Dear editor and the anonymous reviewers,

Thanks a lot for your work and time on our manuscript.

The paper entitled ***"Tracking County-level Cooking Emissions and Their Drivers in China from 1990 to 2021 by Ensemble Machine Learning"*** (**Manuscript ID: essd-2025-104**) by Zeqi Li, et al., has been revised carefully according to the correction requests and review reports.

The authors have addressed all the reviews' comments point-by-point as below. All the corrections and responses have been incorporated into the revised manuscript and supplement (marked with **BLUE COLORED FONTS**).

If further responses and corrections should be made, please don't hesitate to let us know.

Sincerely,

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Reply on RC2:

Dear reviewer,

Thank you very much for your recognition and the valuable suggestions! We have addressed the comments point-by-point as below.

All the corrections have been incorporated into the revised manuscript (manuscript_R1) and the revised supplement (supplement_R1). The point-to-point responses are listed as follows. If further responses and corrections should be made, please don't hesitate to let us know.

Comment 1:

In the Introduction, it is recommended to more systematically review existing domestic and international methodologies for constructing cooking emission inventories, along with their limitations. The study's innovations in spatiotemporal resolution, pollutant coverage, and emission estimation accuracy should be quantitatively emphasized. In addition, the discussion of health risks associated with cooking emissions would benefit from stronger empirical evidence. The roles of ensemble machine learning and SHAP in addressing key scientific challenges should also be clarified, thereby strengthening the logical connection between methodological choices and research objectives.

Response 1:

We sincerely appreciate the valuable suggestions from the reviewers, which have significantly improved our Introduction section. We have made the following additions:

(1) We have systematically revised and supplemented the review of domestic and international methodologies for constructing cooking emission inventories and their limitations (lines 67-99):

Internationally, some efforts have been made to develop cooking emission inventories. High-resolution emission datasets have been established for small-scale regions, such as Greater Athens in Greece and the Red River Delta in Vietnam, through field surveys and measurements (Fameli et al., 2022; Huy et al., 2021). However, at larger scales (e.g., national or global), cooking sources are often omitted from anthropogenic emission inventories or only roughly estimated using uniform emission factors and simplistic statistics like food supply or meat consumption (Huang et al., 2023; Saha et al., 2024). These methods and data are difficult to apply to China because, as mentioned above, cooking inventories in China require localized emission factors and estimation methods that explicitly consider regional differences.

Domestic inventories also exhibit the characteristic of being "precise at small scales but coarse at large scales," making it difficult to balance accuracy and breadth (Cheng et al., 2022; Jin et al., 2021; Liang et al., 2022; Wang et al., 2018a). These limitations are mainly due to the difficulty in obtaining high-quality data, particularly activity level data, over large spatiotemporal scales and at fine spatial resolutions. Some studies have collected key data for emission calculations by cuisine-specific emission factor testing, door-to-door surveys of restaurants and online fume monitoring systems, and thereby established high-resolution inventories of single years in cities or districts such as Beijing, Shanghai, and Shunde (Lin et al., 2022b; Wang et al., 2018b, 2018a; Yuan et al., 2023). These studies have provided valuable localized basic data

for China's cooking emission inventories. However, obtaining accurate cooking activity data (e.g., restaurant numbers) remains challenging at larger temporal and spatial scales. Traditional China's national cooking emission inventories either use simplistic statistical data (such as population and catering consumption expenditure) as proxies for activity levels, or linearly extrapolate the activity levels of one city to other areas based on these simple statistics (Cheng et al., 2022; Jin et al., 2021; Liang et al., 2022; Wang et al., 2018a). These simplifications and linear assumptions result in high uncertainties and low spatial resolution. Recent studies have more accurately estimated national cooking emissions based on data from digital maps or catering service platforms (Li et al., 2023; Zhang et al., 2024b). However, these inventories are limited to recent years, as they rely on newly developed data platforms.

Apart from lacking accuracy and breadth, another limitation of existing cooking emission inventories is their limited pollutant coverage. Previous studies on cooking emissions primarily focused on $PM_{2.5}$ (whose organic component is primary organic aerosol, POA) and volatile organic compounds (VOCs) (Jin et al., 2021; Wang et al., 2018a, 2018b). However, recent advancements in the framework for organic compounds in the full volatility range (including VOCs, intermediate-volatility organic compounds (IVOCs), semi-volatile organic compounds (SVOCs), and organic compounds with even lower volatility (xLVOCs)) have revealed the previously overlooked significant contributions of I/SVOCs to secondary organic aerosols (SOAs) (Chang et al., 2022; Zhang et al., 2021). Although our latest study has supplemented the inventory with organics in the full volatility range (Li et al., 2023), the emissions for certain highly toxic pollutants of particular concern emitted from cooking- notably ultrafine particles (UFPs) and polycyclic aromatic hydrocarbons (PAHs) - remain lacking (Chen and Zhao, 2024; Jørgensen et al., 2013; Lachowicz et al., 2023; Lin et al., 2022a). This gap limits our comprehensive assessment of the environmental and health risks associated with cooking emissions.

We have also added a summary of the limitations of existing inventories (lines 115-118):

In summary, limited by the difficulty in obtaining high-quality activity data, there is currently a lack of an accurate, long-term, high-resolution national cooking emission, and existing inventories remain deficient in their coverage of important toxic pollutants such as PAHs and UFPs. This hinders studies on $PM_{2.5}$ modeling, source apportionment, and health risk analysis.

(2) We have quantitatively emphasized the innovations of this study in spatiotemporal resolution, pollutant coverage, and emission estimation accuracy (lines 130-138).:

We expect to achieve breakthroughs in spatiotemporal resolution, pollutant coverage, and emission estimation accuracy. This study represents the first long-term (nearly 31 years) high-resolution (county-level) inventory, whereas existing national inventories were mostly limited to single years or recent years at provincial resolution. Besides, our study covers key pollutant categories from cooking emissions, including organics in the full volatility range, PAHs, and UFPs that were not included in other national inventories. In terms of estimation accuracy, we adopted cuisine-specific emission factors, considered dynamically changing purification facility installation proportions (PFIPs) driven by provincial policies, and used precise county-level activity data to calculate emissions more accurately and better reflect regional differences. Finally, this study will provide important data and new perspectives for researching the impacts of cooking emissions on air pollution and human health, facilitating the development of targeted emission control policies.

(3) Regarding the health risks associated with cooking emissions, as recommended, we have supplemented stronger empirical evidence, including specific hazardous components, disease association evidence, toxicity experimental results, and exposure risk assessment studies. Specifically, we have added the following content to the main text (lines 49-55).

