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A Data-Driven Credit Scoring Framework for Ozone Pollution

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ABSTRACT
With the intensification of environmental pollution, how to effectively evaluate and communicate the health and economic impacts of air quality has become a key issue in environmental governance and public service. This study focuses on the worsening trend of ozone pollution across China and proposes a credit scoring model for ozone pollution targeting both the general public and industry users. The model adopts a hybrid framework combining rule-based scoring and machine learning correction. Specifically, initial scores are calculated based on ozone concentrations, meteorological conditions, and temporal factors, followed by refinement through a stacking ensemble of algorithms including Random Forest, XGBoost, and LightGBM, enhancing accuracy and generalizability. The model is trained and validated using daily national meteorological and ozone data from March 2023 to March 2024. Cross-validation shows robust performance in RMSE, MAE, and R^2 metrics. Finally, the study examines limitations in data coverage, cross-industry collaboration, and model adaptability. Despite these constraints, the proposed framework demonstrates practical value by providing data-driven insights for fine-grained pollution governance and contributing to the development of China's environmental credit system.

KEYWORDS
Ozone pollution; Environmental credit; Hybrid modeling; Stacking model; Data product; Environmental big data

1 Introduction

With the rapid expansion of urban agglomerations and industrial activities in China, regional and compound air pollution has become a pressing environmental issue. Although the implementation of the Air Pollution Prevention and Control Action Plan has led to a notable decline in fine particulate matter concentrations, surface-level ozone pollution has shown an opposite trajectory—marked by increasing severity, expanding spatial coverage, and more frequent large-scale and persistent pollution episodes.

Unlike $PM_{2.5}$, ozone is a secondary pollutant formed through complex photochemical reactions involving volatile organic compounds (VOCs) and nitrogen oxides (NO_x), and is highly sensitive to meteorological conditions. Its colorless and odorless nature makes it difficult for the public to perceive or avoid, posing hidden risks to human health. In recognition of its underestimated health impacts, the World Health Organization significantly revised the recommended ozone concentration limits in its 2021 Global Air Quality Guidelines, signaling a growing global concern about ozone exposure.

Despite the policy efforts, the dissemination and utilization of ozone-related information remain limited. Existing systems, such as the Air Quality Index (AQI), often lack fine-grained data, interactivity, and contextual adaptability, which hampers effective risk communication and public engagement. Moreover, although ozone monitoring data is publicly accessible, it has not been effectively converted into actionable knowledge. Public understanding and response capacity remain low, and enterprises lack quantifiable tools to assess ozone-related environmental risks—thereby constraining the effectiveness of pollution mitigation strategies.

In this context, developing ozone-based environmental credit information products that are both quantifiable and application-oriented is essential for supporting modern environmental governance and fostering multi-stakeholder collaboration in air pollution control.

2 Related work

Environmental credit evaluation has emerged as a policy tool to promote sustainable development by introducing quantifiable environmental performance indicators. In China, institutional efforts began with the 2013 “Corporate Environmental Credit Evaluation Measures”, aiming to assess corporate compliance and responsibility, and to implement a system of incentives and penalties based on environmental performance. Over time, such systems have been increasingly integrated into financial services, public procurement, and market regulation, enhancing environmental governance through transparency and accountability.

Parallel to this, credit scoring models have evolved from traditional statistical approaches to modern machine learning

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techniques. While logistic regression remains widely used for its interpretability and robustness, methods such as support vector machines and neural networks have been applied to domains with imbalanced data or complex patterns [2-4]. Hybrid modeling approaches that combine statistical and machine learning methods offer improved stability, accuracy, and explanatory power, and have been successfully applied in domains including banking, finance, and risk assessment [5-6].

In the domain of environmental health, numerous studies have quantified the health impacts of air pollutants using exposure-response relationships derived from epidemiological research. Tools such as BenMAP(Environmental Benefits Mapping and Analysis Program) are widely used to estimate health outcomes and economic losses attributable to pollution, particularly for pollutants like $PM_{2.5}$ and O_3 [7-9]. These studies provide essential coefficients linking pollutant concentrations with health endpoints such as mortality and morbidity rates, forming the scientific basis for risk quantification.

While these streams of research offer solid foundations, they have largely remained separate. Existing environmental credit systems focus predominantly on corporate compliance, with limited integration of population health risk data or pollutant exposure metrics. Likewise, most health impact assessments yield aggregate statistics or economic valuations, which are not readily transformed into actionable public information.

This study addresses this gap by constructing an environmental credit scoring model based on urban ozone pollution data, incorporating exposure-response coefficients from established epidemiological literature as a core scoring reference. In doing so, it explores a novel pathway to translate environmental risk data into publicly interpretable, credit-like information products that support participatory environmental governance.

