.78	11.45	10.35
Autumn														
R ²	0.49	0.58	0.40	0.46	0.53	0.46	0.37	0.55	0.63	0.67	0.39	0.55	0.49	0.52
MBE	10.93	6.35	12.13	8.84	8.12	7.32	6.63	6.95	3.23	4.45	9.29	3.83	5.47	2.27
MAE	11.58	8.03	12.54	9.99	9.62	9.98	9.12	8.35	5.77	6.11	10.66	6.82	8.00	6.16
RMSE	13.67	10.01	16.18	12.53	11.77	12.16	11.58	9.82	7.29	7.52	12.81	8.57	9.85	7.85
Winter														
R ²	0.39	0.51	0.34	0.20	0.36	0.23	0.25	0.45	0.58	0.53	0.26	0.44	0.22	0.38
MBE	10.79	2.10	7.69	9.07	5.02	3.56	2.71	6.84	−0.62	2.17	7.02	−0.54	1.27	−2.60
MAE	11.42	5.59	9.01	10.46	8.02	9.33	7.29	8.12	4.86	5.42	9.27	6.27	8.40	6.43
RMSE	13.54	7.36	12.09	13.25	10.19	11.78	9.51	9.86	6.30	6.93	11.56	7.80	10.46	8.15

CH-Chimere, EM-Emep, EN-Ensemble, MO-Mocage, MA-Match, LO-Lotos, EU-Euradim. For each station, the maximum value is denoted in bold, but the minimum is in bold italics.

The R² values show considerable variation depending on the season of the year. The highest values were found in summer and autumn, while the lowest were in winter. The R² values in Racibórz ranged from 0.22 (*Euradim*-spring) to 0.70 (*Ensemble*-summer). For Belsk, these values were correspondingly lower, ranging from 0.22 (*Lotos*-winter)

to 0.67 (*Ensemble-autumn*). All R^2 values were statistically significant. The MBE values indicate a general tendency to overestimate observed values. The highest values were noted during autumn and winter. The MBE values in Racibórz varied between 1.37 ppb (*Emep-summer*) and 12.13 ppb (*Ensemble-autumn*). Lower values of MBE were noted in Belsk and ranged from 0.10 ppb (*Emep-spring*) to 9.34 (*Mocage-summer*). The MAE values in Racibórz ranged from 5.59 ppb (*Emep-winter*) to 12.54 ppb (*Ensemble-autumn*). For Belsk, these values were correspondingly lower and ranged from 5.01 ppb (*Ensemble-spring*) to 14.25 ppb (*Mocage-summer*). The RMSE values in Racibórz varied from 7.36 ppb (*Emep-winter*) to 16.18 ppb (*Ensemble-autumn*) while in Belsk from 6.30 ppb (*Emep-winter*) to 14.25 ppb (*Mocage-Summer*). The higher RMSE values compared with MAE values were noted for each season and for both locations, which indicates an appearance of large residual values. Both MAE and RMSE show the better statistical performance of CAMS forecasts in spring (Belsk) and summer (Racibórz).

3.4. Performance of MLR and ANN Models

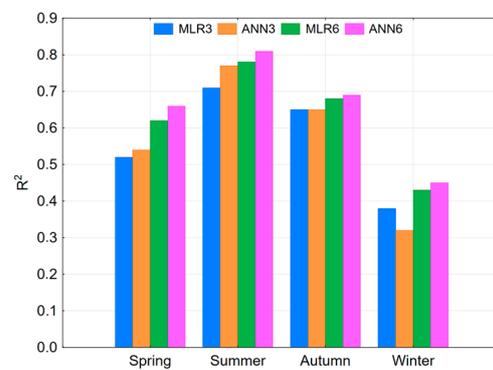
Various models for predicting surface O_3 are possible, ranging from the MLR model to sophisticated artificially intelligent ones such as XGBoost, based on many predictors containing chemical and weather components. Here we use two types of forecast model. i.e., MLR and ANN, which are adapted to a limited number of input variables available at the sites. The former aims to model the linear input-output relationship, and the latter one is to account for the possible nonlinearity effects between input variables and output.