Moreover, cooking emissions contain multiple hazardous components, such as ultrafine particles (UFPs) and polycyclic aromatic hydrocarbons (PAHs), which are linked to health problems including cardiovascular disease, oxidative stress, and lung cancer (Kim et al., 2024; Lin et al., 2022b; Naseri et al., 2024; Xu et al., 2020). Experiments have proved that both gaseous organics and $PM_{2.5}$ emitted from cooking exhibit much more negative biological effects like cytotoxicity compared to ambient $PM_{2.5}$ (Guo et al., 2023). Consequently, cooking emissions can increase $PM_{2.5}$ concentrations and toxicity, thereby exacerbating air pollution and associated disease burdens (Chafe et al., 2014; Wang et al., 2017; Zhang et al., 2024a).

(4) Regarding ensemble machine learning and SHAP, we have supplemented their roles in addressing key scientific challenges as recommended. First, we introduce the roles of ensemble machine learning and SHAP in addressing key scientific challenges in atmospheric science. The updated content appears in lines 100-110 of the main text:

In recent years, machine learning has been widely applied in atmospheric pollution research due to its powerful capability to process large-scale spatiotemporal datasets and capture complex nonlinear relationships within them (Liu et al., 2023; Prodhan et al., 2022a; Zhang and Zhao, 2024; Zheng et al., 2021). Models such as Random Forest (RF), eXtreme Gradient Boosting (XGBoost), and Deep Neural Networks (DNN) have demonstrated strong performance in predicting pollutant concentration time series and identifying spatial distributions (Chen et al., 2024; Prodhan et al., 2022b; Ren et al., 2022; Wu et al., 2024; Xu et al., 2023). Ensemble machine learning models further achieve better and more stable results by combining predictions from individual base models (Liu et al., 2023; Ren et al., 2022). They can help supplement sparse datasets, serving as an effective alternative for obtaining key data that would otherwise be computationally expensive or inaccessible to collect (Ren et al., 2022; Shi et al., 2024; Xiao et al., 2018). When integrating machine learning with SHapley Additive exPlanations (SHAP) additivity algorithm, the key factors for the predictive target and their influence patterns can be identified (Hou et al., 2022; Yang et al., 2023)**.**

Meanwhile, we also explain how these models help us overcome key challenges in our study. The additional content appears in lines 110-114 of the main text:

Most importantly, these approaches hold significant potential to address key challenges in cooking emission inventory development. Where conventional activity data at large spatiotemporal scales are unavailable, ensemble machine learning models can predict long-term, high-resolution activity levels by capturing complex relationships between cooking activities and fundamental socioeconomic indicators. Coupled with SHAP analysis, they can provide insights into how socioeconomic factors influence emission trends. However, such efforts have not yet been made.

Comment 2:

In Section 2.1, the high-resolution cooking activity data used for model training only cover the period from 2015 to 2021. It remains unclear whether these data are sufficient to support reliable backcasting of activity levels for earlier periods such as the 1990s and early 2000s. The authors are advised to explicitly discuss the potential temporal bias introduced by this limited training window and to clarify whether any sensitivity analysis or validation was conducted to assess its impact on historical emission estimates and associated uncertainties.

Response 2:

Thank you for your comment. We acknowledge that the limited training window may introduce potential temporal bias to the historical emission estimates. However, since earlier-period data are unavailable, we have employed models with the best possible extrapolation capabilities for estimation, which have demonstrated significant improvements over traditional methods. Following your suggestion, we have supplemented the manuscript with: (1) explicit acknowledgment of potential bias, (2) sensitivity analysis validating the model's extrapolation capability through stratified testing across counties at different development stages, (3) cross-validation using trends from other relevant statistical data, and (4) discussion of how this bias affects uncertainties in historical emission estimates. We believe these additions enhance the scientific rigor of our study. The specific revisions are as follows:

In the methods section (2.1), we added a note (lines 206-208) about potential bias introduced by modeling with 2015–2021 data, emphasizing subsequent validation and uncertainty evaluation:

Notably, the modeling data only covers the period from 2015 to 2021, as earlier data are unavailable. This may introduce some bias when backcasting activity levels for earlier periods. We further validate the backcasted activity levels and evaluate their uncertainties.

In the model evaluation section (3.1), we added a discussion (lines 354-367) on temporal bias from the limited training window, including sensitivity analysis and validation:

While the model demonstrates good performance for near-term extrapolation, greater uncertainty may exist when backcasting to earlier periods, which include more underdeveloped counties. To evaluate this, we conduct sensitivity analyses by training on the top 70% GDP-ranked counties and testing on the bottom 30%. For commercial catering (the most complex case, as shown in Fig. S4), the ensemble models test-set R^2 remained robust (R^2=0.719), outperforming the best statistical models (R^2=0.523). For real-world backcasting of historical data, the 2015 – 2021 training data already include some less-developed regions that can represent early-stage conditions, mitigating extreme extrapolation risks. Additionally, we further validate the historical trends of predicted activity data based on the limited available historical data (Fig. S5). From 1990 to 2021, the growth rate of commercial cooking activity levels was intermediate between population growth and tertiary GDP. The temporal evolution resembles that of the chain restaurant number (slow early growth followed by acceleration), though the chain restaurant number is more stable as they exclude small independent restaurants. We also incorporate chain restaurant revenue data (available since 2004), which corroborates the fluctuations in our predictions including the post-2015 rapid growth driven by food delivery platforms and the 2020 pandemic-driven decline (Maimaiti et al., 2018; Zhao et al., 2021). Therefore, while temporal extrapolation may introduce biases (uncertainties are quantified in Section 3.3), our multi-pronged validation demonstrates the reasonableness and optimality of our backcasted estimates.

