

Research article

Thirty years of air quality change in North Dakota: Seasonal trends and machine-learning forecasts of NO₂ and SO₂

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Abstract: Long-term air quality patterns in the Northern Great Plains remain insufficiently characterized, particularly for gaseous pollutants that are sensitive to seasonal atmospheric processes and regional emission changes. This study provides a multidecadal analysis of nitrogen dioxide (NO₂) and sulfur dioxide (SO₂) concentrations from 1995 to 2025 at two monitoring stations in Fargo and Bismarck, North Dakota, using seasonally averaged (summer and winter) observations. Historical trends show substantial declines in both pollutants over the 30-year period, with winter concentrations consistently exceeding summer values. To evaluate future air quality trajectories, four machine-learning models (i.e., random forest, extreme gradient boosting, support vector machine, and a feedforward neural network) were trained using engineered lag features and standardized predictors. Model validation with independent 2020–2024 data demonstrated that the neural network achieved the highest predictive accuracy across all scenarios, with coefficients of determination exceeding 0.96 and minimal forecast error. Using a recursive forecasting framework, pollutant levels were projected from 2025 to 2050. The forecasts indicate continued improvement in some cases, stabilization in others, and slight upward tendencies for specific pollutant-season combinations, particularly winter NO₂ in Bismarck and summer SO₂ in both cities. These results highlight that while historical emission reductions have been highly effective, future progress may not be uniform across pollutants or seasons.

The findings underscore the importance of sustained monitoring and proactive regulatory planning to preserve North Dakota's historically clean air.

Keywords: nitrogen dioxide; sulfur dioxide; machine learning; seasonal trends; long-term prediction, North Dakota

Abbreviations: NO₂ - Nitrogen dioxide; SO₂ - Sulfur dioxide; PM_{2.5} - Fine particulate matter with an aerodynamic diameter ≤ 2.5 μm ; RF - Random Forest; XGBoost - Extreme Gradient Boosting; SVM - Support Vector Machine; NN - Neural Network; US EPA - United States Environmental Protection Agency; RMSE - Root mean square error; MAE - Mean absolute error; MSE - Mean squared error; ppb - Parts per billion; O₃ - Ozone

1. Introduction

Air quality is a critical component of environmental health and atmospheric sustainability [1], yet its long-term evaluation remains uneven across the United States, particularly in sparsely populated regions, such as the Northern Great Plains. North Dakota, located in the Upper Midwest of the United States, experiences a continental climate characterized by short, warm summers and long, cold winters, with substantial temperature variability during the transitional spring and fall seasons [2–4]. These climatic conditions strongly influence atmospheric mixing, pollutant dispersion, and seasonal accumulation processes, making regional air-quality dynamics distinct from those observed in more densely populated urban regions [5,6]. Over the past several decades, North Dakota's air quality has been influenced by a combination of industrial development, energy production, transportation emissions, and regional atmospheric transport [7,8]. The rapid expansion of oil and gas extraction in the Bakken formation has raised concerns regarding potential impacts on regional air pollution. Previous studies have shown that energy extraction activities can increase concentrations of particulate matter (PM_{2.5}), elemental carbon, and other aerosol species, even when observed levels remain within federal regulatory limits [9–11]. For example, Gebhart et al. (2018) reported increased haze and reduced visibility in Theodore Roosevelt National Park associated with emissions from the Bakken region, while airborne measurements by Schwarz et al. (2015) quantified black carbon emissions from flaring and diesel activity, highlighting the region as a measurable source of soot in national inventories [11,12]. Additional wintertime studies have demonstrated that cold-season atmospheric stagnation events can promote rapid aerosol aging and secondary ammonium nitrate formation, further emphasizing the sensitivity of the Northern Great Plains atmosphere to seasonal chemical processes [13,14]. While particulate pollution has received increasing attention, gaseous pollutants, such as nitrogen dioxide (NO₂) and sulfur dioxide (SO₂), remain critical indicators of combustion-related emissions and industrial activity [15,16]. NO₂ is primarily associated with vehicle exhaust, fossil fuel combustion, and energy production, whereas SO₂ is largely emitted from coal combustion, oil refining, and industrial processes. Both pollutants play important roles in atmospheric chemistry, contributing to secondary aerosol formation, acid deposition, and regional haze. Long-term exposure to elevated levels of these pollutants has also been associated with adverse environmental and human

health outcomes, including respiratory and cardiovascular effects [17,18]. Despite their importance, relatively little research has examined the long-term temporal behavior of NO₂ and SO₂ in rural regions of the Northern Great Plains. Across the United States, substantial improvements in air quality have occurred since the implementation of federal and state emission control regulations. However, understanding whether these improvements persist in sparsely monitored regions requires systematic long-term analysis. In North Dakota, existing studies have primarily focused on short-term pollution events, industrial emissions, and particulate matter dynamics, leaving the multidecadal evolution of gaseous pollutants largely unexplored. Moreover, traditional atmospheric modeling approaches often require extensive meteorological and emissions datasets, which may be limited in rural monitoring networks.

The traditional methods for air quality forecasting, such as deterministic chemical transport models and statistical regression comprehensive meteorological and emissions input data that may be inaccessible or inconsistent in rural monitoring networks, and they often fail to accurately represent nonlinear temporal dependencies in limited observational data. Recent advances in machine-learning techniques offer new opportunities for analyzing environmental time series and forecasting pollutant behavior using historical observations [19]. Data-driven models, such as random forest (RF), extreme gradient boosting (XGBoost), support vector machine (SVM), and artificial neural networks (NN) have demonstrated strong capabilities in capturing nonlinear relationships and temporal dependencies in air-quality datasets. These methods can provide reliable predictions even in data-limited environments, making them particularly suitable for rural monitoring systems. This study addresses the existing knowledge gap by performing the first multidecadal analysis of seasonal NO₂ and SO₂ concentrations in North Dakota with machine-learning forecasting techniques. Previous research in the area has mostly looked at the aerosols, visibility problems, and particulate matter that come from Bakken oil and gas activity [9–11]. However, the long-term seasonal behavior of gaseous pollutants, especially NO₂ and SO₂, at urban monitoring stations has not been systematically characterized over a multidecadal horizon, and data-driven forecasting methods have not been used to predict where these pollutants will go in the future in the region. Therefore, this study extends beyond the current literature that focuses on the Bakken by moving the analytical focus to the dynamics of gaseous pollutants and adding machine-learning-based long-range forecasts as a methodological development. Specifically, we analyze 30 years (1995–2025) of observations from two long-term monitoring stations located in Fargo and Bismarck. Four supervised learning algorithms (i.e., RF, XGBoost, SVM, and NN) are employed to characterize historical trends and generate forecasts of pollutant concentrations through 2050. The objectives of this study are to (i) evaluate long-term seasonal trends in NO₂ and SO₂ across two major urban centers in North Dakota, (ii) develop predictive machine-learning models capable of capturing temporal dependencies in pollutant concentrations, (iii) generate long-range forecasts of seasonal pollutant behavior through 2050 using a recursive prediction framework, and (iv) assess model performance using independent validation data from 2020–2024. By integrating historical trend analysis with advanced machine-learning approaches, this study provides a comprehensive evaluation of how gaseous air pollutants have evolved in the Northern Great Plains and how they may change in the coming decades. The results contribute to a deeper understanding of regional atmospheric dynamics and offer valuable insights for environmental monitoring, emission management, and future air-quality policy in North Dakota.

2. Methods

2.1. Study area

This study focuses on two urban monitoring locations in Eastern and Central North Dakota, Fargo (Cass County) and Bismarck (Burleigh County), which together represent the state's largest population centers and distinct emission environments (Fig.1). Fargo is located in the eastern Red River Valley near the Minnesota border and is characterized by relatively higher traffic density, residential combustion sources, and regional transport influences from the Upper Midwest. Bismarck, situated in central North Dakota along the Missouri River, experiences lower population density but is influenced by energy-related activities, including oil and gas development in the broader Bakken region, as well as seasonal residential heating emissions. Both cities experience a continental climate with strong seasonal contrasts, including cold winters prone to temperature inversions and warmer summers with enhanced atmospheric mixing. These meteorological conditions play a critical role in shaping seasonal air quality patterns, particularly for combustion-related pollutants, such as NO₂ and SO₂. While neither location consistently exceeds U.S. National Ambient Air Quality Standards, episodic pollution events associated with winter stagnation, regional transport, and industrial activity have been documented.