Prediction of 1 h mean of surface O_3 every 3 h from 0:00 GMT for each season of the year was based on observed meteorological data measured (every 3 h) at the stations. Using Statistica 12, ANN package, the models were developed for 2 independent sets of input data. The former one consisted of the following predictors: the hour of the day, temperature [$^{\circ}C$], and relative humidity [%]. The latter one additionally takes into account: temperature 3 h back, relative humidity 3 h back, and surface O_3 concentration 24 h back [ppb]. Particular data sets were implemented for the automatic network designer function. The input data set was divided into training (70%), test (15%), and validation (15%) subsets. Participants for each subset were selected randomly. Testing three-layer MLP with different functions of activation and different number of neurons in the hidden layer, the most appropriate topology of network structure was found. Table 3 presents the architecture of ANN for the validation subset used in the prediction.

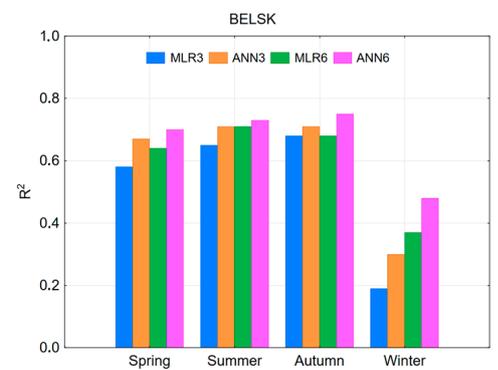
Depending on the number of input data sets, the best architecture of ANN models consisted of 3 or 6 neurons in the input layer, from 4 to 10 in the hidden layer, and 1 neuron in the output layer. The models used the gradient quasi-Newton BFGS (Broyden-Fletcher-Goldfarb-Shanno) learning algorithm. The selection of the best networks was performed considering the same statistical measures (evaluative statistics) used for quality checking of the CAMS forecasts (see Table 2). Table 4 presents the values of evaluative statistics using MLR and ANN for both sets of input data, for each season of the year separately for Racibórz and Belsk stations. Both kinds of models were developed based on two sets of input data, including three predictors (hour of the day, temperature, relative humidity) or six predictors (hour of the day, temperature, relative humidity, temperature 3 h back, relative humidity 3 h back, previous day's surface O_3 concentration). Performance indexes for ANN models were calculated for the validation data subset. The visual reference of results from Table 4, presenting the relative ranking of individual models, is shown in Figures 8–11.

Table 3. Structure of ANN networks selected for surface O₃ prediction.

Season	ANN Structure	Error Function	Activation Function (Hidden Layer)	Activation Function (Output Layer)
Racibórz				
Spring	3-5-1	BFGS	Tanh	Linear
	6-7-1	BFGS	Tanh	Linear
Summer	3-8-1	BFGS	Tanh	Exponential
	6-8-1	BFGS	Tanh	Linear
Autumn	3-10-1	BFGS	Tanh	Logistic
	6-4-1	BFGS	Logistic	Linear
Winter	3-8-1	BFGS	Logistic	Exponential
	6-7-1	BFGS	Tanh	Exponential
Belsk				
Spring	3-5-1	BFGS	Logistic	Exponential
	6-8-1	BFGS	Logistic	Logistic
Summer	3-8-1	BFGS	Exponential	Exponential
	6-7-1	BFGS	Exponential	Linear
Autumn	3-4-1	BFGS	Logistic	Linear
	6-10-1	BFGS	Exponential	Tanh
Winter	3-8-1	BFGS	Tanh	Tanh
	6-9-1	BFGS	Tanh	Tanh



(a)



(b)

Figure 8. Coefficient of determination (R^2) for Racibórz (a) and Belsk (b) by model and season. MLR3—MLR based on a set of 3 input data, ANN3—ANN based on a set of 3 input data, MLR6—MLR based on a set of 6 input data, ANN6—ANN based on a set of 6 input data.

Table 4. Comparative statistics for MLP and ANN models for validation subset (MLR 3 = multiple linear regression with an input data set consisting of three predictors, ANN 3 = artificial neural network with an input data set consisting of three predictors, MLR 6 = multiple linear regression with an input data set consisting of six predictors, ANN 6 = artificial neural network with an input data set consisting of three predictors). MBE, MAE and RMSE are in ppb.