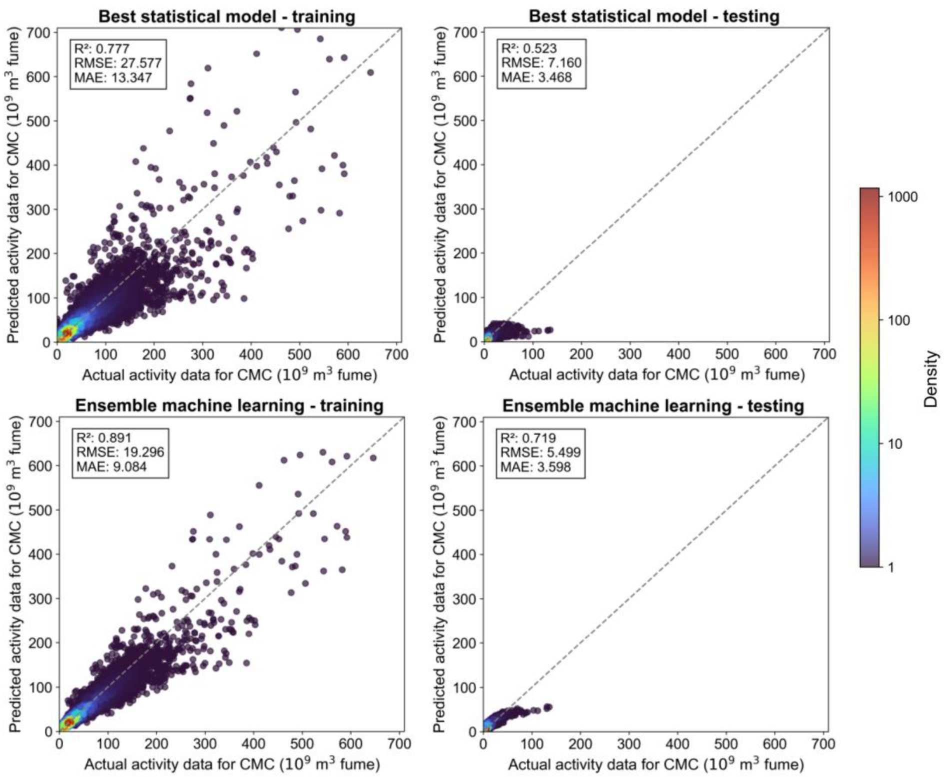

Figure S4. Sensitivity test of the best statistical model (power function regression) and ensemble machine learning model in extrapolating activity levels for counties with different GDP levels.

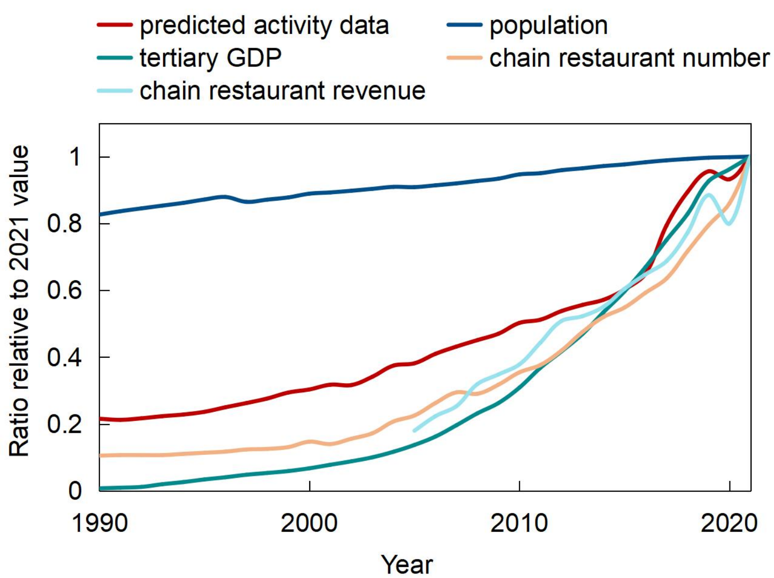

Figure S5. Comparison of the historical trends of predicted national commercial cooking activity levels with other relevant statistical data. For comparability, all data are normalized to the ratio relative to their 2021 values.

In the emission results (Section 3.3), we have considered the impact of backcasting biases on historical emission estimates and re-estimated the uncertainty ranges of emissions. The revised results have been updated in the main text, and the uncertainty estimation methods have been detailed in the supplement. In the lines 420-422 in the main text, we revised:

The uncertainty ranges are determined through Monte Carlo simulations referencing previous studies (Chang et al., 2022;

Nan Li, 2017), incorporating cumulative biases introduced by extrapolating historical emissions using limited training data (see Text S3 for details).

The revised uncertainty ranges have been updated in Figure 4:

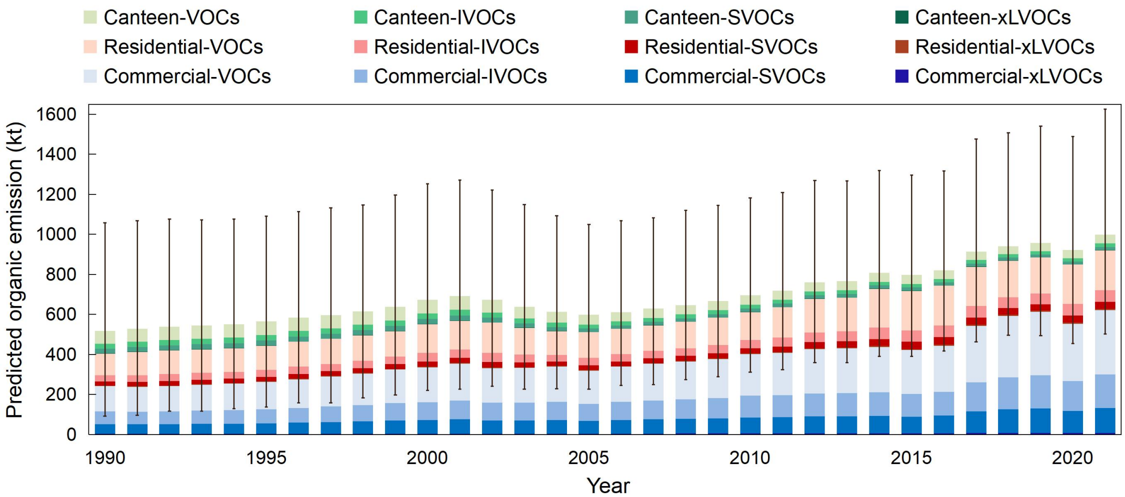

Figure 4: Organic emissions in the four volatility ranges from the three cooking sectors from 1990 to 2021 in China.

In the supplement, we added:

Text S3. Uncertainty analysis for historical emission estimates

We use Monte Carlo simulations to estimate emission uncertainties by considering probabilistic distributions of key parameters (emission factors, activity data, installation proportions of fume purification facilities and purification efficiencies). Our approach for quantifying probabilistic distributions and coefficients of variation (CVs) for parameters aligns with our prior work (Li et al., 2023). Notably, we considered biases introduced by extrapolating historical emissions using data from a limited temporal window. As shown in Figure 2b, when estimating 2015-2016 and 2020-2021 using 2017 – 2019 data, deviations were observed (difference between black and red lines). The largest deviation occurred for 2015 commercial cooking results (1.49% overestimation). We conservatively estimated a 2% error for extrapolation over one year and assumed the error compounds annually. For example, backcasting from 2017 to 1990 introduces a cumulative error of 1.02^{27} = 70.7%. This extrapolation-derived uncertainty in activity levels was incorporated into the baseline CVs. For example, the CV for activity data in 1990 increased by a factor of 1.707. Using these adjusted CVs for activity data and other parameters'CV, we perform 10,000 Monte Carlo simulations to derive uncertainty ranges at 95% confidence level.