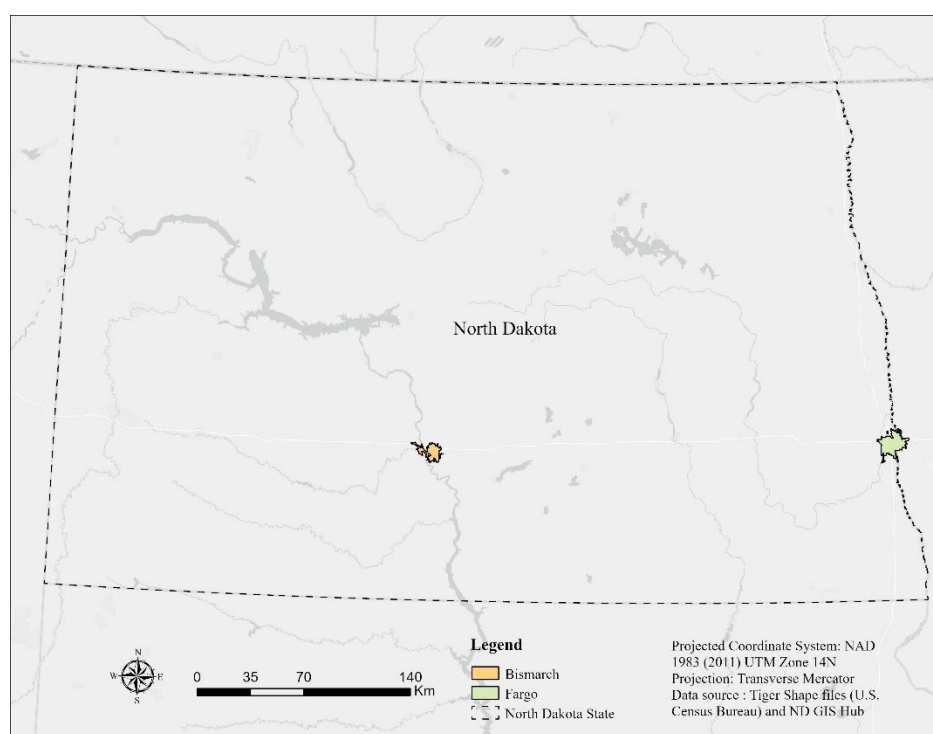


Figure 1. Study area map showing the locations of Bismarck and Fargo within North Dakota.

2.2. Data acquisition

This study analyzed daily NO₂ and SO₂ concentrations from 1995 to 2025 at two stations (Bismarck and Fargo). All data handling and preparation were done in R (version 4.3) using the *tidyverse* [20] suite of packages for data manipulation. This included reading raw data, merging datasets, and filtering by date and location. Dates were managed with the *lubridate* package [21] to simplify group by season. For each year, daily values were aggregated into two seasonal averages: summer (May–August) and winter (November–February of the following year). This grouping ensured that winter periods encompassed the correct four-month window even though they went into the next calendar year. Putting the data together into seasonal averages made the short-term noise less noticeable and made the main seasonal patterns and long-term trends easier to see for modeling.

2.3. Data scaling

A number of predictor features were created to capture temporal dependencies in the seasonal time series. Lag features were created by shifting the seasonal time series by one or more steps so that the model for a given season had access to the pollutant values from previous seasons (e.g., the previous winter or summer). These lagged values capture temporal autocorrelation and reflect how pollutant conditions evolve from one season to the next. Moving average features were also constructed to represent longer-term trends and reduce the influence of short-term variability. Then, z-score normalization was used to standardize all of the predictors and target variables so that they could be compared. This scaling was performed with the help of the *caret* package [22], which provides convenient preprocessing functions. Scaling ensures that the different features (including original pollutant levels and engineered lags/moving averages) are on similar ranges, preventing any single feature from unduly dominating model training due to scale alone. The use of the *caret* package also facilitated an efficient workflow for data splitting and cross-validation, as described below.

2.4. Machine learning models and training procedure

Four different machine learning models were developed to forecast seasonal pollutant levels: RF, XGBoost, SVM, and NN. The implementations were drawn from established R packages. The RF model was trained using the *randomForest* package [23]. It builds an ensemble of regression trees, and in this study, the number of trees was set to 500. The XGBoost was implemented using the *xgboost* package [24]. This package uses a gradient-boosting method that adds trees one at a time to make predictions more accurate. This optimized gradient-boosting framework builds trees one at a time, and each new tree fixes the mistakes made by the previous ones. The XGBoost model was trained with a learning rate of 0.3 and a maximum tree depth of 6. The SVM was implemented using the *e1071* package [25], which works by finding the best hyperplane to divide the classes. In this study, the SVM was run with a radial kernel, cost = 1, and default gamma. The NN model with a single hidden layer was trained using the *nnet* package [26], treating the task as a nonlinear regression problem. The model consisted of one hidden layer with five nodes and a weight decay of 0. Before training, the dataset was divided into a training period (1995–2019) and a validation period (2020–2024). Meteorological factors, including temperature, wind speed, and atmospheric stability indicators, were excluded as

inputs to the model. The exclusion was based on two principal reasons: first, continuous and comprehensive meteorological records throughout the entire 30-year study period at both stations were not consistently accessible in a format compatible with the seasonal aggregation framework employed; and second, limiting model inputs to lagged pollutant observations yields a more concise and temporally coherent forecasting system, thereby overcoming the additional uncertainty associated with projecting meteorological covariates decades into the future. This technique, however, constrains the model's ability for mechanistic interpretation, since the impact of certain atmospheric factors on pollutant concentrations cannot be directly measured. The models were fit on the training set, using only historical data up to 2019. The models were trained using lag-based predictor variables (Year, lag1, lag2, and a three-period moving average). Hyperparameters had been determined before training and were not refined by an automated grid-search method. The RF model was applied with 500 trees. The SVM model used a radial basis function kernel with default parameters. The XGBoost model was trained using a learning rate of 0.10, a maximum tree depth of 3, and 300 boosting rounds. The NN model had one hidden layer with five nodes, a weight decay value of 0.01, and a maximum of 1000 training rounds (Table 1).

To maintain temporal independence, model performance was assessed by an independent holdout validation method. Data from 1995 to 2019 were used for model training, while data from 2020 to 2024 were designated just for validation. This temporal division precluded subsequent data from affecting model development and ensured unbiased assessment of forecasting performance. All models were trained on the scaled feature set, and the continuous target variable was the mean seasonal concentration of the pollutant in the upcoming season.

Table 1. Hyperparameter settings used for machine-learning models.

