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# Tracking county-level cooking emissions and their drivers in China from 1990 to 2021 with ensemble machine learning

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**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.

## 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.

**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.

**Table S1.** The initial resolution and source of predictor variables

| indicator type | statistical indicator | initial resolution | data source |
|---|---|---|---|
| population-related | population | county-level | Chinese County Statistical Yearbook |
| | number of employees in enterprises | county-level | Chinese County Statistical Yearbook |
| | number of students in middle schools | county-level | Chinese County Statistical Yearbook |
| | number of students in primary schools | county-level | Chinese County Statistical Yearbook |
| economy-related | urbanization rate | county-level | Chinese County Statistical Yearbook |
| | total GDP | county-level | Chinese County Statistical Yearbook |
| | GDP of primary industries | county-level | Chinese County Statistical Yearbook |
| | GDP of secondary industries | county-level | Chinese County Statistical Yearbook |
| | GDP of tertiary industries | county-level | Chinese County Statistical Yearbook |
| | per capita disposable income | county-level | Chinese County Statistical Yearbook |
| catering-related | number of employees in the catering and accommodation industry | city-level | China Urban Statistical Yearbook |
| | household per capita oil consumption | province-level | China Market Statistics Yearbook |
| | household per capita meat consumption | province-level | China Market Statistics Yearbook |
| | number of chain restaurants | province-level | China Market Statistics Yearbook |

**Table S2.** PAH species considered in this study and their TEFs

| Type | Name | Molecular formula | Benzene ring numbers | TEF | Reference for TEFs |
|---|---|---|---|---|---|
| priority PAHs | Naphthalene | $C_{10}H_8$ | 2 | 0.001 | (Nisbet et al., 1992) |
| | Acenaphthylene | $C_{12}H_8$ | 3 | 0.001 | (Nisbet et al., 1992) |
| | Acenaphthene | $C_{12}H_{10}$ | 3 | 0.001 | (Nisbet et al., 1992) |
| | Fluorene | $C_{13}H_{10}$ | 3 | 0.001 | (Nisbet et al., 1992) |
| | Phenanthrene | $C_{14}H_{10}$ | 3 | 0.001 | (Nisbet et al., 1992) |
| | Anthracene | $C_{14}H_{10}$ | 3 | 0.001 | (Nisbet et al., 1992) |
| | Fluoranthene | $C_{16}H_{10}$ | 4 | 0.05 | (Larsen et al., 1998) |
| | Pyrene | $C_{16}H_{10}$ | 4 | 0.001 | (Nisbet et al., 1992) |
| | Benz(a)anthracene | $C_{18}H_{12}$ | 4 | 0.1 | (Nisbet et al., 1992) |
| | Chrysene | $C_{18}H_{12}$ | 4 | 0.01 | (Nisbet et al., 1992) |
| | Benzo(b)fluoranthene | $C_{20}H_{12}$ | 4 | 0.1 | (Nisbet et al., 1992) |
| | Benzo(k)fluoranthene | $C_{20}H_{12}$ | 4 | 0.1 | (Nisbet et al., 1992) |
| | Benzo(a)pyrene | $C_{20}H_{12}$ | 5 | 1 | (Nisbet et al., 1992) |
| | Indeno(1,2,3-cd)pyrene | $C_{22}H_{12}$ | 5 | 0.1 | (Nisbet et al., 1992) |
| | Dibenz(a,h)anthracene | $C_{22}H_{14}$ | 5 | 1 | (Malcolm et al., 1994) |
| | Benzo(g,h,i)perylene | $C_{22}H_{12}$ | 6 | 0.01 | (Nisbet et al., 1992) |
| non-priority PAHs | Cyclopenta(c,d)pyrene | $C_{18}H_{10}$ | 4 | 0.1 | (Malcolm et al., 1994) |
| | Benzo(e)pyrene | $C_{20}H_{12}$ | 5 | 0.01 | (Malcolm et al., 1994) |
| | Perylene | $C_{20}H_{12}$ | 5 | 0.001 | (Malcolm et al., 1994) |
| | Coronene | $C_{24}H_{12}$ | 7 | 0.001 | (Malcolm et al., 1994) |
| | Benzo(b)chrycene | $C_{22}H_{14}$ | 5 | - | No TEF has been suggested. |

**Table S3.** Values and sources of EFs for various pollutants emitted from cooking activities

Organics in the full volatility range

| | | VOC EF | IVOC EF | SVOC EF | xLVOC EF | Sources |
|---|---|---|---|---|---|---|
| Commercial cooking (μg/m$^3$) | uncontrolled | 4077 | 2113 | 1570 | 98.89 | (Li et al., 2023) The EF for commercial cooking varies across counties. Here, we list the national average EFs for commercial cooking. |
| | controlled | 1631 | 845.1 | 627.8 | 39.56 | |
| Residential cooking (g/kg oil)[b] | uncontrolled[a] | 13.51 | 3.948 | 2.446 | 0.3939 | |
| Canteen cooking (g/meal)[b] | uncontrolled | 0.8328 | 0.3414 | 0.3037 | 0.01496 | |
| | controlled | 0.3590 | 0.1498 | 0.1329 | 0.006552 | |

Particles

| | | $PM_{2.5}$ EF | Sources | | | UFP EF | Sources |
|---|---|---|---|---|---|---|---|
| Commercial cooking (μg/m$^3$) | uncontrolled | 2874 | Calculated by POA/81.5% (Li et al., 2023) | Commercial cooking (#/m$^3$) | uncontrolled[c] | $1.715\times10^{11}$ | (Kim et al., 2024; Zhang et al., 2010) |
| | controlled | 1149 | | | controlled | $9.529\times10^{11}$ | |
| Residential cooking (g/kg oil)[b] | uncontrolled[a] | 3.016 | | Residential cooking (#/kg oil)[b] | uncontrolled[a] | $9.705\times10^{14}$ | (Chen et al., 2018, 2017; Géhin et al., 2008) |
| Canteen cooking (g/meal)[b] | uncontrolled | 0.2227 | | Canteen cooking (#/meal)[b] | uncontrolled[c] | $3.420\times10^{13}$ | Taking EF for commercial cooking and converting units |
| | controlled | 0.09659 | | | controlled | $6.156\times10^{12}$ | |

PAHs

| | | Gaseous PAH EF[e] | Particulate PAH EF[e] | $BaP_{eq}$ EF[f] | Sources |
|---|---|---|---|---|---|
| Commercial cooking (μg/m$^3$) | uncontrolled[d] | 139.0 | 38.44 | 26.73 | (Li et al., 2003) |
| | controlled | 58.78 | 17.14 | 11.58 | |
| Residential cooking (g/kg oil)[b] | uncontrolled[a] | 0.006730 | 0.002174 | 0.001295 | (Feng et al., 2021; Lin et al., 2022; Ye et al., 2013) |
| Canteen cooking (g/meal)[b] | uncontrolled[d] | 0.001102 | $2.225\times10^{-5}$ | $5.102\times10^{-5}$ | (Chen et al., 2007) |
| | controlled | 0.0004718 | $9.024\times10^{-6}$ | $2.230\times10^{-5}$ | |

[a] Only uncontrolled EFs are considered for residential cooking because residential chimneys generally do not have specialized purification facilities (Liang et al., 2022).