We hope these comprehensive additions satisfactorily address your concerns about bias introduced by this limited training window.

Comment 3:

In Section 2.1, between 1990 and 2020, numerous counties in China underwent administrative changes, including mergers, splits, and renaming. The authors should provide a detailed explanation of how historical data were spatially mapped to the standardized 2020 county boundary system. Furthermore, they should address whether this harmonization process might introduce artificial discontinuities or aggregation errors, and whether any validation was performed to assess the accuracy and consistency of the spatial mapping.

Response 3:

We sincerely appreciate the reviewer's valuable feedback regarding the spatial harmonization of historical county-level data. We apologize for not providing sufficient details about our data processing methodology for administrative changes in the original manuscript.

In fact, we carefully addressed this issue by manually processing annual administrative boundary changes rigorously following official government reports. We have added detailed explanations of this processing procedure in the revised manuscript and supplement. As suggested, we have also clarified the potential local discontinuities or aggregation errors that may arise from this harmonization process and described the validation steps we performed.

The revised main text (lines 177-181) now states:

Given the changes in China's county administrative divisions over the past 31 years (Yu et al., 2018), we trace the renaming, merging, and splitting events of counties according to official government reports, mapping the data of each year to the county administrative system of 2020 (a total of 2848 counties) to ensure continuity across years. Detailed descriptions of the spatial mapping and data processing procedures are provided in Text S1.

The detailed explanations have been added to the supplement_R1:

Text S1. Data processing and spatial mapping of county-level administrative changes in China (1990-2020)

Between 1990 and 2020, numerous counties in China underwent administrative changes. We address this issue by manually processing annual administrative boundary changes rigorously following the official government.

Each county in the statistical dataset and government reports is assigned a unique identifier (CID), which will be updated whenever an administrative change occurs. By linking the annual statistical data to these CIDs, we are able to establish a consistent mapping across years. The administrative changes from 1990 onward are traced according to the official "List of Changes in County-level Administrative Divisions of the People's Republic of China" released by the government. These changes primarily involved renaming (e.g., a county being upgraded to a district or prefecture-level city, with no change in boundaries), mergers, or splits.

Most reported changes were renaming, which allowed us to establish a one-to-one correspondence of IDs for accurate data handling. For mergers, we applied a many-to-one relationship based on the IDs reported in government documents, summing or calculating weighted averages based on the population or GDP of the year of the mergers. For splits, data were allocated based on population or GDP weights in the year of the splits, while non-additive variables retained their original values. We processed administrative changes annually from 2021 back to 1990, ensuring that all changes were ultimately mapped to the 2020 county administrative system.

We acknowledge that mergers and splits may introduce local artificial discontinuities or aggregation errors, particularly in cases where counties with significantly different socioeconomic characteristics were involved. However, given that, on average, fewer than 10 counties underwent mergers or splits annually between 1990 and 2020, the impact of these changes is likely minimal relative to the total of over 2,800 counties nationwide.

Finally, all administrative changes were manually validated based on government reports to ensure the accuracy and consistency of the spatial mapping. Additionally, we aggregated the processed county-level data to the city and provincial level and cross-checked them with officially reported higher-level statistics to further verify the accuracy and consistency of our data.

Comment 4:

In Section 2.2, while the ensemble model integrates Random Forest, XGBoost, MLP, and DNN, the final fusion is implemented via ridge regression. This linear and relatively simple approach may not fully capture the complementary strengths of the base models. The authors are encouraged to consider alternative fusion strategies, such as weighted averaging, stacking ensembles, or dynamic weight allocation based on validation performance, and to provide comparative results to justify the choice of ridge regression.

Response 4:

We sincerely appreciate your insightful suggestion regarding the ensemble fusion strategies. In response, we have conducted additional comparative experiments evaluating multiple fusion approaches, including weighted averaging, dynamic weight allocation, and stacking ensembles. Notably, the ridge regression we adopted is a type of stacking ensemble with ridge regression as the meta-model. To further compare with stacking ensembles with other meta-models, we also considered stacking ensembles using elastic net, decision tree, and gradient boosting as meta-models. The details of the experiments and their results have been added in Text S2 and Table S6 in the supplement_R1. Finally, Ridge regression demonstrated a good balance between performance and efficiency, making it a worthy choice.

Specifically, we have added the explanation of the reasons for choosing ridge regression as the integration method in the main text (lines 249-253):

To combine the advantages of these four models, we use ridge regression as the integrator to build an ensemble machine learnling model (McDonald, 2009). Ridge regression is chosen for its ability to balance model complexity and generalization through regularization, which helps prevent overfitting (Ebrahimi et al., 2024; McDonald, 2009). Furthermore, as validated in Text S2 and Table S6, ridge regression demonstrates a favorable balance between performance and computational efficiency when compared to other fusion strategies.

We also added the details of comparative experiments and results of multiple fusion strategies in the supplemnt_R1, including the weighted averaging, stacking ensembles, and dynamic weight allocation based on the validation performance that you suggested:

Text S2. Performance comparison of different ensemble fusion strategies

There are various fusion strategies to integrate individual machine learning models. Among them, weighted averaging combines base model predictions using certain weights (Neloy et al., 2022). To obtain reasonable weights, dynamic weight allocation can be made based on validation performance (Li et al., 2015; Yan et al., 2022). Another powerful approach is the stacking ensemble, which trains a meta-model to optimally combine predictions from individual machine learning models (Huang et al., 2024; V and P, 2025). The meta-model itself can employ various algorithms, including ridge

regression, elastic net, decision trees, or gradient boosting (Bakasa and Viriri, 2023; Carneiro et al., 2022; Rahman et al., 2024; Rauschenberger et al., 2021).

We trained several ensemble methods using our training set and evaluated them by the test dataset, with results summarized in Table S6. Since the predicted performance for residential and institutional cooking was already excellent, we focused our evaluation on the most complex commercial cooking sector. Both weighted averaging and dynamic weight allocation demonstrated relatively poor performance, particularly on the test set. In comparison, stacking ensembles generally performed better. The decision tree meta-model achieved the best performance on the training set but showed degraded results on the test set, likely indicating overfitting. The ridge regression meta-model performed well on both training and test sets. When using gradient boosting as the meta-model, we observed a slight improvement in test results (R^2 increased by ~0.4%), but at the cost of increased model complexity and computation time. Considering all factors - including prediction accuracy, computational efficiency, and implementation stability - ridge regression emerged as the most suitable choice for our application.