Model	Hyperparameter	Value
RF	Number of trees (ntree)	500
SVM	Kernel	Radial basis function
	Cost (C)	Default
	Gamma	Default
XGBoost	Learning rate (eta)	0.10
	Maximum tree depth	3
	Number of boosting rounds	300
NN	Hidden layer size	5
	Weight decay	0.01
	Maximum iterations	1000

2.5. Forecasting and validation

The trained models were used in a recursive forecasting system to predict pollutant concentrations from 2025 to 2050. Starting from the last observed point (winter 2019–2020 season for the winter series and summer 2019 for the summer series), predictions were generated one season at a time. At each step, the model took as input the most recent lagged features. For the first forecast (e.g., summer 2020), these lag features came from the last available true observations (e.g., winter 2019–2020 for a one-season lag). After obtaining a prediction for 2020, that forecasted value was then used as an input

(as if it were an “observed” lag) to predict the next season (e.g., winter 2020–2021), and so forth. In this manner, forecasts were produced iteratively for each subsequent season through 2050, with each model feeding its own previous predictions into the next step. This repeated strategy enabled multi-step forecasting even though the models were trained as one-step predictors. Model performance was then assessed by comparing the forecasts with the observed values in the held-out validation period (2020–2024). The metrics used for evaluation were the coefficient of determination (R^2), root mean square error (RMSE), mean absolute error (MAE), and mean squared error (MSE). These metrics were computed for each combination of site, season, and model, providing a quantitative assessment of accuracy. For instance, R^2 indicates the proportion of variance in the 2020–2024 observations explained by the model’s predictions, while MAE and RMSE measure the typical prediction error in the original concentration units. All calculations were done on the unscaled (original) values so that error metrics are in meaningful units (parts-per-billion, ppb). To make sure that the whole modeling process could be repeated, from data preprocessing to model training and validation, it was scripted. Forecast outputs for 2025 to 2050 and all performance metrics were then exported to spreadsheets using the *openxlsx* package [27] to visualize the prediction in a table.

2.6. Data limitations

This study is affected by several data limitations, including missing years of monitoring and inconsistent station coverage. All monitoring stations did not record $PM_{2.5}$ or ozone measurements for every year, and several sites had long periods with missing or irregular data. Some stations operated only in specific years, while others recorded specific pollutants but lacked a complete dataset needed for long-term analysis. These gaps made a difference in the temporal coverage of each site, making it difficult to build a uniform dataset. In addition, variations in data completeness, reporting frequency, and instrument upgrades may introduce measurement inconsistencies across the monitoring network. Because of these issues, the analysis relied only on years and stations with usable data. Despite these limitations, the study delivers a valuable first step in predicting future air quality in North Dakota.

3. Results and discussion

3.1. Historical trends and seasonal patterns

The 30-year time series of seasonally averaged NO_2 and SO_2 concentrations show that both pollutants have dropped steadily and significantly in Fargo and Bismarck. The U.S. Environmental Protection Agency (US EPA, 2024) says that stricter emission standards, cleaner fuels, and better combustion efficiency have all led to improvements in air quality across the country [28]. In Fargo, winter NO_2 levels dropped from about 25 ppb in the middle of the 1990s to less than 10 ppb by 2025, which is a drop of more than 60% (Fig.2b). Summer NO_2 levels (Figure 2a), which were always lower than winter levels, went down from about 15 ppb to less than 7 ppb during the same time. This difference between seasons shows how temperature affects mixing in the atmosphere: in the winter, temperature inversions stop pollution from moving up and down and keep them close to the surface, while in the summer, convection makes dilution better. In Bismarck (Figure 2c, Figure 2d), yearly trends were similar, but the actual amounts were a little lower than in Fargo. This difference is likely

due to the fact that the two towns have different pollution patterns. In Fargo, higher traffic density and regional transportation factors from the Upper Midwest significantly contribute to winter NO₂ buildup. In Bismarck, household combustion for space heating and proximity to energy-related industrial activities in the wider Bakken area may enhance winter peaks compared to summer. The differences in emission structure between cities help explain why the yearly contrast between the two stations is bigger at one place than what air mixing alone would suggest. The levels of SO₂ dropped even more sharply. In Fargo, the amount of SO₂ in the winter dropped from about 12 ppb in 1995 to less than 2 ppb by 2025, which is more than 80% (Figure 3b). The amount of SO₂ in the summer was already low in the 1990s (Figure 3a) and has gotten even lower in the last few years. These cuts fit with the end of high-sulfur coal use in regional power plants and the use of technologies to remove sulfur from flue gas. Bismarck showed similar patterns, with winter SO₂ levels dropping from about 10 ppb to less than 2 ppb (Figure 3c, 3d).

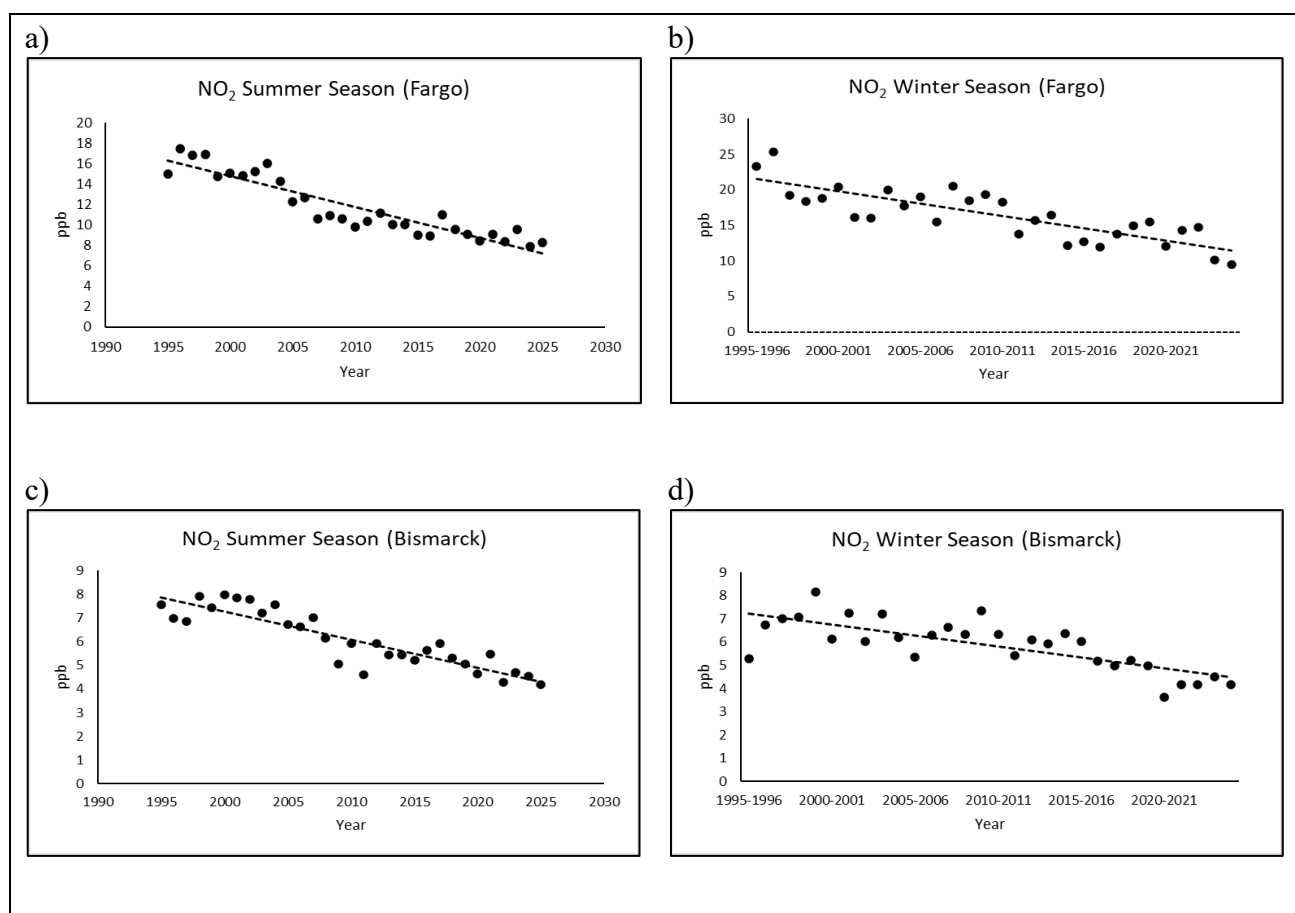


Figure 2. a) Summer season NO₂ Fargo station; b) Winter season NO₂ Fargo station; c) Summer season NO₂ Bismarck station; d) Winter season NO₂ Bismarck station.