[b] Unit conversions of EFs for residential and canteen cooking refer to the Supplementary Materials of Li et al., 2023.

[c] The removal efficiency of UFP is taken as the average (82%) of the removal efficiencies of 2 commercially available pollution control facilities (in-house dual-stage filtration system and electrostatic precipitator) (Gysel et al., 2018)

[d] In the absence of removal efficiencies for PAHs, we assume that the removal efficiencies for gaseous and particulate PAH are equal to those for VOCs and $PM_{2.5}$, respectively (Li et al., 2023).

[e] The test EFs of gaseous and particulate PAHs for commercial cooking are available from non-Chinese restaurants, Chinese restaurants, and fast food restaurants. Therefore, the final commercial cooking PAH EFs were weighted according to the proportions of these three types of restaurants in China (3.2%: 68.5%: 28.3%, from Li et al., 2023).

[f] The $BaP_{eq}$ EFs are calculated from the PAH EFs and TEFs for the PAH species in Table S2.

**Table S4.** Purification facility installation proportion for CMC in each province.

| Province | 1990 | 1991 | 1992 | 1993 | 1994 | 1995 | 1996 | 1997 | 1998 | 1999 | 2000 | 2001 | 2002 | 2003 | 2004 | 2005 | 2006 | 2007 | 2008 | 2009 | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 | 2016 | 2017 | 2018 | 2019 | 2020 | 2021 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Beijing | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.12 | 0.24 | 0.35 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.53 | 0.65 | 0.65 | 0.65 | 0.65 | 0.65 | 0.65 | 0.65 | 0.77 | 0.88 | 1.00 | 1.00 |
| Tianjin | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.12 | 0.24 | 0.35 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.53 | 0.65 | 0.65 | 0.77 | 0.88 | 1.00 | 1.00 | 1.00 | 1.00 |
| Hebei | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.12 | 0.24 | 0.35 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.53 | 0.65 | 0.65 | 0.65 | 0.65 | 0.77 | 0.88 | 1.00 | 1.00 | 1.00 |
| Shanxi | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.12 | 0.24 | 0.35 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.53 | 0.65 | 0.65 | 0.65 | 0.65 | 0.65 | 0.65 | 0.65 | 0.65 |
| Inner Mongolia | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.12 | 0.24 | 0.35 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.53 | 0.59 | 0.65 | 0.65 | 0.65 | 0.65 |
| Liaoning | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.12 | 0.24 | 0.35 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.53 | 0.65 | 0.65 | 0.77 | 0.88 | 1.00 | 1.00 | 1.00 | 1.00 |
| Jilin | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.12 | 0.24 | 0.35 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.64 | 0.64 | 0.65 | 0.65 | 0.65 |
| Heilongjiang | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.12 | 0.24 | 0.35 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.53 | 0.59 | 0.65 | 0.65 | 0.65 | 0.65 |
| Shanghai | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.16 | 0.31 | 0.47 | 0.53 | 0.65 | 0.65 | 0.65 | 0.65 | 0.65 | 0.65 | 0.65 | 0.65 | 0.77 | 0.88 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 |
| Jiangsu | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.12 | 0.24 | 0.35 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.53 | 0.59 | 0.65 | 0.65 | 0.65 | 0.77 |
| Zhejiang | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.12 | 0.24 | 0.35 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.53 | 0.59 | 0.65 | 0.65 | 0.65 | 0.65 |
| Anhui | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.12 | 0.24 | 0.35 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.53 | 0.59 | 0.65 | 0.65 | 0.65 | 0.65 |
| Fujian | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.12 | 0.24 | 0.35 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.53 | 0.59 | 0.65 | 0.65 | 0.65 | 0.65 |
| Jiangxi | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.12 | 0.24 | 0.35 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.53 | 0.59 | 0.65 | 0.65 | 0.65 |
| Shandong | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.12 | 0.24 | 0.35 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.53 | 0.59 | 0.65 | 0.65 | 0.65 |
| Henan | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.12 | 0.24 | 0.35 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.53 | 0.65 | 0.65 | 0.65 | 0.65 | 0.77 | 0.88 | 1.00 | 1.00 |
| Hubei | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.12 | 0.24 | 0.35 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.53 | 0.59 | 0.65 | 0.65 | 0.65 |
| Hunan | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.12 | 0.24 | 0.35 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.53 | 0.59 | 0.65 | 0.65 | 0.65 |
| Guangdong | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.12 | 0.24 | 0.35 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.53 | 0.65 | 0.65 | 0.65 | 0.65 | 0.65 | 0.65 | 0.65 | 0.65 | 0.65 |
| Guangxi | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.12 | 0.24 | 0.35 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.53 | 0.59 | 0.65 | 0.65 | 0.65 |
| Hainan | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.16 | 0.31 | 0.47 | 0.53 | 0.65 | 0.65 | 0.65 | 0.77 | 0.88 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 |
| Chongqing | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.12 | 0.24 | 0.35 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.53 | 0.65 | 0.65 | 0.65 | 0.65 | 0.77 | 0.88 | 1.00 | 1.00 |
| Sichuan | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.12 | 0.24 | 0.35 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.53 | 0.59 | 0.65 | 0.65 | 0.65 | 0.65 |
| Guizhou | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.12 | 0.24 | 0.35 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.53 | 0.59 | 0.65 | 0.65 | 0.65 | 0.65 |
| Yunnan | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.12 | 0.24 | 0.35 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.53 | 0.59 | 0.65 |
| Xizang | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.12 | 0.24 | 0.35 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.53 | 0.59 | 0.65 |
| Shaanxi | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.12 | 0.24 | 0.35 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.53 | 0.59 | 0.65 | 0.65 |
| Gansu | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.12 | 0.24 | 0.35 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.64 | 0.64 | 0.65 | 0.65 |
| Qinghai | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.12 | 0.24 | 0.35 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.53 | 0.59 | 0.65 |
| Ningxia | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.12 | 0.24 | 0.35 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.53 | 0.59 |
| Xinjiang | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.12 | 0.24 | 0.35 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.64 | 0.64 | 0.65 | 0.65 |