Index	MLR3	ANN3	MLR6	ANN6	MLR3	ANN3	MLR6	ANN6
	Racibórz				Belsk			
	Spring							
R ²	0.52	0.54	0.62	0.66	0.58	0.67	0.64	0.70
MBE	0.04	-0.74	-0.01	-0.46	0.00	-0.31	-1.23	0.22
MAE	6.55	5.91	5.85	5.12	5.01	4.09	4.75	4.01
RMSE	8.38	7.72	7.49	6.61	6.31	5.24	6.04	5.18
	Summer							
R ²	0.71	0.77	0.78	0.81	0.65	0.71	0.71	0.73
MBE	-0.02	0.12	-0.02	-0.15	-0.16	-0.57	0.00	-0.43
MAE	6.62	5.49	5.68	5.08	5.76	5.31	5.32	5.21
RMSE	8.39	7.29	7.27	6.54	7.48	6.87	6.81	6.65
	Autumn							
R ²	0.65	0.65	0.68	0.69	0.68	0.71	0.68	0.75
MBE	-0.04	-0.10	-0.02	-0.09	0.03	0.69	0.02	0.69
MAE	5.64	5.41	5.30	5.18	4.75	4.26	4.52	4.07
RMSE	7.03	6.75	6.57	6.43	6.04	5.54	5.98	5.19
	Winter							
R ²	0.38	0.32	0.43	0.45	0.19	0.30	0.37	0.48
MBE	0.13	0.07	0.40	0.04	-0.16	-1.13	0.13	-0.68
MAE	6.48	6.34	5.94	5.84	6.96	6.74	6.00	5.86
RMSE	8.05	7.69	7.37	7.23	8.49	8.28	7.49	7.16

For each station, the maximum value is denoted in bold, but the minimum is in bold italics.

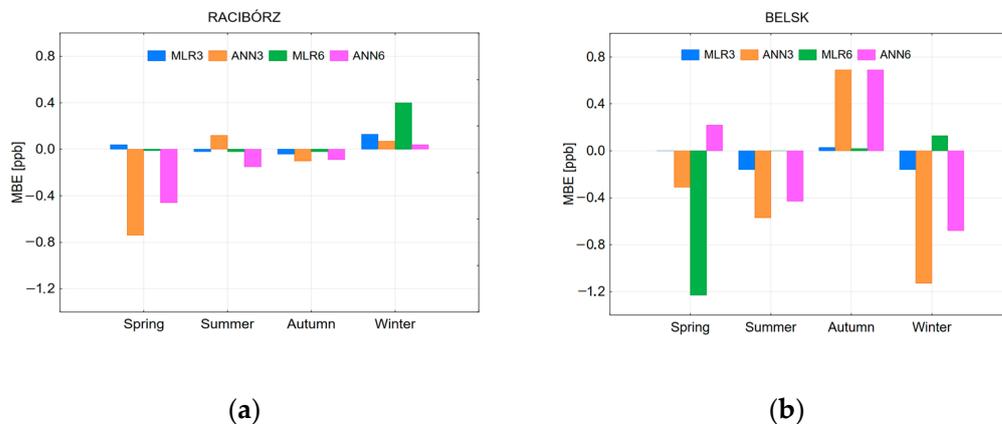


Figure 9. The same as Figure 8 but for mean bias error (MBE) for Racibórz (a) and Belsk (b).

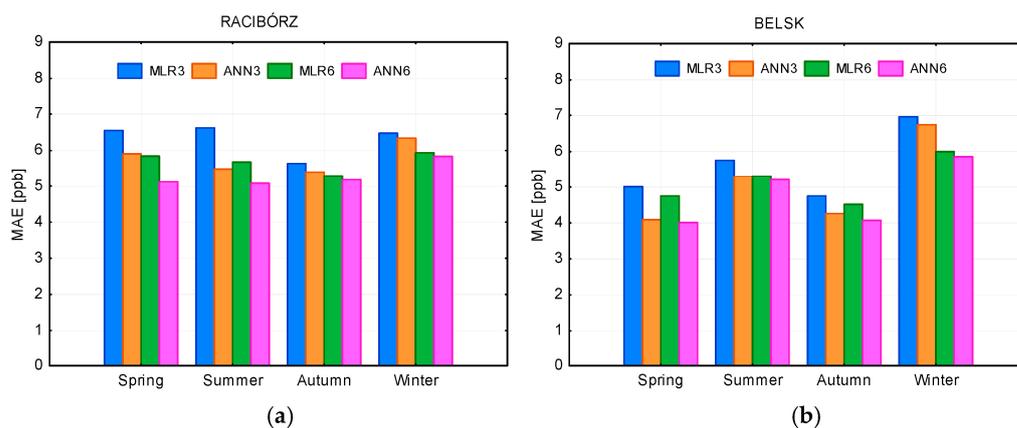


Figure 10. The same as Figure 8 but for mean absolute error (MAE) for Racibórz (a) and Belsk (b).