The drops in both NO₂ and SO₂ show that federal and state air quality laws, such as the Clean Air Act Amendments of 1990 and later changes, are working [29]. However, the fact that seasonal variability, especially the higher winter concentrations, keeps happening shows that weather still has an effect on how pollutants build up. This finding aligns with Evanoski-Cole et al. (2017), who

recorded winter haze events in the Bakken region caused by atmospheric stagnation and localized emissions [10].

Even though these overall changes are good, there are some small changes in the time series that need to be looked at. For example, after 2015, winter NO₂ levels in Bismarck showed a small upward trend. According to Schwarz et al. (2015), who observed increased black carbon emissions during peak production years, this temporal coincidence is consistent with the growth of oil and gas extraction in the larger Bakken area[12]. The two monitoring stations in this research reflect metropolitan contexts, and the data do not provide direct linking to particular industrial sources; hence, it is crucial to recognize that this attribution is based on temporal correlation rather than direct source apportionment. The geographic and evidentiary breadth of this dataset, which represents circumstances at two urban monitoring sites in Fargo and Bismarck and may not be typical of larger statewide air quality dynamics, should thus be taken into consideration when drawing inferences about Bakken-driven emission patterns.

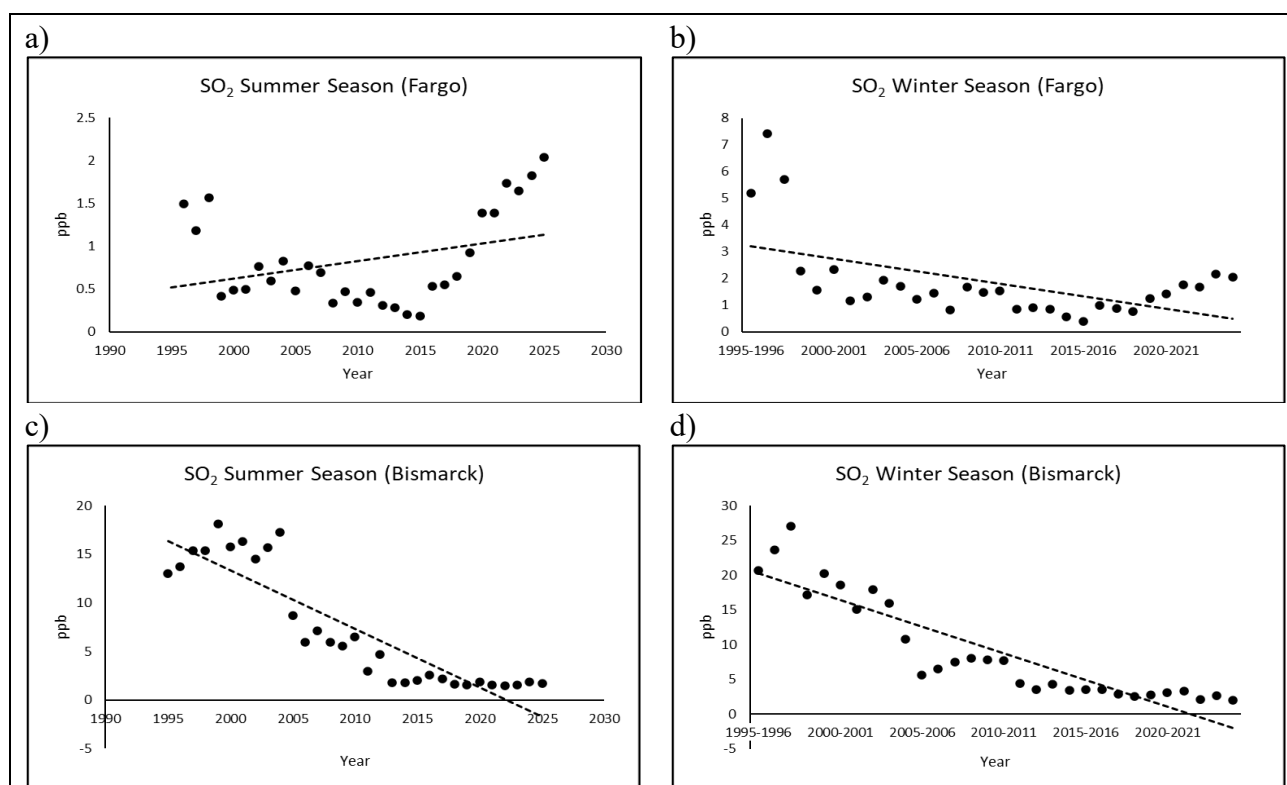


Figure 3. a) Summer season SO₂ Fargo station; b) Winter season SO₂ Fargo station; c) Summer season SO₂ Bismarck station; d) Winter season SO₂ Bismarck station.

3.2. Validation accuracy

This study trained four machine-learning models (i.e., RF, XGBoost, SVM, and NN) on historical data from 1995 to 2019 and tested them on data from 2020 to 2024. We calculated performance metrics (RMSE, MAE, and R²) for each pollutant, season, and city separately, which gave us 16 different forecasting scenarios (Table S2).

In almost all cases, the NN did better than all the other models. For most pollutant-season combinations, it got R^2 values over 0.96 and RMSE values under 1.5 ppb (Figure 4, 5). This better performance shows that the NN can find nonlinear patterns and complex temporal dependencies in the time series. For instance, in the Fargo winter NO_2 case, the NN got a R^2 of 0.98 and an RMSE of 1.12 ppb. The second-best model, RF, got a R^2 of 0.94 and an RMSE of 1.87 ppb (Figure 4b).

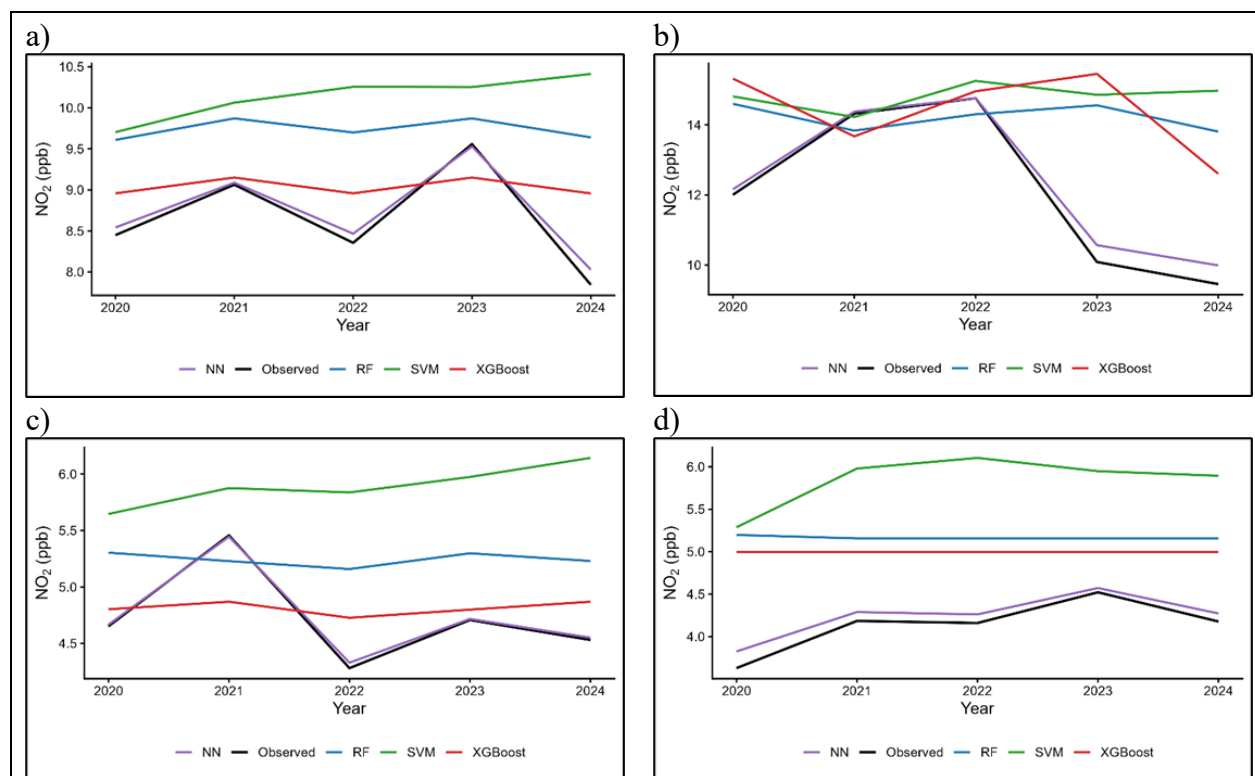


Figure 4. a) Summer season NO_2 Fargo station model validation; b) Winter season NO_2 Fargo station model validation; c) Summer season NO_2 Bismarck station model validation; d) Winter season NO_2 Bismarck station model validation.