3 Ozone pollution credit scoring model

3.1 Indicator system design

3.1.1 Pollution performance layer

At the core of the scoring model is the pollution performance layer, which assesses ozone pollution levels and potential health risks using quantitative concentration metrics. The key input is the Maximum Daily 8-hour Average Ozone Concentration (M8H_O_3), a widely recognized standard in global air quality management. This metric captures the highest average ozone level over any consecutive 8-hour period in a given day, offering a more health-relevant exposure measure than hourly peaks by balancing short-term fluctuations with cumulative effects.

Scoring standards are developed with reference to both China's Ambient Air Quality Standards (GB 3095-2012) and the World Health Organization's Global Air Quality Guidelines (2021). Under the Chinese standard, the Class II limit for ozone is 160 μg/m^3, above which pollution is considered excessive. In contrast, WHO guidelines recommend keeping the annual mean of M8H_O_3 below 100 μg/m^3 to minimize health risks.

By synthesizing these standards and considering the health and environmental impacts of ozone, the model defines a multi-level grading scheme. Ozone concentrations are classified into intervals and assigned corresponding scores, forming a scientifically grounded and operationally effective evaluation framework for pollution severity. This provides the quantitative foundation for the model's credit scoring layer.

Table 1 Ozone pollution scoring criteria

Ozone Concentration (μg/m^3)	Score	Description
0-100	100	Clean air level. No significant impact on human health or the environment.
100-160	$100-\frac{(O_{3,8h-max}-100)\times 25}{v60}$	Near the health risk threshold. Sensitive groups may experience mild respiratory discomfort; afternoon outdoor exposure should be monitored.
160-200	$75-\frac{(O_{3,8h-max}-160)\times 25}{40}$	Light pollution. General population may experience eye and respiratory irritation. Long outdoor stays and intense physical activity should be reduced.
200-300	$50-\frac{(O_{3,8h-max}-200)\times 25}{100}$	Moderate to heavy pollution. Symptoms such as coughing and wheezing may worsen. Sensitive groups are advised to avoid outdoor activities.
300-400	$25-\frac{(O_{3,8h-max}-300)\times 25}{100}$	Severe pollution. May cause widespread respiratory and cardiovascular effects; acute health incidents possible. Staying indoors with windows closed is recommended.
>400	0	Extreme pollution. Catastrophic threat to human health and ecosystems; risk of large-scale health crises.

3.1.2 Health risk layer

The health risk layer serves as a critical component of the ozone pollution credit scoring model, aiming to quantify the potential public health threat posed by ozone exposure and incorporate it into the scoring mechanism.

Excess risk (ER) is a widely used metric in environmental health studies, which expresses the percentage increase or decrease in health events corresponding to a specific change in pollutant levels, providing an intuitive measure of population risk. The formula is as follows:

$$ER = [exp(\beta \times 10) - 1] \times 100\% \#(1)$$

where β is the exposure–response coefficient, defined as the logarithm of the increase in mortality risk per unit rise in pollutant concentration.

According to prior research, a 10 μg/m^3 increase in 8-hour maximum ozone concentration $O_{3,8h\text{-}max}$(lag0~1) is associated with a 0.43% increase in non-accidental mortality(95% CI: 0.04%–0.82%). This value provides a scientific basis for the health impact adjustment in our model.

Accordingly, the health risk factor is introduced as a penalty term in the base score. For every 10 μg/m^3 increase in ozone, the score is reduced by 0.43×K, where K is a tunable weight reflecting regional population vulnerability and healthcare capacity. The formula is as follows:

$$\text{health\_risk}_{\text{penalty}} = \frac{O_{3,8h-max}}{10} \times 0.43 \times K \#(2)$$

3.1.3 Adjustment layer

To further refine the credit score, the adjustment layer incorporates meteorological conditions and temporal characteristics into the scoring system. This dynamic correction reflects both the environmental mechanisms of ozone formation and the periodic patterns of human activity. The layer includes two components: meteorological adjustment factors and temporal adjustment factors.

3.1.3.1 Meteorological adjustment factors

Meteorological variables have a direct influence on the generation, accumulation, and dispersion of ozone. This model uses temperature, wind speed, and relative humidity as correction inputs. The adjustments are defined as follows:

（1）Temperature penaltyBased on the enhanced rate of photochemical reactions at high temperatures, which accelerate ozone formation through increased VOCs and NO_x photolysis.