**Table S5.** Purification facility installation proportion for CTC in each province.

| Province | 1990 | 1991 | 1992 | 1993 | 1994 | 1995 | 1996 | 1997 | 1998 | 1999 | 2000 | 2001 | 2002 | 2003 | 2004 | 2005 | 2006 | 2007 | 2008 | 2009 | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 | 2016 | 2017 | 2018 | 2019 | 2020 | 2021 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Beijing | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.16 | 0.32 | 0.48 | 0.64 | 0.64 | 0.64 | 0.64 | 0.64 | 0.70 | 0.77 | 0.83 | 0.83 | 0.83 | 0.83 | 0.83 | 0.83 | 0.89 | 0.94 | 1.00 | 1.00 |
| Tianjin | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.16 | 0.32 | 0.48 | 0.64 | 0.64 | 0.64 | 0.64 | 0.64 | 0.64 | 0.64 | 0.64 | 0.70 | 0.77 | 0.83 | 0.89 | 0.94 | 1.00 | 1.00 | 1.00 | 1.00 |
| Hebei | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.16 | 0.32 | 0.48 | 0.64 | 0.64 | 0.64 | 0.64 | 0.64 | 0.64 | 0.64 | 0.70 | 0.77 | 0.83 | 0.83 | 0.83 | 0.89 | 0.94 | 1.00 | 1.00 | 1.00 |
| Shanxi | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.16 | 0.32 | 0.48 | 0.64 | 0.64 | 0.64 | 0.64 | 0.64 | 0.70 | 0.77 | 0.83 | 0.83 | 0.83 | 0.83 | 0.83 | 0.83 | 0.83 |
| Inner Mongolia | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.16 | 0.32 | 0.48 | 0.64 | 0.64 | 0.64 | 0.64 | 0.64 | 0.64 | 0.70 | 0.77 | 0.83 | 0.83 | 0.83 | 0.83 |
| Liaoning | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.16 | 0.32 | 0.48 | 0.64 | 0.64 | 0.64 | 0.64 | 0.64 | 0.64 | 0.64 | 0.64 | 0.70 | 0.77 | 0.83 | 0.89 | 0.94 | 1.00 | 1.00 | 1.00 | 1.00 |
| Jilin | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.16 | 0.32 | 0.48 | 0.64 | 0.64 | 0.64 | 0.64 | 0.64 | 0.64 | 0.64 | 0.64 | 0.64 | 0.64 | 0.64 | 0.64 | 0.64 | 0.70 | 0.77 | 0.83 | 0.83 |
| Heilongjiang | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.16 | 0.32 | 0.48 | 0.64 | 0.64 | 0.64 | 0.64 | 0.64 | 0.64 | 0.64 | 0.64 | 0.64 | 0.64 | 0.64 | 0.70 | 0.77 | 0.83 | 0.83 | 0.83 | 0.83 |
| Shanghai | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.21 | 0.43 | 0.64 | 0.70 | 0.77 | 0.83 | 0.83 | 0.83 | 0.83 | 0.83 | 0.83 | 0.83 | 0.89 | 0.94 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 |
| Jiangsu | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.16 | 0.32 | 0.48 | 0.64 | 0.64 | 0.64 | 0.64 | 0.64 | 0.64 | 0.64 | 0.64 | 0.64 | 0.64 | 0.64 | 0.70 | 0.77 | 0.83 | 0.83 | 0.83 | 0.89 |
| Zhejiang | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.16 | 0.32 | 0.48 | 0.64 | 0.64 | 0.64 | 0.64 | 0.64 | 0.64 | 0.64 | 0.64 | 0.64 | 0.64 | 0.64 | 0.70 | 0.77 | 0.83 | 0.83 | 0.83 | 0.83 |
| Anhui | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.16 | 0.32 | 0.48 | 0.64 | 0.64 | 0.64 | 0.64 | 0.64 | 0.64 | 0.64 | 0.64 | 0.64 | 0.64 | 0.64 | 0.70 | 0.77 | 0.83 | 0.83 | 0.83 | 0.83 |
| Fujian | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.16 | 0.32 | 0.48 | 0.64 | 0.64 | 0.64 | 0.64 | 0.64 | 0.64 | 0.64 | 0.64 | 0.64 | 0.64 | 0.64 | 0.70 | 0.77 | 0.83 | 0.83 | 0.83 | 0.83 |
| Jiangxi | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.16 | 0.32 | 0.48 | 0.64 | 0.64 | 0.64 | 0.64 | 0.64 | 0.64 | 0.64 | 0.64 | 0.64 | 0.64 | 0.64 | 0.64 | 0.70 | 0.77 | 0.83 | 0.83 | 0.83 |
| Shandong | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.16 | 0.32 | 0.48 | 0.64 | 0.64 | 0.64 | 0.64 | 0.64 | 0.64 | 0.64 | 0.64 | 0.64 | 0.64 | 0.64 | 0.64 | 0.70 | 0.77 | 0.83 | 0.83 | 0.83 |
| Henan | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.16 | 0.32 | 0.48 | 0.64 | 0.64 | 0.64 | 0.64 | 0.64 | 0.64 | 0.64 | 0.64 | 0.70 | 0.77 | 0.83 | 0.83 | 0.83 | 0.89 | 0.94 | 1.00 | 1.00 |
| Hubei | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.16 | 0.32 | 0.48 | 0.64 | 0.64 | 0.64 | 0.64 | 0.64 | 0.64 | 0.64 | 0.64 | 0.64 | 0.64 | 0.64 | 0.64 | 0.70 | 0.77 | 0.83 | 0.83 | 0.83 |
| Hunan | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.16 | 0.32 | 0.48 | 0.64 | 0.64 | 0.64 | 0.64 | 0.64 | 0.64 | 0.64 | 0.64 | 0.64 | 0.64 | 0.64 | 0.64 | 0.70 | 0.77 | 0.83 | 0.83 | 0.83 |
| Guangdong | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.16 | 0.32 | 0.48 | 0.64 | 0.64 | 0.64 | 0.64 | 0.64 | 0.64 | 0.64 | 0.70 | 0.77 | 0.83 | 0.83 | 0.83 | 0.83 | 0.83 | 0.83 | 0.83 | 0.83 |
| Guangxi | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.16 | 0.32 | 0.48 | 0.64 | 0.64 | 0.64 | 0.64 | 0.64 | 0.64 | 0.64 | 0.64 | 0.64 | 0.64 | 0.64 | 0.64 | 0.70 | 0.77 | 0.83 | 0.83 | 0.83 |
| Hainan | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.21 | 0.43 | 0.64 | 0.70 | 0.77 | 0.83 | 0.83 | 0.89 | 0.94 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 |
| Chongqing | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.16 | 0.32 | 0.48 | 0.64 | 0.64 | 0.64 | 0.64 | 0.64 | 0.64 | 0.64 | 0.64 | 0.70 | 0.77 | 0.83 | 0.83 | 0.83 | 0.89 | 0.94 | 1.00 | 1.00 |
| Sichuan | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.16 | 0.32 | 0.48 | 0.64 | 0.64 | 0.64 | 0.64 | 0.64 | 0.64 | 0.64 | 0.64 | 0.64 | 0.64 | 0.64 | 0.70 | 0.77 | 0.83 | 0.83 | 0.83 | 0.83 |
| Guizhou | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.16 | 0.32 | 0.48 | 0.64 | 0.64 | 0.64 | 0.64 | 0.64 | 0.64 | 0.64 | 0.64 | 0.64 | 0.64 | 0.70 | 0.77 | 0.83 | 0.83 | 0.83 | 0.83 |
| Yunnan | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.16 | 0.32 | 0.48 | 0.64 | 0.64 | 0.64 | 0.64 | 0.64 | 0.64 | 0.64 | 0.64 | 0.64 | 0.64 | 0.70 | 0.77 | 0.83 |
| Xizang | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.16 | 0.32 | 0.48 | 0.64 | 0.64 | 0.64 | 0.64 | 0.64 | 0.64 | 0.64 | 0.64 | 0.64 | 0.64 | 0.70 | 0.77 | 0.83 |
| Shaanxi | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.16 | 0.32 | 0.48 | 0.64 | 0.64 | 0.64 | 0.64 | 0.64 | 0.64 | 0.64 | 0.64 | 0.64 | 0.64 | 0.70 | 0.77 | 0.83 | 0.83 |
| Gansu | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.16 | 0.32 | 0.48 | 0.64 | 0.64 | 0.64 | 0.64 | 0.64 | 0.64 | 0.64 | 0.64 | 0.64 | 0.64 | 0.70 | 0.77 | 0.83 |
| Qinghai | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.16 | 0.32 | 0.48 | 0.64 | 0.64 | 0.64 | 0.64 | 0.64 | 0.64 | 0.64 | 0.64 | 0.64 | 0.64 | 0.70 | 0.77 | 0.83 |
| Ningxia | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.16 | 0.32 | 0.48 | 0.64 | 0.64 | 0.64 | 0.64 | 0.64 | 0.64 | 0.64 | 0.64 | 0.64 | 0.64 | 0.70 | 0.77 |
| Xinjiang | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.16 | 0.32 | 0.48 | 0.64 | 0.64 | 0.64 | 0.64 | 0.64 | 0.64 | 0.64 | 0.64 | 0.64 | 0.64 | 0.70 | 0.77 | 0.83 |