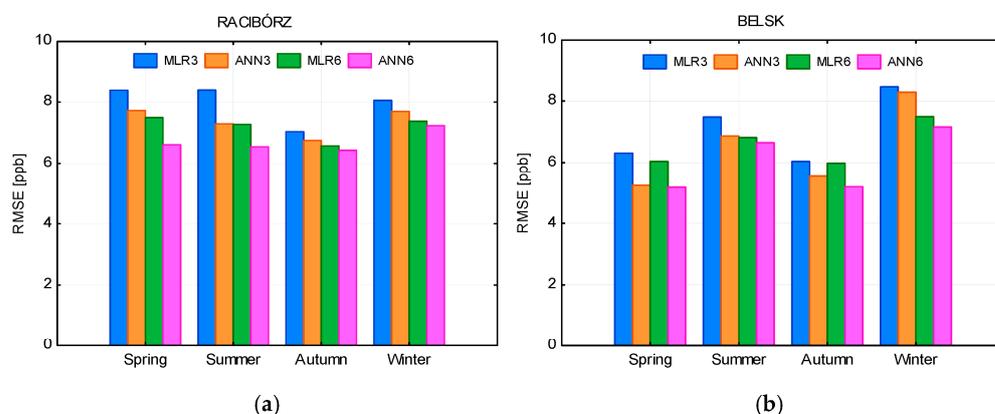


Figure 11. The same as Figure 8 but for root mean square error (RMSE) for Racibórz (a) and Belsk (b).

MLR model that was trained by a set of three input data (MLR3) explains up to 71% of the variance in surface O_3 in Racibórz (summer) and up to 68% at Belsk (autumn). In turn, the ANN models trained by the same set of input data (ANN3) explains up to 77% in Racibórz (summer) and up to 71% at Belsk (summer and autumn). The use of a larger set of six input data results in improved model performance. The MLR6 model explains up to 78% in Racibórz and up to 71% at Belsk, while the ANN6 model explains up to 81% in Racibórz and up to 75% at Belsk. Generally, high R^2 values are for summer and autumn but the lowest for winter. It's worth noting that during summer, distinctly higher R^2 values were noted for Racibórz station. During other seasons the R^2 values between both stations were comparable.

The MBE values are small, ranging between -0.74 ppb (ANN3-spring) and 0.40 ppb (MLR6-winter) in Racibórz and between -1.23 ppb (MLR6-winter) and 0.69 ppb (ANN3-autumn) at Belsk. It shows great variation depending on the season and the kind of models. All models tend to slightly overestimate surface O_3 concentrations. When comparing stations, higher absolute values of MBE were noted in Belsk.

Analyzing MLR3 models, the MAE value ranged between 5.64 ppb (autumn) and 6.62 ppb (summer) in Racibórz and between 4.75 ppb (autumn) and 6.96 ppb (winter) at Belsk. For ANN3 models, the MAE value ranged from 5.41 ppb (autumn) to 6.34 ppb (winter) in Racibórz and from 4.09 ppb (spring) to 6.74 ppb (winter) at Belsk. Addition of lagged ozone data and two lagged meteorological predictors reduced the MAE value by MLR6 models to 5.30 ppb (autumn) in Racibórz and to 4.52 ppb (autumn) at Belsk and of ANN6 models to 5.08 ppb (summer) in Racibórz and to 4.01 ppb (spring) at Belsk. For both models, the highest MAEs were noted for the winter months.

The results of RMSE follow a similar pattern to MAE, although its value in all cases is slightly higher than MAE because of higher sensitivity to outliers. For MLR3 models, trained with a set of three input data, RMSE ranged between 7.03 ppb (autumn) and 8.39 ppb (summer) in Racibórz and between 6.04 ppb (spring) and 8.49 ppb (winter) at Belsk. ANN3 models perform slightly better with RMSE between 6.75 ppb (autumn) and 7.69 ppb (winter) in Racibórz and between 5.24 ppb (spring) and 8.28 ppb (winter) in Belsk. Minimum RMSE for MLR6 models (trained with a set of 6 input data) were equal to 6.57 ppb (autumn) in Racibórz and 5.98 ppb (autumn) in Belsk. RMSE for ANN6 models reduced to 6.43 ppb (autumn) in Racibórz and to 5.18 ppb (spring) at Belsk.