The R^2 values for RF and XGBoost were usually between 0.90 and 0.95, which means they did about the same job. Both ensemble methods were better because they could combine predictions from many base learners, which made them more stable and less variable. In some cases, they had higher RMSE values than the NN, especially when the data changed a lot over time, such as in Bismarck winter NO_2 (Figure 4d). SVM did not work as well all the time (R^2 values ranged from 0.85 to 0.93), and in some cases, RMSE values were higher. This relative underperformance may be due to the small size of the training dataset and the difficulty of adjusting kernel parameters for time series data. Even with these problems, SVM still made good predictions and could be helpful in situations where being able to understand the results and speed are more important.

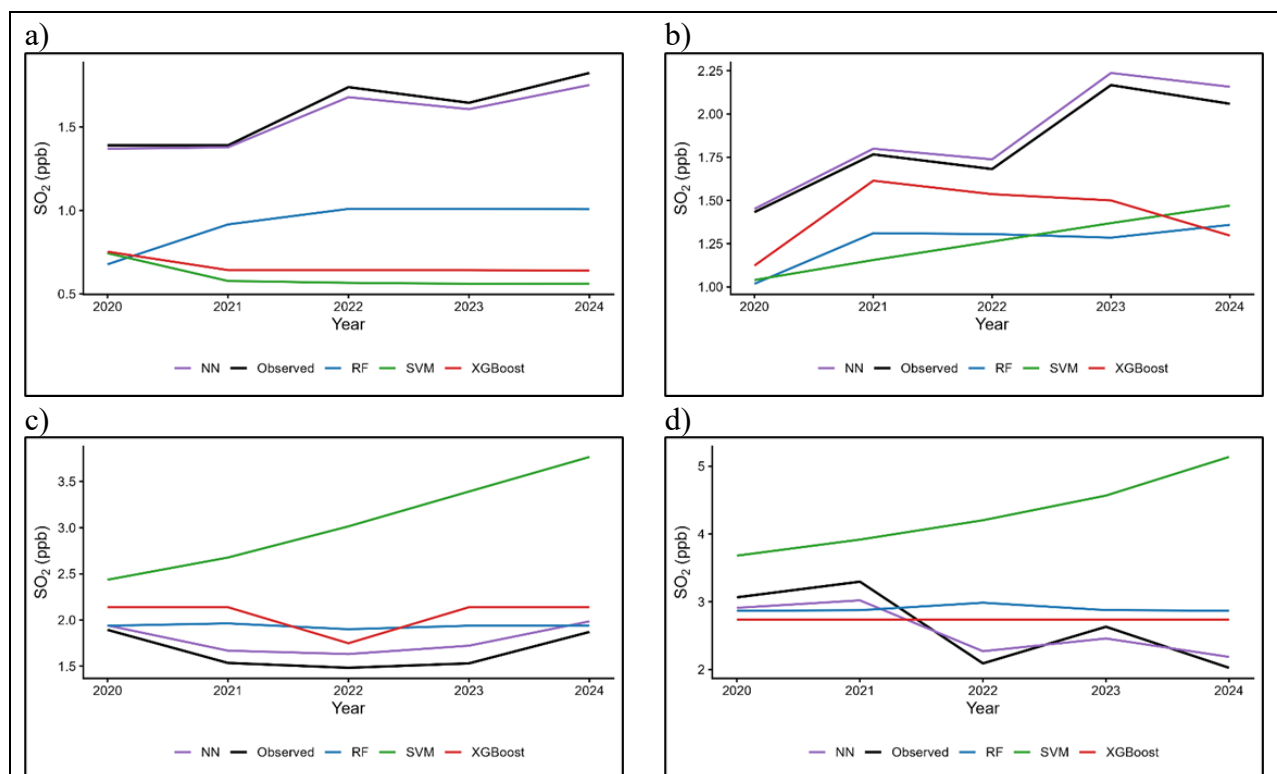


Figure 5. a) Summer season SO₂ Fargo station model validation; b) Winter season SO₂ Fargo station model validation; c) Summer season SO₂ Bismarck station model validation; d) Winter season SO₂ Bismarck station model validation.

The validation results show that machine learning models, especially neural networks, work very well for predicting air quality in rural areas during different seasons. The high R^2 values show that the models were able to accurately capture the data's underlying time structure. The low RMSE and MAE values show that the forecast errors are small compared to the observed concentrations. Recent studies that have used machine learning to predict air quality in cities and factories have similar results [30]. But it is important to remember that the model's performance changed depending on the situation. For example, the R^2 values (0.92–0.94) for summer SO₂ forecasts in both cities were a little lower than those for other scenarios. This could be because the concentrations have been so low in recent years, which reduces predictive precision due to a lower signal-to-noise ratio. The recursive forecasting framework spreads accumulated uncertainty, which happens when mistakes in early forecasts are made and shown in later time steps. This limitation shows how important it is to update and validate models on a regular basis as new observational data comes in. Comparing this method to ML-based studies that looked at air quality projections in other regions, it shows that data-driven models are useful for predicting pollutant trends in places where tracking is not very common. Studies utilizing seasonally segmented frameworks with meteorological covariates have shown that the primary predictive variables systematically vary by season, with temperature and NO₂ co-variability influencing warm-season dynamics, while combustion-related variables assume greater explanatory power in winter [31,32]. While this study's purely lag-based method works well for modeling trends, it lacks meteorological inputs that would allow a fundamental understanding of the predicted seasonal changes. Incorporating weather factors, such as temperature, wind speed, and air stability measures,

would be to improve future models because it would allow for more accurate interpretations within the current framework.

3.3. Forecasting from 2025 to 2050

Using the best-performing NN model, pollutant concentrations were projected from 2025 to 2050 under the assumption that current emission trends and regulatory conditions remain stable. Since the framework for forecasting is recursive, meaning that each prediction is used as input for the next step, formal confidence intervals were not calculated for the projected values. The cumulative error in predictions over the next several years (2025–2030) is very modest, while projections for the years leading up to 2050 have a lot more uncertainty. Figures 6 and 7 illustrate predicted trends. These should be seen as central tendency estimates, with the awareness that the range of possible outcomes gradually grows over the 25-year horizon. The predictions show that air quality will be affected in different ways by pollutants, seasons, and cities in the future.

The amount of NO₂ in Fargo's winter air is expected to stay around 8 ppb until 2050, with only small changes from year to year (Figure 6b). This downward trend indicates that further reductions might require additional regulatory interventions or technological innovations that improve existing methodologies. In contrast, the amount of NO₂ in Fargo in the summer is expected to slowly drop, reaching 5 ppb by the middle of the century (Figure 6a). This continued improvement is probably due to the fleet's ongoing shift to cleaner vehicles and the continued drop in fossil fuel use.

