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 RC1:

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:

Introduction: Consider briefly introducing unique characteristics of Chinese cooking and the special requirements of these characteristics for the construction of emission inventories, which will help international readers better understand the importance of the research.

Response 1:

Thank you for the insightful comments and suggestions to help enhance the international appeal of our manuscript. Based on your suggestions, we have supplemented the relevant information about Chinese cooking in the introduction (lines 59-66):

Chinese cooking emissions exhibit unique characteristics that require special consideration in emission inventory development (Zhao and Zhao, 2018). The widespread use of high-temperature oils, various seasonings, and special techniques like stir-frying generates pollutants with complex chemical compositions (Chen et al., 2018; Zhao and Zhao, 2018). Furthermore, cooking styles vary greatly across different regions in China, which have historically developed into multiple distinct cuisine systems (Li et al., 2023; Lin et al., 2022b). To accurately capture these emission patterns and quantify their impact, the emission estimate needs to incorporate cuisine-specific multi-pollutant emission factors while explicitly accounting for regional variations through spatial resolution representation (Lin et al., 2022b; Zhao and Zhao, 2018).

We believe this addition will help international readers better understand the unique characteristics and importance of Chinese cooking.

Comment 2:

Line 165-166: Clarify how "variables of lower importance" were determined (e.g., specific threshold for RF feature importance scores).

Response 2:

Thank you for your valuable suggestion. We have added the following sentence (lines 186-189) of the manuscript_R1 to clarify how we determined "variables of lower importance":

Variables were first ranked by RF model importance scores, with those scoring <5% considered for potential removal because of low importance (Alduailij et al., 2022; Ye et al., 2022). Each candidate variable was then temporarily excluded, and only those whose removal resulted in an R^2 decline of <1% were permanently discarded – ensuring no critical features were lost (Altmann et al., 2010; Zhu et al., 2023).

Comment 3:

Line 215-217: "directly calculates county-level cooking emissions" is inaccurate. The emissions of this study are still estimated through machine learning predictions, not direct estimates, so the statement needs to be revised.

Response 3:

Thank you for your insightful comment. We agree that the term “directly calculates” could be inaccurate. To better describe our methodology, we have revised the wording to "precisely estimates", which more accurately reflects the advantage of our approach - by conducting activity-level modeling and emission estimation at the county-level spatial scale from the outset, we ensure high-resolution results. The revised sentence (lines 25-27) now reads:

Unlike previous inventories that rely on simplistic proxy data such as population for calculation and downscaling, our inventory precisely calculates county-level cooking emissions, providing more accurate emission estimates and spatial distributions.

Comment 4:

Figure 3: Provide sector-specific spatial distributions (commercial/residential/canteen) for a representative year in the supplement.

Response 4:

Thank you for your suggestion. We have added a figure (Figure S6) in the supplement_R1 showing the sector-specific spatial distributions of cooking emissions for the representative year (2021):

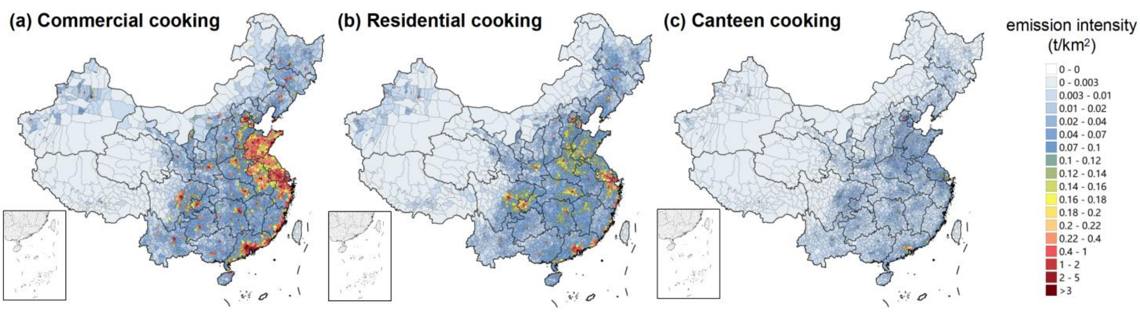

Figure. S6. Sector-specific spatial distributions of cooking emissions in 2021.

Additionally, we have added the following sentence (lines 376-377) in the main text to guide readers to this figure:

Fig. 3 provides high-resolution spatial distribution maps of cooking organic emissions in China from 1990 to 2021, while Fig. S6 provides the sector-specific spatial distributions of cooking organic emissions for a representative year (2021).

Comment 5:

Lines 332-333: Provide percentage contributions of key regions (Beijing-Tianjin-Hebei, Yangtze Delta, etc.) to national total emissions.

Response 5:

Thank you for your suggestion. We have supplemented the percentage contributions of key regions to the national total emissions in the revised manuscript (lines 384-386). The updated text now reads:

The North China Plain region, the Yangtze River Delta, the Pearl River Delta, and the Sichuan-Chongqin region became the four key emission zones, contributing 20.2%, 19.9%, 8.63%, and 7.98%, respectively, of the nation's total cooking organic emissions.

Reference:

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