Comparing model performance in terms of the number of input data (three or six), it appears that ANN, in all cases, is somewhat better than MLR. It seems that the inherent element of nonlinearity in ANN models provides a more accurate surface O₃ forecast compared with MLR. The inclusion of additional input data, e.g., lagged surface O₃ values (24 h back) and meteorological variables (temperature and relative humidity 3 h back), resulted in better performance of both kinds of models. However, improvement is slightly better for MLR than for ANN models.

3.5. Comparison of Performance of MLR and ANN with CAMS Simulations

The architecture of the MLR and ANN model was built using the meteorological variable measured in stations. Figures 12–15 present the results of the best CAMS forecast (blue), ANN3 (orange), and ANN6 (green) in terms of R², MBE, MAE, and RMSE for Racibórz and Belsk stations. Depending on the season, the best CAMS forecast was: *Emep* (50% of cases), *Ensemble* (40%), *Mocage* (3.3%), *Match* (3.3%), and *Euradim* (3.3%).

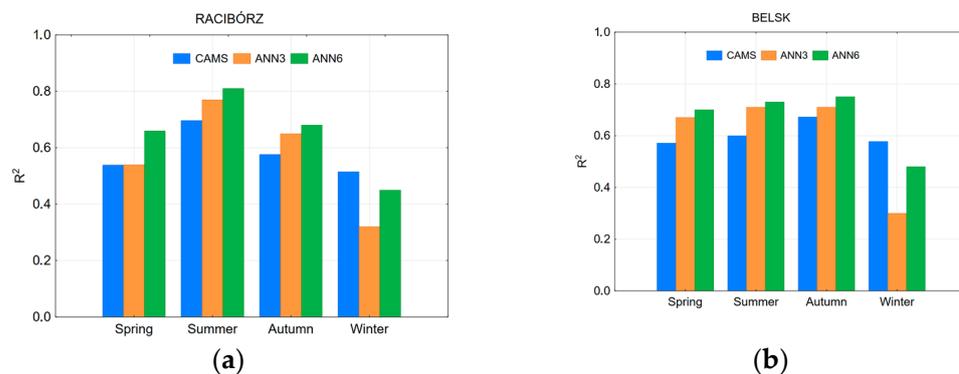


Figure 12. R² for the best CAMS forecast, ANN3 and ANN6 for Racibórz (a) and Belsk (b).

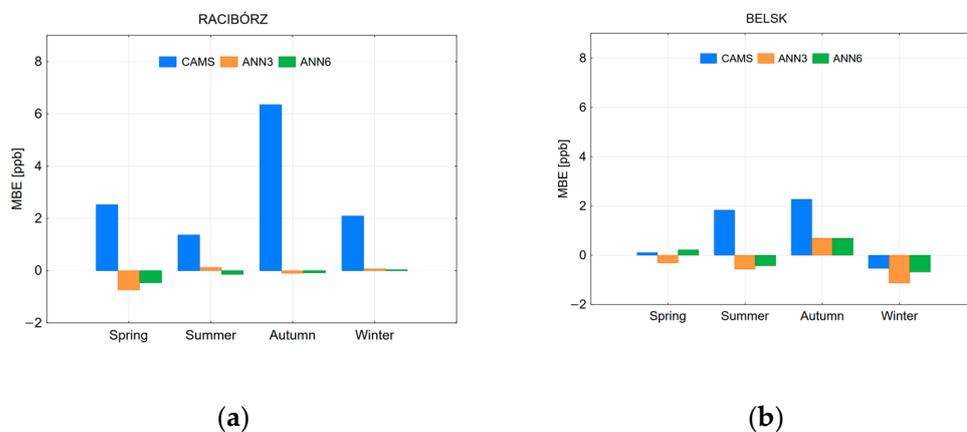


Figure 13. MBE for the best CAMS forecast, ANN3 and ANN6 for Racibórz (a) and Belsk (b).