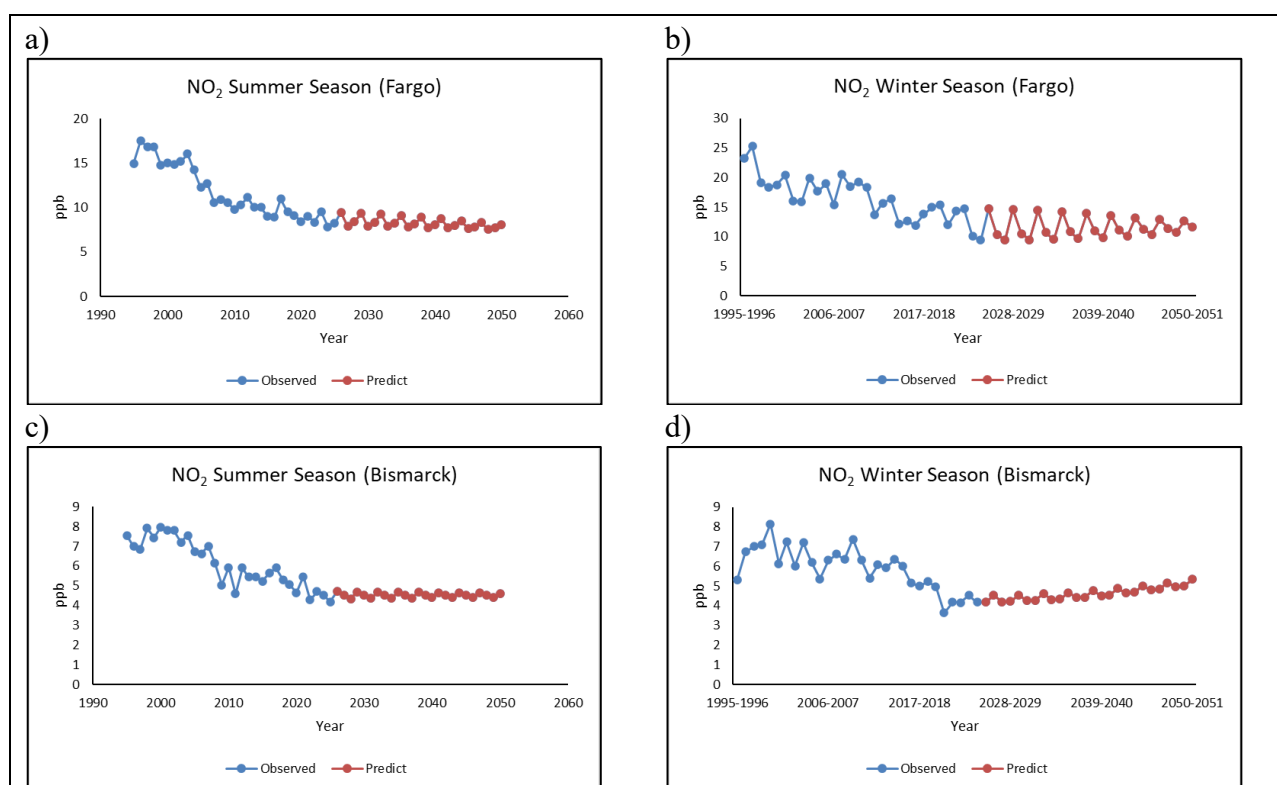


Figure 6. a) Summer season NO₂ Fargo station prediction; b) Winter season NO₂ Fargo station prediction; c) Summer season NO₂ Bismarck station prediction; d) Winter season NO₂ Bismarck station prediction.

Bismarck's predicted winter NO₂ values indicate a troubling trend, increasing from around 7 ppb in 2025 to 9 ppb by 2050 (Figure 6d). According to Evanoski-Cole et al. (2017), this upward trend suggests that localized emission sources, possibly linked to ongoing oil and gas extraction activities, may cancel out broader regional improvements [10]. This is in line with the higher levels of nitrogen oxide that were found during winter haze events in the Bakken region. Even though the expected NO₂ levels are still a long way below the EPA's yearly limit of 53 ppb, this sudden change in the trend of growth needs immediate attention from the responsible authorities. Under the current rules of the Clean Air Act, small rises like these might not lead to required reduction unless certain levels are broken. This could leave a control gap for localized industry emission growth in rural areas. Targeted such actions as setting up better monitoring networks for the environment near active extraction zones, limiting emissions from upstream oil and gas operations, and including air quality impact assessments in the processes for approving energy projects could help stop things from getting worse. The regulatory implications of these results would be strengthened by future research that links this observed pattern to the body of policy literature on industrial emission regulation in rural areas that produce energy. Summer NO₂ levels in Bismarck are expected to stay stable at around 6 ppb (Figure 6c), which is in line with the trend in Fargo during the summer. Predictions for sulfur dioxide are less stable. In both cities, winter SO₂ is expected to stabilize around 1.5–2.0 ppb (Figure 7b, 7d). This is because fuels with a lot of sulfur are rapidly disappearing. But the amount of SO₂ in the air in Fargo and Bismarck is slowly going up in the summer, going from almost zero in 2025 to about 1.5 ppb by 2050 (Figure 7a, 7c). This unexpected trend may be driven by increased emissions from episodic or seasonal sources that become more active during summer. Climate change may further amplify these emissions by increasing the frequency and intensity of natural and human-induced combustion events [33,34]. For example, smoke transported from large wildfires in the western United States has been linked to episodic increases in SO₂ and particulate matter in regions downwind of the Northern Plains during summer [35]. Seasonal agricultural residue burning and occasional industrial flaring associated with oil and gas operations may also contribute to elevated SO₂ concentrations, producing signals that are difficult to isolate in station-level time series analyses [36,37]. In addition, long-range transport from major emission sources in upwind states under prevailing summer circulation patterns may further enhance SO₂ levels [38]. Future research should examine whether similar summer increases in SO₂ concentrations are observed in monitoring records from other rural continental regions.

From a statistical perspective, it is worth mentioning that the predicted increase in summer SO₂ starts baseline. The recursive prediction framework may allow for an increase of up to 1.5 ppb by 2050, but the exact amount of the increase is unknown. Since the summer SO_k series has a generally low variance, an analysis of the training data shows that a few years with high readings may be excessively impacting the model's predicted trajectory. These years could be linked to episodic transport of smoke from wildfires or agricultural burning events. The susceptibility to unusual years in the training dataset is a recognized weakness of lag-based recursive models used for low-concentration series, underscoring the need for care in making definitive inferences from this specific prediction trajectory.