**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 |

**Table S7: The values of validation metrics of all models for activity levels of three cooking sectors on the training data set.**

| Model | Commercial cooking | | | Residential cooking | | | Canteen cooking | | |
|---|---|---|---|---|---|---|---|---|---|
| | $R^2$ | RMSE ($10^9$ $m^3$) | MAE ($10^9$ $m^3$) | $R^2$ | RMSE (kt) | MAE (kt) | $R^2$ | RMSE ($10^6$ meals) | MAE ($10^6$ meals) |
| Multiple linear regression | 0.737 | 21.464 | 14.301 | 0.949 | 0.803 | 0.416 | 0.966 | 4.825 | 2.272 |
| Non-negative least squares regression | 0.635 | 22.341 | 17.271 | 0.903 | 1.174 | 0.869 | 0.960 | 5.072 | 2.095 |
| Generalized linear models with exponential link | 0.689 | 25.860 | 13.019 | 0.401 | 3.014 | 2.518 | 0.541 | 17.351 | 13.258 |
| Poisson regression | 0.504 | 26.836 | 17.285 | 0.048 | 3.911 | 2.804 | 0.243 | 19.056 | 14.923 |
| Power function Regression | 0.779 | 18.184 | 9.664 | 0.985 | 0.312 | 0.163 | 0.978 | 2.894 | 1.692 |
| RF | 0.982 | 8.013 | 3.885 | 0.997 | 0.135 | 0.060 | 0.995 | 1.056 | 1.055 |
| XGBoost | 0.936 | 11.450 | 6.029 | 0.996 | 0.114 | 0.048 | 0.997 | 1.183 | 1.161 |
| MLP | 0.887 | 14.642 | 7.651 | 0.993 | 0.205 | 0.108 | 0.989 | 1.726 | 1.273 |
| DNN | 0.898 | 12.395 | 6.822 | 0.994 | 0.178 | 0.092 | 0.986 | 2.412 | 1.325 |
| Ensemble machine learning model | 0.985 | 7.852 | 3.915 | 0.997 | 0.095 | 0.059 | 0.995 | 1.054 | 1.116 |

**Table S8: Comparison of cooking emissions in this study with those in previous studies.** Bolded words represent this study.

| region and year | inventory studies | VOC emissions (kt) | $PM_{2.5}$ emissions (kt) |
|---|---|---|---|
| **China, 2012** | **this study** | **416** | **334** |
| China, 2012 | Wang et al., 2018a | 66.0 | |
| **China, 2017** | **this study** | **520** | **376** |
| China, 2017 | Jin et al., 2021 | 34.0 | |
| **China, 2018** | **this study** | **531** | **384** |
| China, 2018* | Cheng et al., 2022 ($PM_{2.5}$=POA/81.5%=1.8OC/81.5%) (Huang, 2023) | - | 5.57 |
| **China, 2019** | **this study** | **539** | **389** |
| China, 2019 | Liang et al., 2022 | 234 | |
| **China, 2020** | **this study** | **524** | **379** |
| China, 2020 | Zhang et al., 2024 | 557 | 82.1 |

* Cheng et al provided multi-year organic carbon (OC) emissions for China, and we use their most recent year (2018) for comparison. We apply the conversion relationship mentioned in the main text to convert OC into $PM_{2.5}$ for comparison. The emission results from Cheng et al. were significantly lower than those of this study because their calculations were based solely on meat consumption, whereas cooking emissions involve not only meat but also vegetables, cooking oil, and other factors. This led to a substantial underestimation of their emissions.