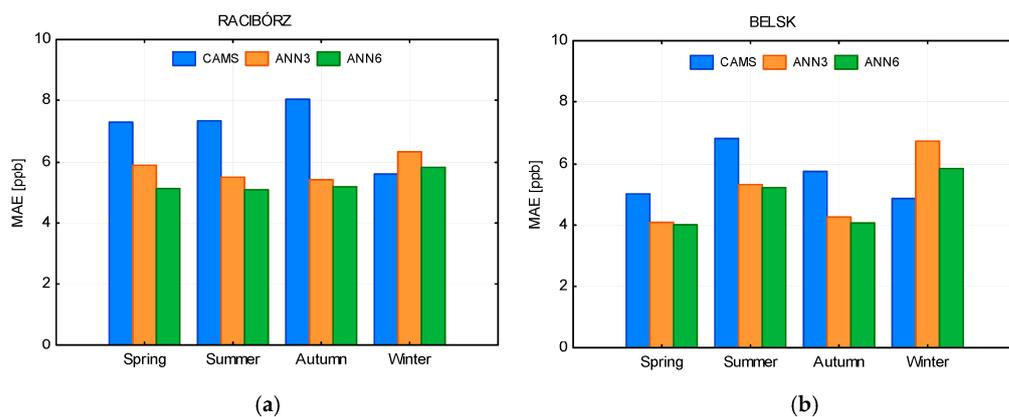


Figure 14. MAE for the best CAMS forecast, ANN3 and ANN6 for Racibórz (a) and Belsk (b).

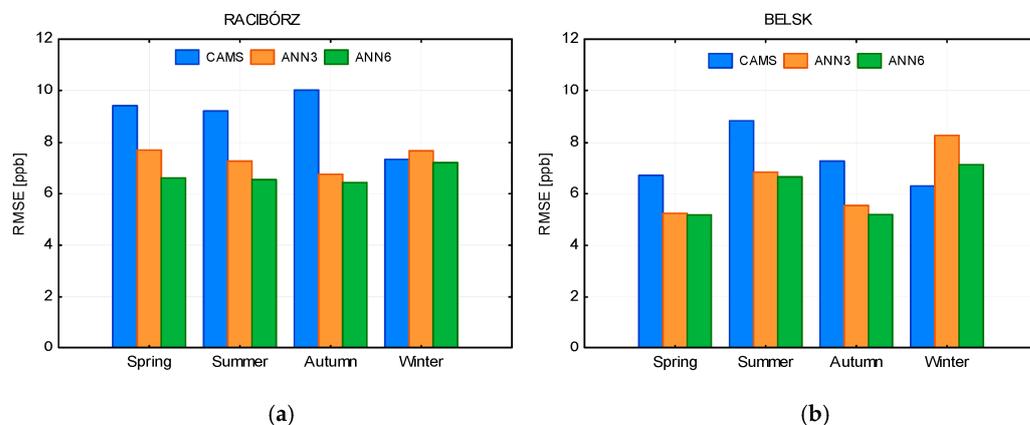


Figure 15. RMSE for the best CAMS forecast, ANN3 and ANN6 for Racibórz (a) and Belsk (b).

Comparing the performance of these three models in terms of R^2 value, it can be stated that for spring, summer, and autumn, the R^2 was higher for ANN3 and ANN6 models, while for winter, the CAMS simulation (*Emep*) was better. MBE values indicate the over-estimation by CAMS simulations for both locations during all seasons, with the exception of winter at Belsk, when small (below 1 ppb) under-estimation by *Match* forecast was recorded. In terms of MAE and RMSE, for spring, summer, and autumn, the forecast by ANN3 and ANN6 were better than those taken from the best CAMS forecast. In the winter season, the CAMS forecast reached a better fit for the measured data. It suggests that ANN with the MLP structure could be an effective tool supporting the prediction of surface O_3 during spring-summer-autumn when there is a real risk of episodes of high surface O_3 .

4. Discussion

This study presents the performance of MLR and ANN (with an MLP approach) in forecasting surface O_3 in rural and suburban locations in Poland. Both models were built using two separate sets of input data containing a limited number (three or six) of predictors. Because surface O_3 is mainly formed by photochemical reactions, the combination of basic meteorological parameters (temperature and relative humidity) with additional variables, including an hour of the day and lagged surface O_3 data, were used as an explanatory variable. Similarly, to Yi and Prybutok [37], Comrie [38], Spellmann [39], Gardner and Dorling [40], Sousa et al. [41], and Yu et al. [43], the results showed that the use of ANN models performs better than linear models what indicate possible interactions and non-linear relationships between predictors and surface O_3 . MLR explained up to 78% of the

variance in surface O₃ in Racibórz and up to 71% in Belsk, while the ANN model explained up to 81% in Racibórz and up to 75% at Belsk.