Table S6. Comparison of different ensemble fusion strategies on training sets and testing sets for commercial cooking

Model	training data set			testing data set		
	R^2	RMSE (10^9 m^3)	MAE (10^9 m^3)	R^2	RMSE (kt)	MAE (kt)
weighted averaging	0.938	13.288	6.956	0.872	17.292	8.802
dynamic weight allocation based on validation performance	0.942	12.918	6.773	0.873	17.229	8.741
stacking ensemble based on elastic net	0.979	7.749	4.387	0.877	16.938	8.135
stacking ensemble based on ridge regression	0.985	7.852	3.915	0.892	15.834	7.968
stacking ensemble based on decision trees	0.988	6.583	3.194	0.886	16.962	9.176
stacking ensemble based on gradient boosting	0.985	7.382	3.344	0.896	15.618	7.847

Comment 5:

In Section 2.3, the test set includes data from 2015-2016 and 2020-2021, which are temporally adjacent to the training period. This design may not adequately evaluate the model's extrapolation performance for earlier years, such as the 1990s. The authors are advised to consider using forward validation or rolling window techniques to assess the model's robustness over longer temporal horizons. It is also recommended to discuss potential structural changes in the data over time and their implications for prediction reliability.

Response 5:

Thank you for your valuable suggestion. We acknowledge that the current evaluation using temporally adjacent test sets may not fully assess the model's extrapolation performance for earlier years, such as the 1990s. However, due to the unavailability of pre-2015 data, implementing forward validation or rolling window techniques would only slightly improve the reliability of predictions for nearby years (post-2015) and would not adequately address the evaluation for longer-term extrapolation. To discuss the model's robustness over longer temporal horizons, we have supplemented the following procedures:

(1) Limitations Statement.

We have explicitly acknowledged the limitations of our modeling and evaluation method in the manuscript:

Lines 206-208: **Notably, the modeling data only covers the period from 2015 to 2021, as earlier data are unavailable. This may introduce some bias when backcasting activity levels for earlier periods. We further validate the backcasted activity levels and evaluate their uncertainties.**

Lines 366-367: **Therefore, while temporal extrapolation may introduce biases (uncertainties are quantified in Section 3.3), our multi-pronged validation demonstrates the reasonableness and optimality of our backcasted estimates.**

(2) Verification of the extrapolation performance of the model.

We have conducted a GDP-tiered predicting test (training on high-GDP counties and testing on low-GDP counties) to simulate extrapolation from recent years to earlier periods, where most counties had lower development levels. This analysis demonstrates that our ensemble machine learning model remains robust performance for extreme extrapolation. The modifications about this test have been detailed in our response to Comment 2.

(3) Verification of the long-term trend of predictions.

We also further validated the historical trends of prediected activity data based on the avaiable historical statistics. This corroborates the reasonableness of our predictions. The modifications about this test have been also detailed in our response to Comment 2.

(4) Evaluation of time-accumulated impact of extrapolation bias effects on prediction uncertainty

We have considered the cumulative errors introduced by extrapolation over time and incorporated these into the uncertainty analysis of emission estimates. The modifications about this test have been also detailed in our response to Comment 2.

These multilayered approaches—while not perfect substitutes for true historical validation—provide systematic evidence of model robustness across temporal and socioeconomic gradients. We hope these modifications address your concerns and improve the transparency and robustness of our study.

Comment 6:

In Section 2.4, although the SHAP method provides valuable insights into feature contributions, it is fundamentally a model interpretability tool rather than a causal inference technique. Using SHAP to identify the "driving forces" behind emission trends may risk confounding, especially in the absence of controls for latent variables. The authors should acknowledge this limitation and consider supplementing the analysis with causal inference methods to strengthen the validity of the claimed relationships.

Response 6:

We sincerely appreciate your recognition of the value of SHAP analysis and your thoughtful comment regarding the imprecision of our terminology in describing SHAP's role. We fully agree that SHAP is a feature importance interpretation tool rather than a causal inference technique. In response, we have carefully revised all relevant terminology throughout the manuscript, removing any language that could imply causal relationships for SHAP (e.g., "driving forces") and replacing it with more precise descriptions such as "identifying feature importance" or "analyzing key influential factors."

Key revisions include:

(1) Abstract: Removed claims about SHAP identifying "driving forces" for emissions.

(2) Introduction: Revised the phrasing (lines 126-128) to:

Finally, we apply the one-factor-at-a-time method to analyze the key drivers of national cooking emissions, while using the SHAP algorithm to identify the key influential factors for county-level emissions.

(3) Data and Method: Updated the methodology description and the Schematics (Figure 1)

Revised the phrasing (lines 152-153) to:

Finally, we apply the one-factor-at-a-time method to analyze the key drivers of national cooking emissions, whereas the SHAP algorithm is used to evaluate the relative importance of features for county-level emissions.

Revised the title of Figure 1 (lines 156-158). Modified the figure by replacing "driver analysis" with "key factor analysis" and explicitly labeling SHAP's output as "feature importance" (previously "emission drivers"). The updated figure is as follows:

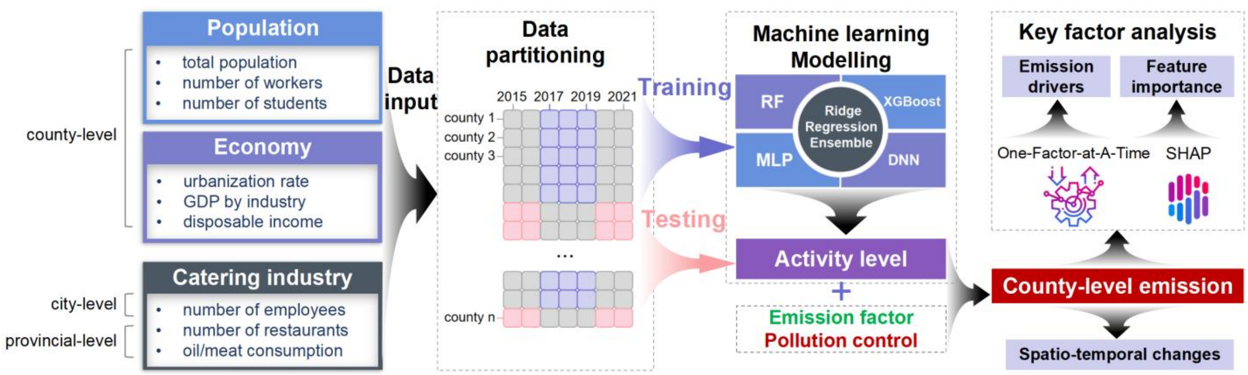

Figure 1: Schematics of the model developed in this study including model development, emission calculation, and key factor analysis.