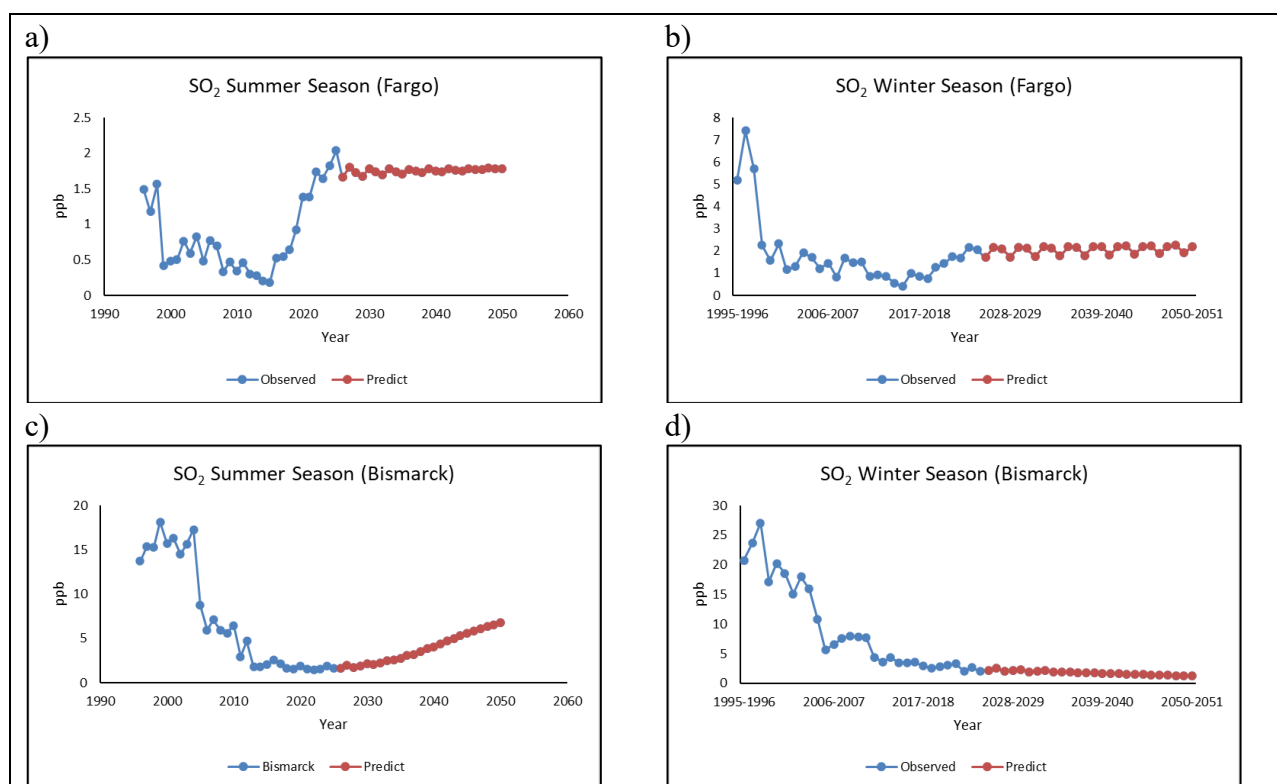


Figure 7. a) Summer season SO₂ Fargo station prediction; b) Winter season SO₂ Fargo station prediction; c) Summer season SO₂ Bismarck station prediction; d) Winter season SO₂ Bismarck station prediction.

These forecasts make a few important points stand out. First, even though past cuts in emissions have worked very well, there is no guarantee that future cuts will work as well and the amount of progress may be different for different pollutants and times of year. Second, localized sources of pollution, especially those related to energy extraction and events that happen only once in a while, can have a big impact on air quality in a region, even in rural areas. Third, the stabilization or slight rise in some pollutant-season combinations indicates that more regulatory measures may be needed to make more progress.

It is very important to stress that these predictions are based on the idea that emissions and regulations will stay the same. Changes that were not expected, like the fast growth of renewable energy, new factories, or changes in how people travel, could have a big effect on the future. This recursive framework for forecasting spreads prediction error at every step, so over the 25-year projection time frame, forecast confidence decreases gradually. Projections for the near period (2025–2035) are more accurately defined by lag characteristics obtained from recent data and should be considered with more confidence. In contrast, forecasts for the 2045–2050 period depend on recursively estimated inputs derived from previous predictions, resulting in additional uncertainty that makes these long-term values more representative of directional trends than exact quantitative standards. For planning or following rules, people who use these predictions should focus on the predictions for the next few years and see the years 2040–2050 as possible scenarios that could be changed as new tracking data comes in. Consistent model retraining with new data will be essential to preserve the efficacy of forecasts over time.

3.4. Limitations and future research

This research has some limitations that must be recognized. First, and most importantly from a methodological perspective, the machine-learning models were trained only on lagged pollutant measurements without meteorological factors, such as temperature, wind speed, and atmospheric stability. The lack of this information is a significant limitation in the predicting system because it is known that temperature inversions and seasonal changes in the atmosphere can cause pollution to build up in the Northern Plains. Future research that includes meteorological factors would enhance both prediction precision and mechanistic understanding. The study is based only on data from two monitoring sites, thus overlooking the comprehensive regional heterogeneity of air quality across North Dakota. Future research should incorporate additional monitoring sites and examine spatial interpolation techniques to generate statewide estimates. Second, the machine-learning models are based on the idea that future emission trends will follow past patterns. This may not be true if big changes in technology or rules happen. Including scenario-based forecasting, such as looking at how adopting renewable energy or more frequent wildfires might affect air quality in the future, would give a better picture of how air quality will change in the future. Third, the recursive forecasting framework adds up uncertainty, especially for long-range projections. Ensemble forecasting methods, which use predictions from more than one model, could help figure out how uncertain this is and make it less so. Fourth, the study only looks at NO₂ and SO₂, but other pollutants, such as PM_{2.5} and O₃, are also very important for measuring air quality and health effects. Subsequent research ought to broaden the analysis to incorporate these pollutants and investigate their interactions with meteorological variables. Machine-learning models are good at making predictions, but they do not help explain why air quality changes. We could learn more about where emissions come from, how the atmosphere works, and how things move through it by combining machine learning with process-based models like chemical transport models. This combined approach would make it easier to understand and more accurate to predict air quality, which would help policymakers make better choices.

4. Conclusion

This study provides a comprehensive 30-year assessment of seasonal NO₂ and SO₂ concentrations in Fargo and Bismarck and offers machine-learning-based forecasts through 2050. The historical analysis confirms substantial long-term declines in both pollutants across seasons and locations, driven by effective state and federal emission regulations. Winter concentrations consistently exceeded summer levels, reflecting known atmospheric stability and seasonal emission patterns in cold northern climates. While historical trends largely indicate successful air-quality improvements, emerging anomalies, such as the late-period rise in summer SO₂ at Fargo, demonstrate that localized fluctuations may still occur despite overall progress. Machine learning evaluation for seasonal forecasting revealed that the NN model overwhelmingly outperformed RF, XGBoost, and SVM across all metrics and scenarios. The NN achieved high predictive accuracy during validation ($R^2 > 0.96$ across all scenarios), with training fit exceeding $R^2 > 0.99$ in most cases, demonstrating its suitability for capturing complex temporal dependencies in seasonal pollutant data. This high predictive fidelity enabled reliable long-range forecasting, with model validation across the 2020–2024 period showing minimal error and

strong generalization capability. Overall, the findings highlight the importance of sustaining comprehensive air-quality monitoring networks in North Dakota and underscore the value of machine-learning models for long-term environmental forecasting. The observed and projected pollutant behaviors suggest that proactive policy maintenance rather than relaxation will be essential to preserve the state's historically clean air, particularly as climate change, development, and episodic events may introduce new variability into the region's atmospheric environment.

Use of AI tools declaration

The authors declare they have not used Artificial Intelligence (AI) tools in the creation of this article.

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The data supporting the findings of this study are publicly available from the United States Environmental Protection Agency (US EPA) Air Quality System (AQS) database.

Faisal Ahmed: Conceptualization; Methodology; Data curation; Formal analysis; Machine learning modeling; Visualization; Writing – original draft; Writing – review and editing; Project administration; Md Nasifur Rahman Sakib: Data acquisition; Data preprocessing; Statistical analysis; Verification of results; Writing – review and editing; Manna Khan: Literature review; Environmental interpretation of results; Validation; Writing – review and editing; Supervision; Sabrina Karim: Review and editing.

Conflict of 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.

References

1. Mustafa ARA, Shokr MS, Alharbi T, et al. (2025) Integration of Google Earth Engine and aggregated air quality index for monitoring and mapping the spatio-temporal air quality to improve environmental sustainability in arid regions. *Sustainability* 17: 3450. <https://doi.org/10.3390/su17083450>
2. Badh A, Akyuz A, Vocke G, et al. (2009) Impact of climate change on the growing seasons in select cities of North Dakota, United States of America. *Int J Clim Change Impacts Responses* 1: 105–118. <https://doi.org/10.18848/1835-7156/CGP/v01i01/37130>
3. Dhukuchhu A, Kaya O, Hatterman-Valenti H (2025) Planting date and cultivar selection effects on cauliflower growth, physiology, and yield performance in North Dakota growing conditions. *Horticulturae* 11: 1314. <https://doi.org/10.3390/horticulturae1111314>
4. Karim S, Ahmed F, Mollick T, et al. (2026) Climate-driven forecasting of agricultural land cover change in North Dakota's Red River Valley using remote sensing and machine learning. *Earth Syst Environ* <https://doi.org/10.1007/s41748-026-01205-4>