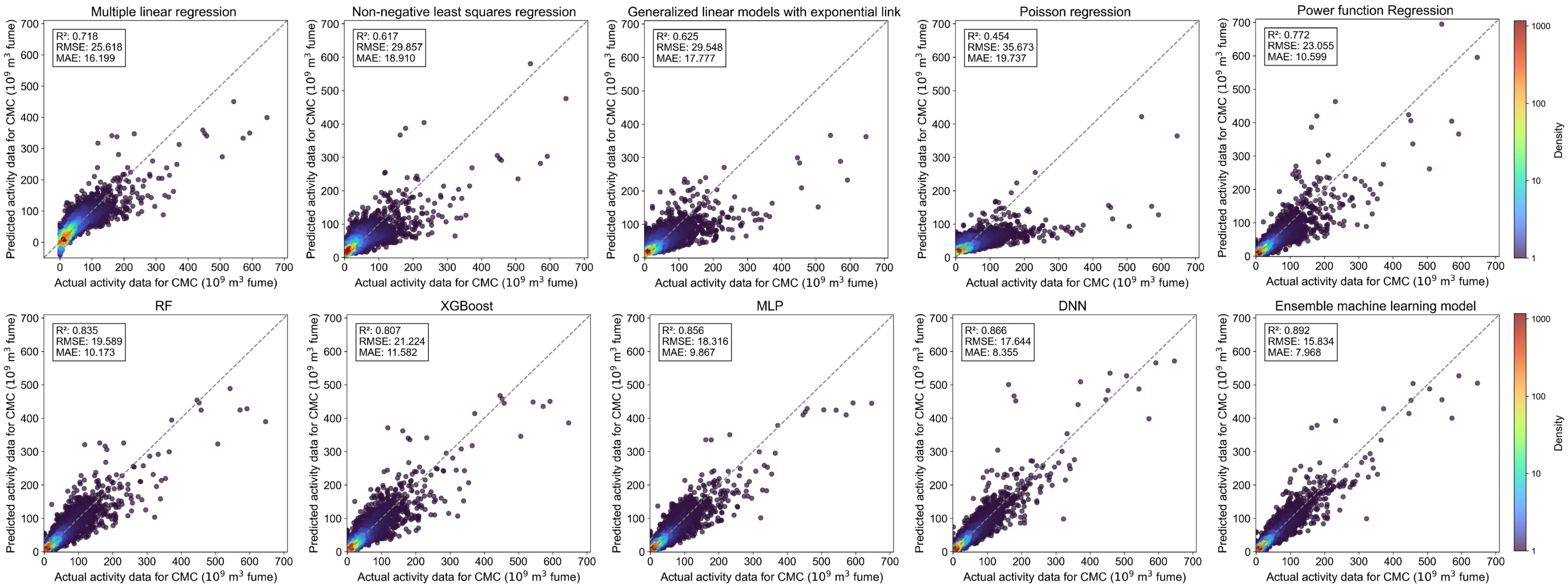


**Figure S1**. The predictive performance of all models on commercial cooking (CMC)

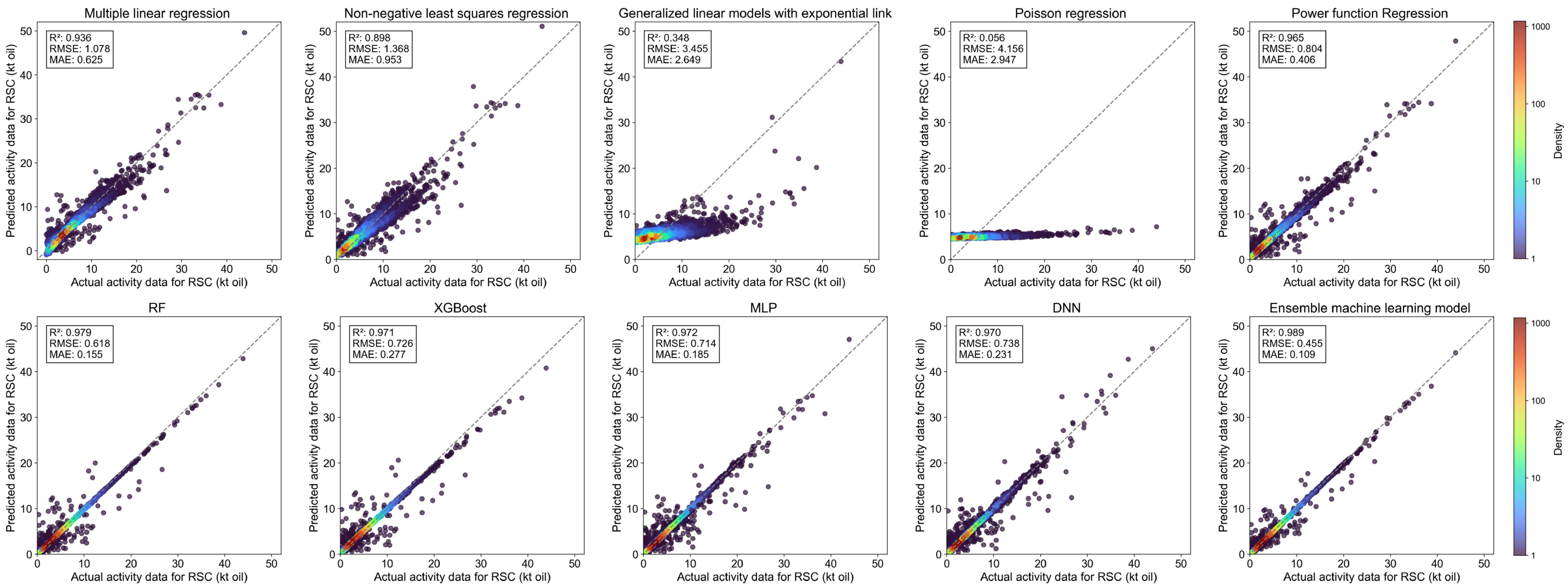


**Figure S2**. The predictive performance of all models on residential cooking (RSC)

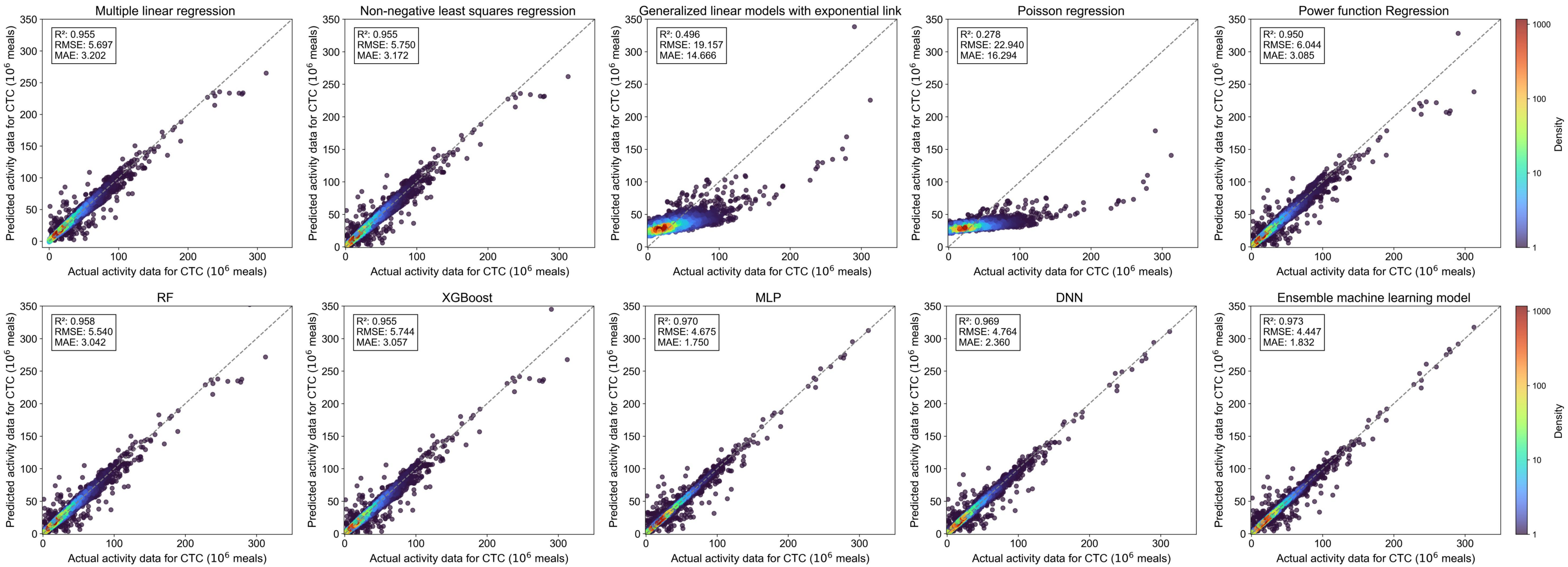


**Figure S3**. The predictive performance of all models on canteen cooking (CTC)

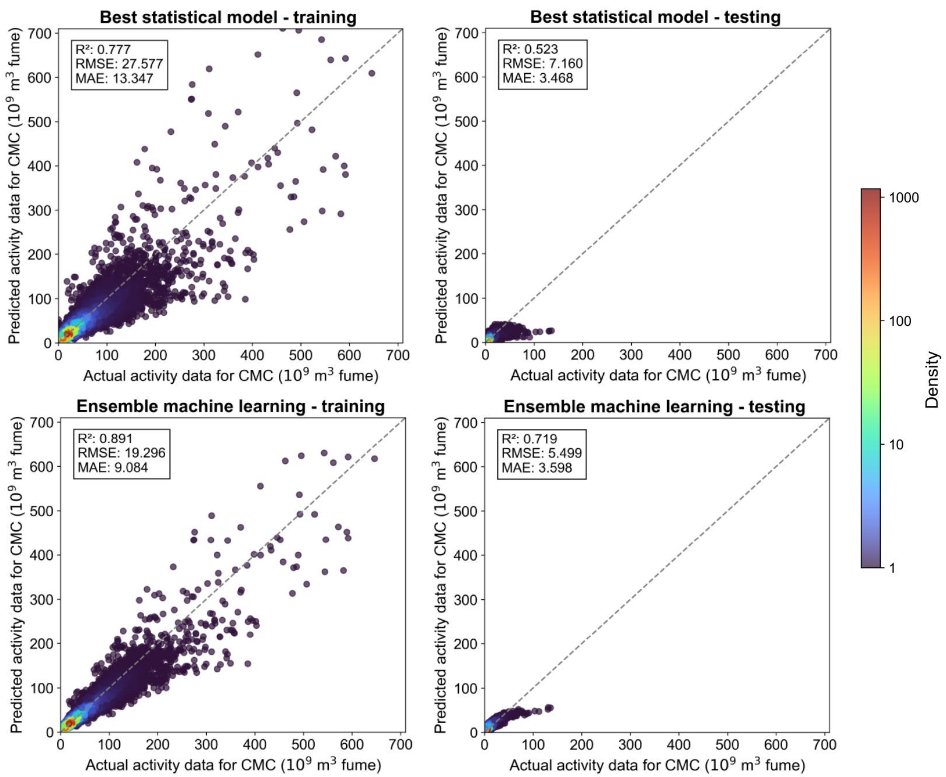