Revised the title of Section 2.4 (line 275) from "Driver analysis of cooking emissions at national and county scales" to **"National driver analysis and county-level feature importance analysis of cooking emissions."**

Clarified the text (lines 297-299) to reflect SHAP's role:

The dominant factors associated with emission changes for counties at different development stages are also worth elucidating, which are crucial for understanding the current and future trends in cooking emissions, and for the targeted development of control strategies.

(4) Discussion: Revised the title of Section 4.2 (lines 557) from "Driving factors of national and county-level cooking emissions" to **"National emission drivers and key influencing factors for county-level emissions."**

Updated the text (lines 607) to describe SHAP's results:

Furthermore, we also pay attention to the key influential factors of cooing emissions of various counties at different development stages, applying the SHAP algorithm for the quantitative analysis.

We greatly appreciate your suggestion to consider using causal inference methods for more rigorous analysis. This is indeed important and worth further investigation. In fact, this aligns with our ongoing work investigating the county-level drivers of CO_2 and air pollutant emissions in China (including cooking emissions). For this follow-up study, we plan to integrate causal techniques such as counterfactual prediction and difference-in-differences analysis to rigorously evaluate policy and socioeconomic impacts on emission trends.

To strengthen our discussion, we have added explicit discussion in the "6 Conclusions and implication" Section (lines 697-701) of SHAP's limitations regarding identifying emission drivers and outlined potential causal analysis methods for future work:

We also acknowledge some limitations of our study. For county-level emissions, while SHAP provides interpretable insights into feature importance, it cannot infer causality to identify the underlying driving factors. Future work could employ causal inference techniques such as counterfactual prediction and difference-in-differences analysis (Dong et al., 2022; Li et al., 2024) to more accurately assess the actual impacts of policy interventions and socioeconomic factors on emission trends, thereby providing more robust evidence to support localized emission reduction policies.

Comment 7:

In Section 3.2, although figure 3 clearly illustrates the spatial expansion of high-emission areas, the underlying socioeconomic drivers such as population migration, urbanization dynamics, and regional policy changes are not explicitly addressed. The authors are encouraged to analyze these factors in more depth and clarify whether such dynamics were incorporated into the modeling framework or considered in the interpretation of the results.

Response 7:

We thank you for pointing out the potential confusion caused by the lack of discussion in Section 3.2 and for your suggestion to conduct a more in-depth analysis of emission driving factors. Notably, Section 3.2 primarily presents the results of emission distribution patterns, while Section 4.1 further discusses the trends in spatial distribution changes of emissions and explains the emission variations using socioeconomic driving factors such as population migration, urbanization dynamics, and regional policy changes. In response to your comments, we have made the following modifications:

(1) In Section 3.2, we have added the following sentence (lines 402-403) to direct readers to the subsequent detailed discussion of socioeconomic driving factors:

Besides, we further analyze the spatiotemporal trends of emission distribution and their underlying socioeconomic drivers in Section 4.1.

(2) At the beginning of Section 4.1, we add a sentence (lines 506-509) to clarify that these socioeconomic drivers were incorporated into the modeling framework and result interpretation as recommended:

Our modeling explicitly incorporates key socioeconomic and policy variables such as population, urbanization rate, and PFIP, and captures their relationships with county-level cooking emissions. Therefore, the spatiotemporal variation trends of emissions can be well explained by these underlying socioeconomic and policy drivers.

(3) In the latter part of Section 4.2, while we had initially included some analysis of socioeconomic drivers (e.g., population migration, urbanization dynamics, and regional policy changes) influencing emission variations, we have now supplemented this with more in-depth analysis following your suggestion. The updated content appears in lines 510-539 of the main text:

Before 2000, the observed changes in emissions could primarily be explained by population and economic factors, since China had few policies for cooking emission control (Zhao, 2004). From 1990 to 1995, emissions across most counties generally increased because of economic development, but emissions in a few counties decreased probably due to population migration. The most significant emission growth was concentrated in Beijing, Shanghai, and the Pearl River Delta region - areas undergoing greatly rapid economic development and urban expansion at the time (Démurger et al., 2002; Gaubatz, 2004). Conversely, emission reductions were typically observed in adjacent areas, suggesting population redistribution toward these emerging economic centers (Fan, 2005). From 1990 to 1995, the migration-driven spatial redistribution of emissions became more pronounced between 1995-2000 (Fan, 2005). For example, Guangdong's emissions became concentrated in the Pearl River Delta, while Zhejiang and Fujian's emissions clustered in the Yangtze River Delta and coastal regions. Besides, emissions from eastern Sichuan are shifting towards Chengdu (the provincial capital of Sichuan) and Chongqing. The migration was probably because these areas became focal points of economic reform during this period, attracting large population influx (Fang et al., 2009), such as Chongqing being designated a directly-controlled municipality in 1997 (Hong, 2004).

From 2000 to 2005, emissions declined in most parts of the country due to the implementation of China's first nationwide pollution control policy targeting cooking emissions in 2001 (see Section 3.3 for details) (State Environmental Protection Administration of China, 2001). However, Guangdong, Zhejiang, and Beijing maintained emission growth during this period, attributable to their exceptional economic expansion and continued population inflow (Kong, 2022; Zhu, 2012). From 2005 to 2010, cooking emissions in most counties in eastern China increased rapidly, likely because the emissions increase driven by rapid economic development outweighed the reductions from pollution control measures (Fleisher et al., 2010). In contrast, emissions in the slower-developing western regions decreased during this period (Fleisher et al., 2010).

During 2010-2021, emissions increased significantly nationwide except in provinces with stringent control policies (Beijing Environmental Protection Bureau, 2018; Feng et al., 2019; Liaoning Provincial Government, 2017; Shanxi Provincial Government, 2017). Coastal regions experienced the most notable emission increases, reflecting their faster economic growth and urbanization rates compared to inland regions (Shi, 2020). This rapid development also led to increased demand for cooking activities and a thriving catering industry due to population growth. Notably, Sichuan also exhibits significant emission increases, likely attributable to its special local cuisine that has attracted tourists nationwide and fostered a thriving catering industry (Li, 2017; Tian and Shen, 2024).

Comment 8:

In Section 3.3, the one-factor-at-a-time method assumes that variables change independently. However, in real-world socioeconomic systems, variables are often highly correlated. It is recommended that the authors assess the potential impact of multicollinearity on the sensitivity analysis results. Additionally, it may be beneficial to explore multivariable perturbation approaches or incorporate causal structural models to validate the robustness of the findings.