When the daily mean temperature exceeds 30°C, each additional 1°C triggers a penalty of 0.5 points, up to a maximum of 2 points per day:

$$\text{TEMP}_{\text{penalty}} = min(max(0,(TEMP - 30) \times 0.5),2) \#(3)$$

（2）Wind speed bonusStrong winds facilitate pollutant dispersion, reducing local ozone accumulation. For each 1 m/s increase in daily average wind speed, 0.2 points are added, up to 1 point per day:

$$\text{WDSP}_{\text{bonus}} = min(max(0,(WDSP \times 0.2),1) \#(4)$$

（3）Relative humidity bonusHigh humidity slows ozone formation by consuming reactive radicals. RH is approximated using the ratio of dew point temperature to actual temperature:

$$RH = \frac{\text{DEWP}}{\text{TEMP}} \#(5)$$

When RH exceeds 60%, each additional 1% yields a 0.2-point bonus, up to 1 point daily:

$$\text{RH}_{\text{bonus}} = min(max((RH - 0.6) \times 20,0),1) \#(6)$$

3.1.3.2 Temporal adjustment factors

Periodic changes in human activity(such as reduced emissions on weekends or public holidays)can significantly affect ozone levels. The following time-based bonuses are applied:

Weekend Bonus: +1 point for Saturdays and Sundays, reflecting lower industrial emissions.

（1）Weekend Bonus: +1 point for Saturdays and Sundays, reflecting lower industrial emissions.

（2）Holiday Bonus: +2 points for national public holidays, considering additional reductions in traffic and social activity.

（3）Conflict Rule: If a day is both a weekend and a holiday, only the higher bonus (+2) is applied to avoid double counting.

$$\text{time}_{\text{bonus}} = \begin{cases} 2, \textit{if public holiday} \\ 1, \textit{if weekend and not a holiday} \\ 0, \textit{otherwise} \end{cases} \#$$

3.2 Model construction

Building upon the previously defined indicator system, this study proposes a two-stage evaluation framework that integrates rule-based scoring with machine learning regression, enabling multidimensional quantification and intelligent prediction of ozone-related environmental credit risk.

3.2.1 Rule-based scoring stage

A rule-based scoring system is first developed based on the core indicators. Threshold intervals are defined for each factor, and daily ozone credit scores are calculated by aggregating individual component scores. The overall rule-based credit score is computed as follows:

$$rule\_score = base\_score - \mathrm{health\_risk}_{\mathrm{penalty}} - \mathrm{TEMP}_{\mathrm{penalty}} + \mathrm{WDSP}_{\mathrm{bonus}} + \mathrm{RH}_{\mathrm{bonus}} + \mathrm{time}_{\mathrm{bonus}} \#(7)$$

Where base_score is derived from ozone concentration, representing the pollution performance layer; health_risk_penalty adjusts for public health impact based on the exposure – response coefficient (0.43 × K); TEMP_penalty, WDSP_bonus, and RH_bonus are meteorological adjustment factors for temperature, wind speed, and relative humidity, respectively; time_bonus accounts for temporal effects such as weekends and public holidays.

The rule-based system follows a "pollution-centered, health-weighted, environment-adjusted" design principle, applying both additive and subtractive mechanisms to reflect comprehensive ozone pollution conditions.

3.2.2 Machine learning-based regression optimization

To enhance the model's capacity for capturing complex, nonlinear relationships and improving generalization performance, a supervised machine learning regression stage is introduced.

In this stage, the rule-based credit score is treated as the target variable, and all relevant features—including ozone metrics, health risk indicators, meteorological factors, and temporal variables—serve as predictors. This forms a high-dimensional input space for regression modeling.

Three ensemble learning algorithms are selected as base models: Random Forest (RF), Extreme Gradient Boosting (XGBoost), and Light Gradient Boosting Machine (LightGBM). Each model is trained independently to learn the nonlinear mapping between inputs and the rule-based score.

To further improve prediction accuracy and model stability, a stacking ensemble strategy is applied. Stacking is a hierarchical ensemble method that leverages the complementary strengths of individual models. Specifically, the process involves:

First layer: Train base models $\{f_{RF}, f_{XGB}, f_{LGB}\}$ using K-fold cross-validation to generate out-of-fold predictions $\{\hat{y}_{RF}, \hat{y}_{XGB}, \hat{y}_{LGB}\}$.

Second layer: Use these predictions, along with original features, as inputs to a meta-learner—a linear regression model that assigns optimal weights:

$$\hat{y} = w_1 \hat{y}_{RF} + w_2 \hat{y}_{XGB} + w_3 \hat{y}_{LGB} + \sum_{i=1}^{d} w'_i x_i \#(8)$$

where $\{w_1, w_2, w_3\}$ are weights for base model outputs, and $\{w'_i\}$ is the weight vector for original input features.

To ensure generalization and computational efficiency, feature selection is conducted to eliminate redundant or weakly correlated variables. Additionally, five-fold cross-validation is used to evaluate performance across subsets, ensuring that the final ensemble model is both robust and interpretable.