5. Biagi B, Brattich E, Cintolesi C, et al. (2025) Dynamical and chemical impacts of urban green areas on air pollution in a city environment. *Urban Clim* 60: 102343. <https://doi.org/10.1016/j.uclim.2025.102343>
6. Zhou M, Xie Y, Wang C, et al. (2024) Impacts of current and climate-induced changes in atmospheric stagnation on Indian surface PM_{2.5} pollution. *Nat Commun* 15: 7448. <https://doi.org/10.1038/s41467-024-51462-y>
7. Clean Air Task Force (2017) Health risks in North Dakota from oil and gas air pollution. *Fact Sheet*. Available from: <https://www.catf.us/resource/health-risks-in-north-dakota/>
8. Allison E, Mandler B (2018) Air quality impacts of oil and gas emissions from production, processing, refining, and use. American Geosciences Institute, Petroleum and the Environment Report. Available from: <https://profession.americangeosciences.org/reports/petroleum-environment-2018/air-quality-impacts-oil-gas/>
9. Prenni AJ, Day DE, Evanoski-Cole AR, et al. (2016) Oil and gas impacts on air quality in federal lands in the Bakken region: An overview of the Bakken Air Quality Study and first results. *Atmos Chem Phys* 16: 1401–1416. <https://doi.org/10.5194/acp-16-1401-2016>
10. Evanoski-Cole AR, Gebhart KA, Sive BC, et al. (2017) Composition and sources of winter haze in the Bakken oil and gas extraction region. *Atmos Environ* 156: 77–87. <https://doi.org/10.1016/j.atmosenv.2017.02.019>
11. Gebhart KA, Day DE, Prenni AJ, et al. (2018) Visibility impacts at Class I areas near the Bakken oil and gas development. *J Air Waste Manag Assoc* 68: 477–493. <https://doi.org/10.1080/10962247.2018.1429334>
12. Schwarz JP, Holloway JS, Katich JM, et al. (2015) Black carbon emissions from the Bakken oil and gas development region. *Environ Sci Technol Lett* 2: 281–285. <https://doi.org/10.1021/acs.estlett.5b00225>
13. Jeon JW, Park SW, Han YJ, et al. (2024) Nitrate formation mechanisms causing high concentration of PM_{2.5} in a residential city with low anthropogenic emissions during cold season. *Environ Pollut* 352: 124141. <https://doi.org/10.1016/j.envpol.2024.124141>
14. CIRES (2019) A new view of wintertime air pollution: Study could help improve air quality in cities across the U.S. West. Cooperative Institute for Research in Environmental Sciences. Available from: <https://cires.colorado.edu/news/new-view-wintertime-air-pollution>
15. Munia MMFJ, Jannat JNJ, Mia MY, et al. (2023) A critical review and prospect of NO₂ and SO₂ pollution over Asia: Hotspots, trends, and sources. *Sci Total Environ* 876: 162851. <https://doi.org/10.1016/j.scitotenv.2023.162851>
16. Elisephane I, Török Z (2025) Environmental determinants of ambient air pollution in urban East Africa: Unveiling critical insights from Kigali, Rwanda. *Sci Afr* 30: e03055. <https://doi.org/10.1016/j.sciaf.2025.e03055>
17. Cohen AJ, Brauer M, Burnett R, et al. (2017) Estimates and 25-year trends of the global burden of disease attributable to ambient air pollution. *Lancet* 389: 1907–1918. [https://doi.org/10.1016/S0140-6736\(17\)30505-6](https://doi.org/10.1016/S0140-6736(17)30505-6)
18. Landrigan PJ, Fuller R, Acosta NJR, et al. (2018) The Lancet Commission on pollution and health. *Lancet* 391: 462–512. [https://doi.org/10.1016/S0140-6736\(17\)32345-0](https://doi.org/10.1016/S0140-6736(17)32345-0)

19. Olawade DB, Wada OZ, Ige AO, et al. (2024) Artificial intelligence in environmental monitoring: Advancements, challenges, and future directions. *Hyg Environ Health Adv* 12: 100114. <https://doi.org/10.1016/j.heha.2024.100114>
20. Wickham H, Averick M, Bryan J, et al. (2019) Welcome to the tidyverse. *J Open Source Softw* 4: 1686. <https://doi.org/10.21105/joss.01686>
21. Grolemund G, Wickham H (2011) Dates and times made easy with lubridate. *J Stat Softw* 40: 1–25. <https://doi.org/10.18637/jss.v040.i03>
22. Kuhn M (2008) Building predictive models in R using the caret package. *J Stat Softw* 28: 1–26. <https://doi.org/10.18637/jss.v028.i05>
23. Liaw A, Wiener M (2002) Classification and regression by randomForest. *R News* 2: 18–22.
24. Chen TQ, Guestrin C (2016) XGBoost: A scalable tree boosting system. In: Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, San Francisco, 785–794. <https://doi.org/10.1145/2939672.2939785>
25. Meyer D, Dimitriadou E, Hornik K, et al. (2024) e1071: Misc functions of the Department of Statistics, Probability Theory Group (Version 1.7-16). R package.
26. Venables WN, Ripley BD (2002) *Modern Applied Statistics with S*. 4 Eds., New York: Springer. <https://doi.org/10.1007/978-0-387-21706-2>
27. Schauburger P, Walker A (2025) openxlsx: Read, write and edit xlsx files (Version 4.2.8). R package. Available from: <https://ycphs.github.io/openxlsx/index.html>
28. US EPA (2024) Air pollution trends continue to link clean air and strong economy. Available from: <https://www.epa.gov/newsreleases/air-pollution-trends-continue-link-clean-air-and-strong-economy>
29. US EPA (n.d.) Clean Air Act overview. Available from: <https://www.epa.gov/clean-air-act-overview/progress-cleaning-air-and-improving-peoples-health>
30. Tırink S (2025) Machine learning-based forecasting of air quality index under long-term environmental patterns: A comparative approach with XGBoost, LightGBM, and SVM. *PLoS One* 20: e0334252. <https://doi.org/10.1371/journal.pone.0334252>
31. Seo JH, Cho J, Hong E, et al. (2026) Seasonally adaptive data-driven ozone prediction in megacity environments. *Environ Res* 293: 123741. <https://doi.org/10.1016/j.envres.2026.123741>
32. Lee J, Barquilla CAM, Park K, et al. (2024) Urban form and seasonal PM2.5 dynamics: Enhancing air quality prediction using interpretable machine learning and IoT sensor data. *Sustain Cities Soc* 117: 105976. <https://doi.org/10.1016/j.scs.2024.105976>
33. Abatzoglou JT, Williams AP (2016) Impact of anthropogenic climate change on wildfire across western US forests. *Proc Natl Acad Sci USA* 113: 11770–11775. <https://doi.org/10.1073/pnas.1607171113>
34. IPCC (2023) *Climate Change 2023: Synthesis Report*. Core Writing Team, Lee H, Romero J, Eds., Geneva: Intergovernmental Panel on Climate Change, 35–115. <https://doi.org/10.59327/IPCC/AR6-9789291691647>
35. Jaffe DA, O'Neill SM, Larkin NK, et al. (2020) Wildfire and prescribed burning impacts on air quality in the United States. *J Air Waste Manag Assoc* 70: 583–615. <https://doi.org/10.1080/10962247.2020.1749731>

36. Crippa M, Janssens-Maenhout G, Dentener F, et al. (2016) Forty years of improvements in European air quality: Regional policy-industry interactions with global impacts. *Atmos Chem Phys* 16: 3825–3841. <https://doi.org/10.5194/acp-16-3825-2016>
37. McLinden CA, Fioletov V, Shephard MW, et al. (2016) Space-based detection of missing sulfur dioxide sources of global air pollution. *Nat Geosci* 9: 496–500. <https://doi.org/10.1038/ngeo2724>
38. Lin M, Horowitz LW, Payton R, et al. (2017) US surface ozone trends and extremes from 1980 to 2014: Quantifying the roles of rising Asian emissions, domestic controls, wildfires, and climate. *Atmos Chem Phys* 17: 2943–2970. <https://doi.org/10.5194/acp-17-2943-2017>



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