**Figure S4.** Sensitivity test of the best statistical model (power function regression) and ensemble machine learning model in extrapolating activity levels for counties with different GDP levels.

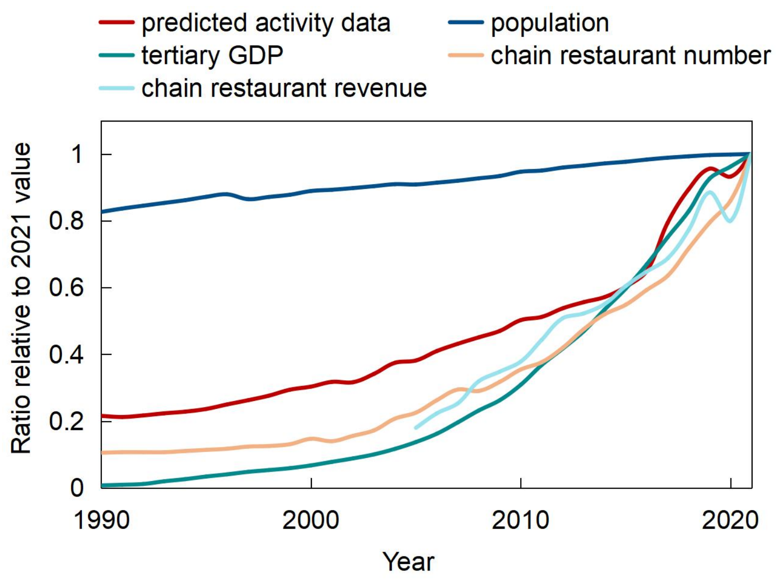


**Figure S5.** Comparison of the historical trends of predicted national commercial cooking activity levels with other relevant statistical data. For comparability, all data are normalized to the ratio relative to their 2021 values.