3.3 Model testing and result analysis

3.3.1 Data sources

This study utilizes daily data from March 2023 to March 2024, including ozone concentration ($M8H\_O_3$, $\mu g/m^3$), meteorological variables (temperature, wind speed, dew point; all at daily resolution), and date attributes (weekend/holiday labels) to construct training and testing datasets.

The 2023 dataset (110,115 records) is used for model training and parameter tuning, while the 2024 dataset (22,840 records) serves as an independent test set to evaluate the model's generalization performance on unseen data.

Ozone data: Tracking Air Pollution in China (TAP) dataset.

Meteorological data: 395 national weather stations in China.

Date attributes: Generated using the chinese_calendar Python package.

3.3.2 Evaluation metrics and testing design

To assess the performance and robustness of the ozone credit scoring model, a 5-fold cross-validation strategy was employed during training.Quantitative evaluation metrics include: Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Coefficient of Determination (R^2). These metrics help quantify the model's accuracy and ensure fair comparison between training and testing phases.

3.3.3 Result analysis

A regression model was constructed using the rule-based credit score (rule_score) as the target variable. Three ensemble learning algorithms(Random Forest, XGBoost, and LightGBM)were adopted as base models. Their outputs were combined using a stacking ensemble strategy to enhance the model's capacity to capture complex nonlinear relationships.

Table 2 Cross-validation results of regression models

Model	RMSE	MAE	R^2
Random Forest	0.07	0.0	0.999
XGBoost	0.67	0.05	0.931
LightGBM	0.67	0.05	0.93
Stacking Ensemble	0.07	0.01	0.999

As shown in the results, all three base models achieved satisfactory performance on the training set, with Random Forest slightly outperforming the others.

The stacking ensemble model achieved an MAE of 0.01, RMSE of 0.07, and an R^2 of 0.999, indicating strong ability to approximate the rule-based score and effectively capture the nonlinear mapping between pollution features and credit score.

Further feature importance analysis revealed that the maximum 8-hour ozone concentration ($M8H\_O_3$) was the most influential factor, followed by temperature (TEMP) and relative humidity (RH). Other features showed relatively low importance, suggesting that meteorological and temporal adjustments have seasonal relevance, playing a more prominent role during specific periods such as high-temperature summer days.

4 Conclusion

This study addresses the increasingly severe issue of ground-level ozone pollution in China by constructing a city-level ozone credit scoring model based on nationwide daily monitoring data. By integrating meteorological factors, temporal adjustment mechanisms, and health risk indicators, the model transforms highly specialized environmental monitoring data into interpretable, integratable, and quantifiable information products. It aims to support the deep application of environmental information resources and provide theoretical and technical foundations for advancing green governance mechanisms.

In model development, a rule-based scoring module was first designed, grounded in environmental science principles and regulatory standards. It incorporates graded ozone concentration thresholds, meteorology-based reward-penalty mechanisms, and holiday-based temporal adjustments, offering strong interpretability and spatial transferability. On top of this, a Stacking Regressor model was introduced to capture complex nonlinear interactions among features, serving as a correction layer that enhances prediction accuracy and generalization by learning from historical data. The resulting two-layered system—combining structural transparency and intelligent refinement—enables quantitative assessment of ozone pollution intensity and health risk levels across regions and time periods.

Model testing using daily ozone data from Tianjin during spring and summer 2023 demonstrated robust adaptability and outlier detection capabilities. Case analyses revealed that the machine learning module successfully identified implicit influence patterns—such as pollution accumulation under high temperature and humidity, low wind speed, or holiday conditions—that deviated from traditional logic rules. This supports more precise risk evaluation and response strategies.

Despite promising outcomes, the model has certain limitations in practical deployment. First, spatial coverage remains uneven; the current model is station-centric and may not reflect micro-scale pollution variations in rural or mountainous areas, calling for integration of satellite data and micro-sensors. Second, the health risk layer lacks localized customization, with limited modeling of differential exposure responses among population subgroups (e. g., by age, region, or vulnerability); incorporating healthcare burden data is a priority for future improvements. Third, the model's dynamic adaptability could be enhanced to better respond to extreme weather events or rapid shifts in industrial structure, requiring online learning and real-time calibration mechanisms.

Looking ahead, as China advances its 14th Five-Year Plan goals for refined and intelligent environmental governance and pursues dual carbon targets, environmental information products are poised for broad development. The proposed ozone credit scoring model represents a meaningful step toward applying environmental big data in public governance. It holds potential to evolve from a scientific prototype into a public service platform, and from a single-point indicator into a comprehensive environmental credit system—supporting coordinated green policy, environmental finance innovation, and ecological civilization capacity-building across sectors.

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