The use of three additional input data, including the surface O₃ concentration from the previous day, improves the quality of the estimation of both models. The gain is up to 18 percentage points for MLR and up to 13 percentage points for ANN models). It is worth noting that statistical models presented in this work used only the basic set of parameters determining surface O₃ formation. Other meteorological parameters or in-situ surface O₃ precursor concentrations (NO_x, VOC) were not included in the presented analysis. We can suggest that the inclusion of these predictors into a set of input data might further improve the results of modeling. MLR and ANN models provided better forecasts for the rural station (Belsk). It is probably related to the greater uniformity and representativeness of non-urban areas.

Surface O₃ forecasts using ANN models were also performed based on CAMS meteorological data. The R² values ranged up to 0.61 in Racibórz (summer) and up to 0.52 in Belsk (autumn), while RMSE values ranged up to 10.35 ppb in both locations. These results, in most cases, were better compared to results obtained by CAMS surface O₃ forecasts but worse when compared with results obtained using measured meteorological data (R² up to 0.81, RMSE up to 6.43 in Racibórz and R² up to 0.75 and RMSE up to 5.18 ppb in Belsk). The performance of statistical models depends crucially on the quality of the forecast of the meteorological field. Using observed parameters is equivalent to using the perfect meteorological forecast.

Furthermore, this study investigates the efficiency of surface O₃ prediction obtained by selected CAMS simulations. Statistical analysis of differences between measurements and CAMS forecasts showed significant overestimations of CAMS results, especially for Racibórz during the autumn season. Comparative analysis indicates better performance of MLR and ANN models trained by a set of six input data compared to CAMS simulations for both locations for all seasons with the exception of winter. Forecasts by MLR and ANN for the cold part of the year are less accurate, with an R² value below 0.5 for both models. It is worth noticing that ANN, with three predictors (temperature, relative humidity, and the hour of the day) provided an even better forecast (except winter) than the best CAMS forecast. Such a simple forecast can be used for any place in Poland, and measurements of surface O₃ are not necessary for the such forecast.

The results of the machine learning algorithm using different categories of predictors (including CAMS surface O₃ simulations) for predicting surface O₃ in Munich (Germany) were presented in the work of Balamurugan et al. [60]. In contrast to the present study, the results concerned the diurnal maximum (from 13:00 to 14:00) of surface O₃ for the whole year without division into seasons. The Extreme Gradient Boosting (XGBoost) approach trained only on meteorology parameters (temperature, relative humidity, boundary layer height, wind speed, and wind direction) explained 77% of the variance of measured surface O₃ with RMSE value ~8 ppb. These results are comparable with MLR6 and ANN3 achieved in the present study. XGBoost trained only on CAMS data showed worse performance. It explained 75% of the variance in surface O₃ with RMSE ~8.5 ppb. The results obtained for the best CAMS simulations in the present study explained up to 70% of the variance in surface O₃ with RMSE equal to 9.21 ppb (Racibórz—Summer). It is worth noticing that the performance of our statistical models in all seasons except winter was clearly better than CAMS alternatives (see Figures 11–14). Balamurugan et al. [60] found that the differences between R² and RMSE for their models based on meteorology and CAMS O₃ forecasts were rather marginal.

5. Conclusions

Surface ozone has been measured in the Polish national network involving monitoring of other gaseous components important for the determination of air quality. This study shows that effective forecasting of surface ozone for rural and suburban sites in Poland is possible using only surface O₃, temperature, and humidity. Monitoring of these weather

variables can be carried out even by simplified weather stations, i.e., with no wind measurements. This low-cost configuration increases the number of locations providing short-term surface O₃ predictions important to local communities.

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Data Availability Statement: The observed surface O₃ from Racibórz and Belsk data is available on the IG PAS Data Portal (<https://dataportal.igf.edu.pl/organization/atmospheric-physics>) (accessed on 25 March 2023). The surface O₃ CAMS data is available through the website <https://ads.atmosphere.copernicus.eu/cdsapp#!/dataset/cams-europe-air-quality-forecasts?tab=form> (accessed on 25 March 2023). The temperature and relative humidity CAMS data are available through the website <https://ads.atmosphere.copernicus.eu/cdsapp#!/dataset/cams-global-atmospheric-composition-forecasts?tab=form> (accessed on 25 March 2023).

Conflicts of Interest: The authors declare no conflict of interest.

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