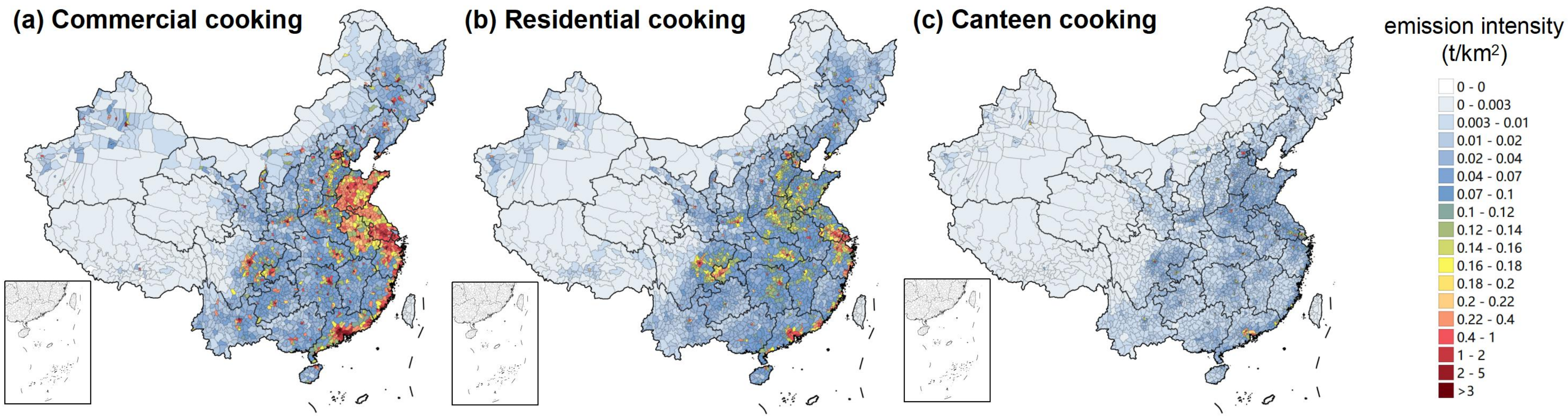


**Figure. S6**. Sector-specific spatial distributions of cooking emissions in 2021.


**Figure. S7**. Map of Chinese provinces.

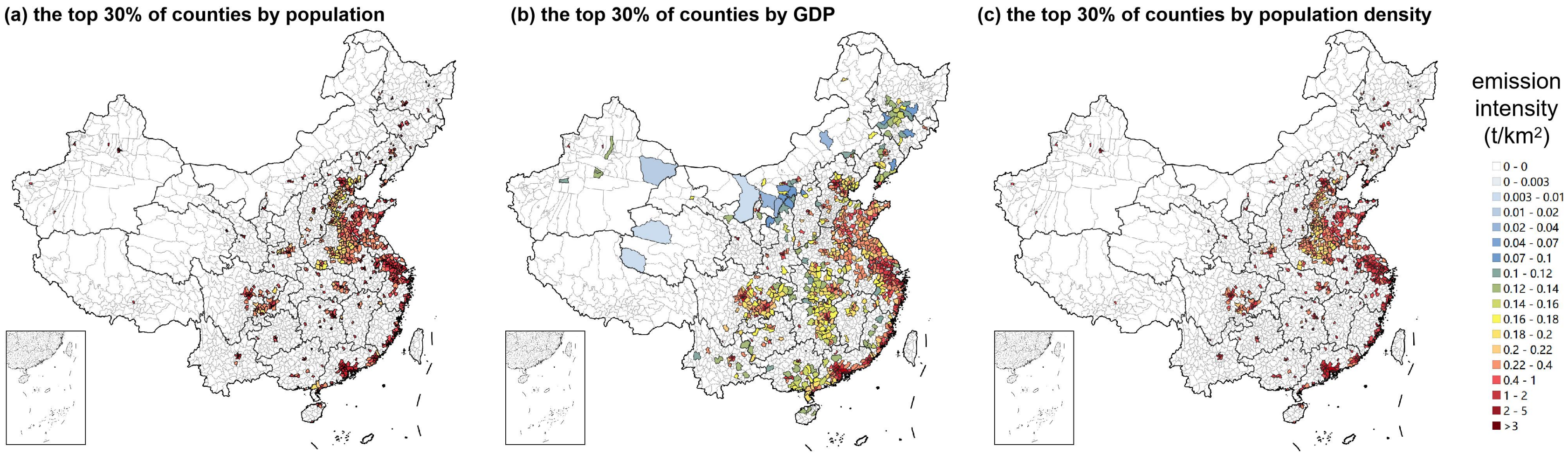


**Figure. S8**. The top 30% of counties by population, GDP, and population density.

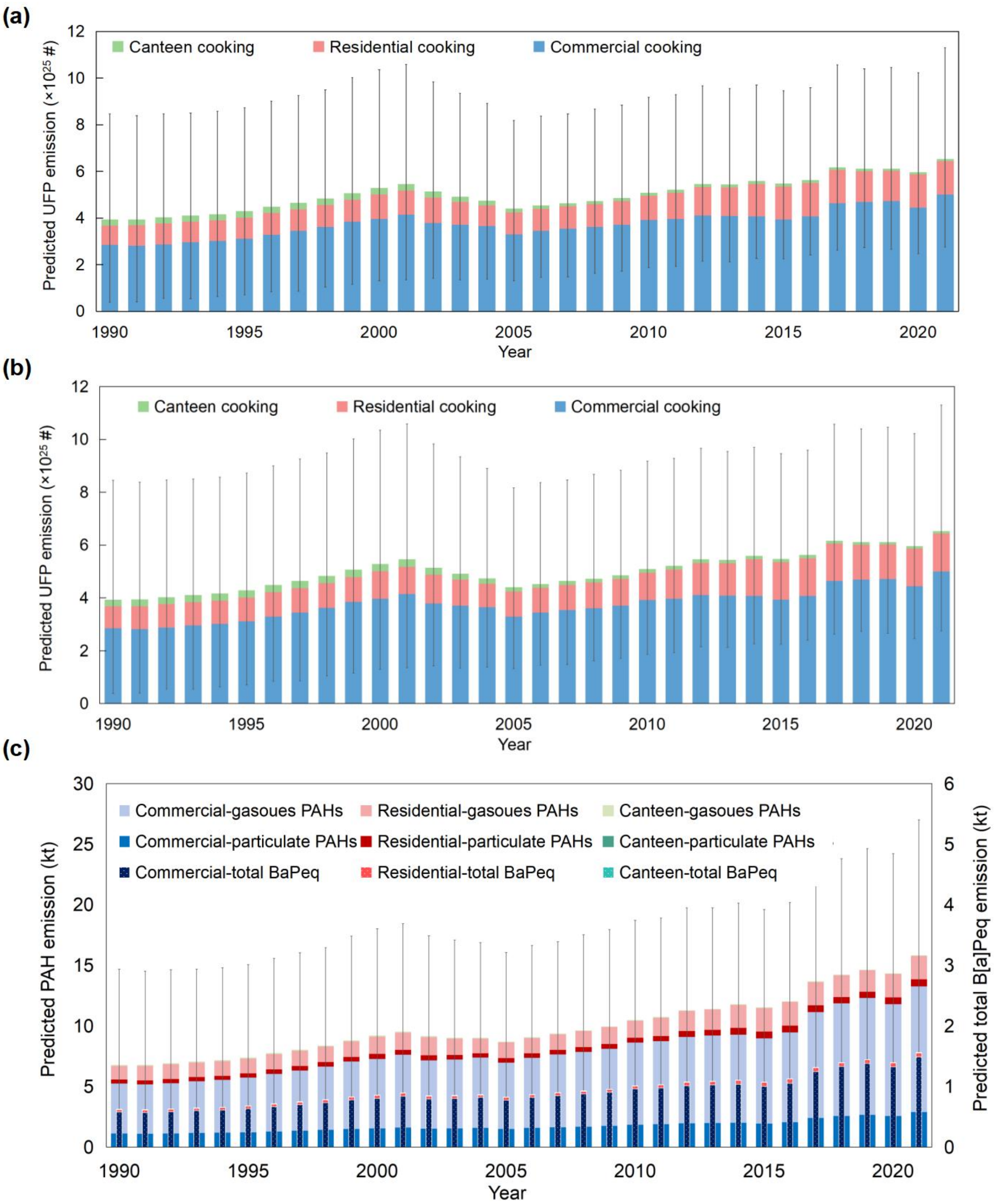


**Figure S9**. $PM_{2.5}$, UFP, and PAH emissions in the four volatility ranges from the three cooking sectors from 1990 to 2021 in China.

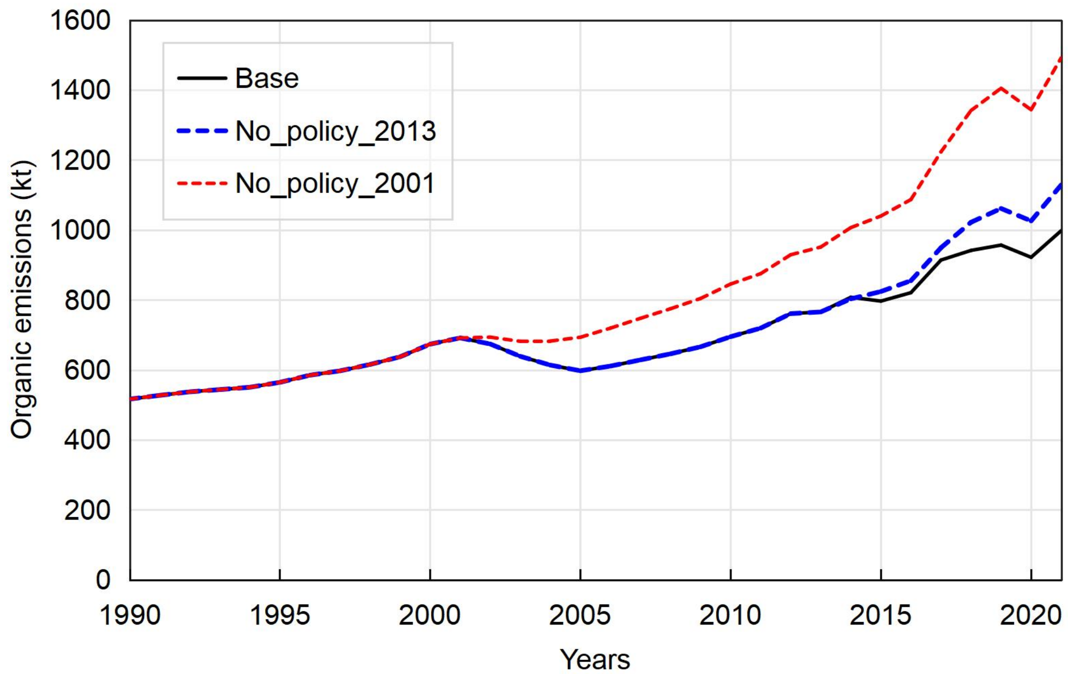