Response 8:

Thank you for your suggestions. Regarding multicollinearity, we have already performed multicollinearity checks in the feature selection section of the methodology and removed variables with collinearity based on the variance inflation factor (VIF). Therefore, the remaining variables are not expected to exhibit significant multicollinearity. This is described in the original text as follows (lines 189-191):

Besides, we perform multicollinearity checks using the variance inflation factor (VIF), gradually removing features with higher VIF values until all remaining features were mutually independent (all VIF values of independent variables were below 10) (Daoud, 2017; Hu et al., 2017).

However, we understand your concern about potential correlations among variables. When variables are correlated or interact with each other, the one-factor-at-a-time method may introduce biases. To assess the potential impact of interaction effects among variables, we conducted a multivariable perturbation analysis. For example, we selected two variables (population and tertiary GDP) that are highly correlated and have significant impacts on emission changes, and used the period from 2010 to 2015 as a test window. When perturbing these variables individually and jointly, we observed that their combined effect on emissions (+80.0 kt) slightly exceeded the sum of their isolated effects (+78.2 kt). This suggests weak interactions between variables and implies that the order of factor adjustments may influence the results of driving force decomposition.

To improve robustness, we refined the original one-factor-at-a-time method by incorporating averaged results from multiple variable adjustment sequences to reduce order-dependent bias. In the original method, variables were adjusted sequentially following a single fixed order. The detailed description of our improved methodology has been incorporated into the manuscript (lines 287-296):

Notably, due to interaction effects among variables, different adjustment sequences may yield distinct driver decomposition results. To enhance the robustness, we mitigate sequence-dependent bias by incorporating the averaged results from multiple adjustment sequences. Specifically, we first identify the top five variables with the largest individual impacts on emission changes in each period. We then consider all possible permutations (120 in total) of these five variables and apply the adjustments accordingly. For variables ranked sixth and below, adjustments are made in descending order of their individual impacts, without considering further permutations, as these variables contribute minimally to emission changes (<2% annually), and exhaustive permutations would be computationally prohibitive. Finally, we calculate the average contribution of each factor across all considered sequences. While this improved approach cannot completely decouple the independent contributions of all variables, it significantly reduces order-dependent biases and enhances the reliability of the driver decomposition.

Based on the refined methodology, we recalculated the driver decomposition results and updated Figure 7 and related data (lines 569-571) in the main text. The results demonstrate only marginal changes that do not affect our main conclusions:

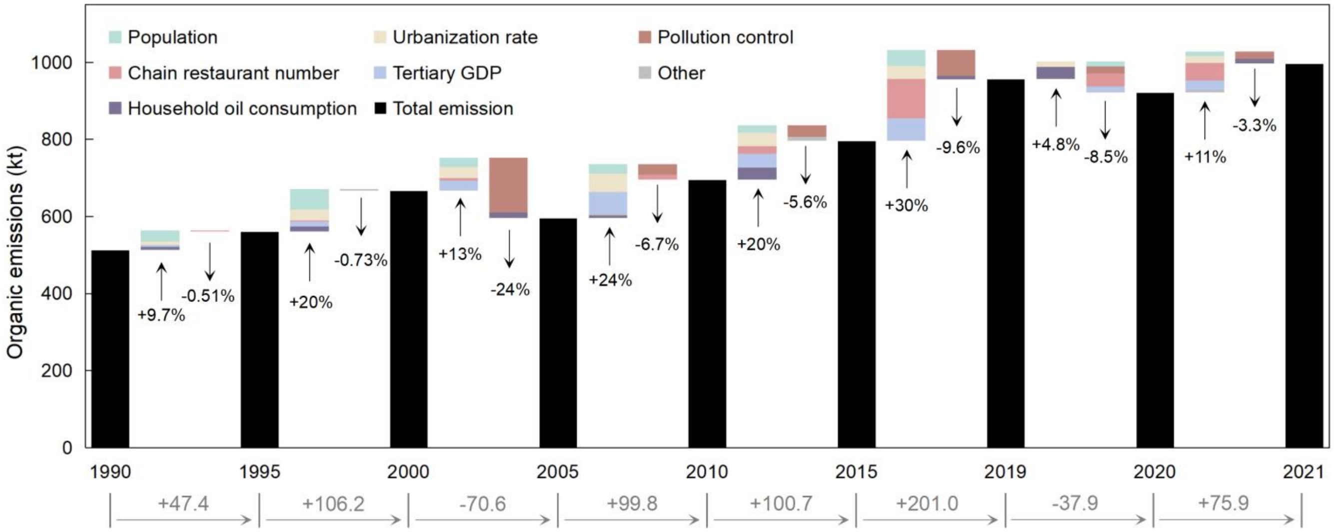

Figure 7: The contribution of various driving factors to the changes in national cooking organic emissions across different periods.

Additionally, we employed counterfactual analysis to assess the actual contribution of policy implementation to emission reductions, as detailed in our response to Comment 9. This causal inference analysis provides more reliable evidence for evaluating the impacts of pollution control policies, and its results are mutually corroborated with those obtained from the one-factor-at-a-time method.

Comment 9:

In Section 4.2, the authors highlight that the dominant drivers of cooking emission growth vary significantly across different time periods, including factors such as population growth, urbanization, industrial restructuring, and the rapid expansion of the catering industry. However, the analysis lacks a quantitative evaluation of the emission reduction effects of policy interventions implemented during these periods. The current discussion on policy impacts remains largely qualitative. It is recommended that the authors incorporate systematic quantitative approaches, such as the development of policy stringency indicators or counterfactual analyses, to comprehensively assess the actual contribution of policy implementation to emission reductions over time.

Response 9:

Thank you for your valuable suggestion to enhance the quantitative evaluation of the emission reduction effects of policy intervention.

In fact, our methodology inherently incorporates the use of policy stringency indicators to estimate the purification facility installation proportion (PFIP), enabling a quantitative assessment of policy impacts. The detailed method was explained in our previous work (Li et al., 2023). Following your suggestion, we have also supplemented a detailed description of this method in the manuscript_R1 to make our methodology more complete, and reliable. The supplementary description (lines 224-228) is as follows:

As for PFIPs, we have established a grading standard for provincial catering emission control stringency and corresponding PFIPs based on field surveys (Li et al., 2023b). By collecting provincial-level catering pollution control policies and considering their implementation timelines and transition periods, we can obtain dynamically changing PFIPs driven by provincial-level control policies. In this study, we also applied this method to estimate PFIPs for 1990-2021 (See Table S4-5 for the PFIPs results over the years).