**Figure S10.** Cooking organic emission trends under scenarios lacking key pollution control policies

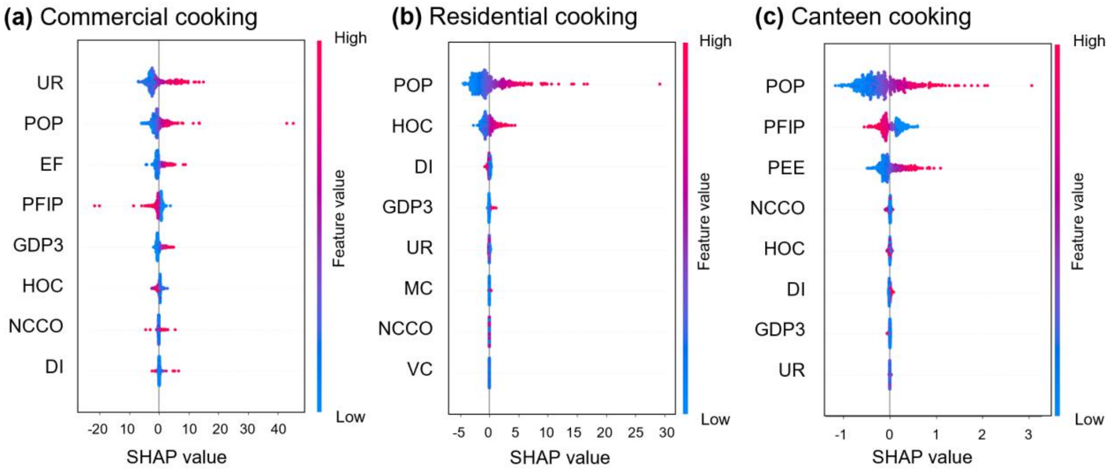


**Figure. S11**. SHAP summary plots of the main influencing factors for the emissions of the three cooking sectors. Each point represents a sample of (district, year), with its color indicating its factor value - blue representing lower variable values, and red representing higher feature values. We only select the top 8 most important factors to display in the figures.

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