Additionally, as suggested, we supplemented counterfactual analyses to quantitatively assess emission reduction effects. We focused on two core policies: the 2001 "Emission Standards of Catering Oil Fume" (policy-2001), representing the Chinese government's first major regulatory focus on cooking emission control; and the 2013 "Action Plan for the Prevention and Control of Air Pollutants" (policy-2013), which prompted provinces to implement comprehensive air pollution controls, including for cooking emissions. The added content (lines 593-606) is as follows:

Additionally, we employ counterfactual analysis to quantitatively assess the emission reduction effects of control policy interventions. Specifically, we examine the two core policies introduced in Section 3.3: Policy-2001 and Policy-2013 (CPGPRC, 2013; State Environmental Protection Administration of China, 2001). While we collect provincial policies to determine province-specific PFIPs, these provincial regulations were largely driven by these two national policies, with variations in provincial response timing and enforcement stringency. Therefore, we sequentially exclude these two policies in our model, simulating counterfactual scenarios where provinces did not further strengthen pollution control measures after the policies were not implemented. The results are shown in Fig. S10. Without Policy-2013, 2021 emissions would have been 13.1% higher. Without both policies, the increase would reach 49.4%, highlighting the significant long-term impact of Policy-2001 in curbing emissions. The more modest effect of Policy-2013 may stem from its focus on comprehensive air pollution control, with catering sources being only a minor component. Moreover, the 2013 policy and subsequent provincial policies primarily emphasized increasing the installation rates of catering fume purification devices without stringent requirements for ensuring the removal efficiency of installed equipment (CPGPRC, 2013). Due to equipment aging and inadequate supervision (Li et al., 2023), the average removal efficiency remained low, resulting in no significant emission reductions despite higher installation rates.

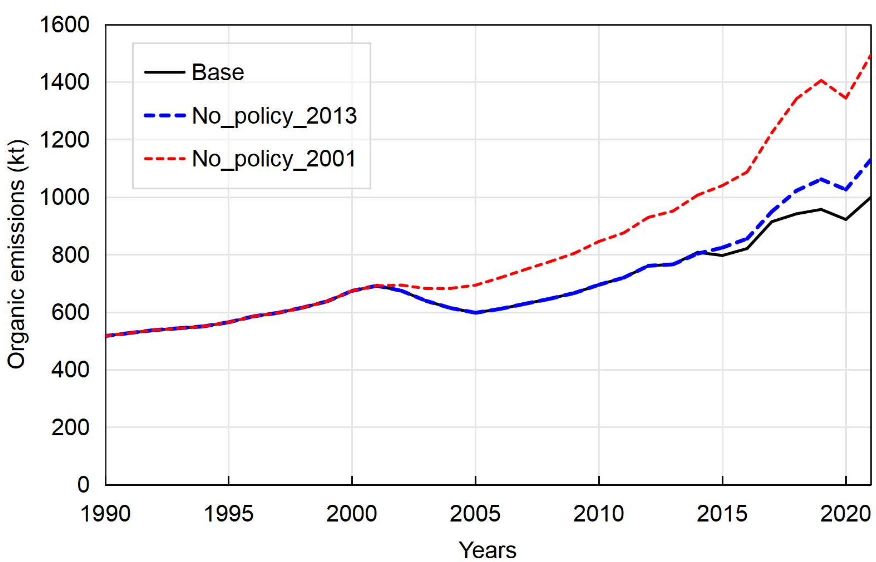

Figure S10. Cooking organic emission trends under scenarios lacking key pollution control policies

Moreover, we have also enriched Section 4.2 with additional quantitative results about driver analysis for pollution control. The added content is as follows:

Lines 561-566: **From 2001 to 2005, while population growth and urbanization also promoted an increase in emissions, the implementation of emission standards in 2001 significantly strengthened pollution control measures (State Environmental Protection Administration of China, 2001), leading to a considerable reduction (-21%) in cooking emissions. From 2005 to 2015, while pollution emission standards continued to be enforced, the lack of new regulatory policies targeting cooking sources limited further pollution control effectiveness, resulting in an average annual reduction of only about 1% (Gao, 2020).**

Lines 576-578: **Meanwhile, stricter pollution control measures led to a more pronounced reduction in emissions (achieving an 8.4% decrease from 2015 to 2019). However, this effect remained relatively limited compared to the rapid growth in total emissions (+30.0% during the same period).**

Comment 10:

In Section 6, the authors note that current pollution control measures are insufficient to curb the continued growth of cooking emissions, particularly in high-emission counties. However, the study does not provide specific, actionable technological pathways or policy instruments. Given that the research has already identified the spatial distribution and socioeconomic characteristics of these high-emission areas, it is recommended to explore differentiated mitigation strategies that take into account emission intensity, population exposure risk, and local resource capacity.

Response 10:

Thank you for your valuable suggestions regarding mitigation strategies. We have expanded the discussion in Section 6 to address your concerns. Based on the findings of our study, we have proposed some specific, actionable technological pathways and policy instruments. However, developing differentiated strategies that account for emission intensity, population exposure, and local resource capacity will require further integration based on our inventory with air quality modeling and regulatory frameworks. Therefore, we have also indicated this as a potential direction for future research efforts. The revised discussion (lines 672-687) in Section 6 regarding policy implications is as follows:

However, our results indicate that existing control measures are insufficient to curb the rapid growth of cooking emissions, necessitating the development of updated and more effective control strategies. Given that cooking is a fundamental human need, reducing emissions by restricting cooking activities or altering dietary habits is not feasible. A more viable approach is to enhance end-of-pipe treatment. However, cooking emission sources are numerous and widespread, making comprehensive control efforts highly labor-intensive. Fortunately, our high-resolution inventory reveals a strong spatial coupling between high emission intensity and population density. Specifically, 30% of counties—covering only 14.5% of the national land area—contribute over 60% of cooking-related organic emissions while housing 60% of the population. These areas face substantial population exposure risks, and prioritizing stricter controls there could effectively mitigate health impacts. Additionally, the limited effectiveness of recent pollution control policies may stem from their sole focus on the installation rate of purification facilities while neglecting actual

purification efficiency. Therefore, future efforts should establish stricter regulations or standards for purification efficiency and strengthen enforcement. Besides, residential emissions have consistently accounted for ~30% of total cooking emissions, yet targeted policies and specialized purification facilities remain scarce. Potential solutions include developing compact purifiers for household kitchens and implementing exhaust purification systems for residential chimneys. Finally, our fine-scale emission inventory can serve as a key input for the air quality modeling and control strategy optimization model, enabling further exploration of differentiated mitigation strategies that consider costs, health benefits, and local resource capacity.

Comment 11:

It is recommended to further modify the format of the manuscript and correct some grammatical errors.

Response 11:

Thank you very much for your suggestions! We have carefully revised the manuscript format to comply with the journal's guidelines and performed a diligent language check to correct grammatical errors throughout the manuscript.

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