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Integrated Model for Estimating GHG Emissions from Municipal Wastewater Treatment in High-population Density Cities

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Abstract
Wastewater treatment industry, a top ten carbon emission source, has been significantly concerned in recent years. However, unclear system boundaries and undisclosed databases make it hard to estimate the greenhouse gas (GHG) emission from the wastewater treatment industry, especially in developing countries. Quantifying the total GHG emission characteristics at national level is helpful to identify the most emitted processes and propose suitable carbon mitigation strategies. This study accurately estimated the GHG emissions from China's wastewater treatment industry by a model combined with operational data integrated methods and Intergovernmental Panel on Climate Change method. Then, the spatial distribution analysis and possible influential factors of total GHG emissions were further investigated by geographic model, Pearson correlation model and principal component analysis. Results showed that the national GHG emission from the total 4,205 wastewater treatment plants (WWTPs) in China in 2017 was 34.18 Mt CO_2-eq, with 64.5% emitted from the consumption of electricity and chemicals. The GHG reduction strategies need to focus on process optimization and improvement at WWTPs, especially for the energy source shift, improved aeration, and on-site N_2O emission from biological treatment process. After analyzing the spatial distribution characteristics, the total emission in the eastern region was approximately four times higher than that in the western region according to the Hu Line. Gross domestic product (GDP) and the treated volume of wastewater had strong positive correlations to the total GHG emissions in most first-tier cities, while there were no significant impacts on non-first-tier cities. Additionally, the impact of wastewater treatment scale on the discharge intensity is not significant, but the impact of technology is relatively obvious.

Keywords: Wastewater treatment, GHG emission, operational data integrated methods, spatial distribution

Nonmenclature

GHG	Greenhouse gas
WWTPs	Wastewater treatment plants
EF	Emission factor
IPCC	Intergovernmental Panel on Climate Change
USEPA	United States Environmental Protection Agency
EDGAR	Emissions Database for Global Atmospheric Research
ODIM	Operational data integrated methods
TN	Total nitrogen
COD	Chemical oxygen demand
AAO	Anaerobic-anoxic-oxic
AO	Anoxic-oxic
SBR	Sequencing batch reactors
OD	Oxidation ditch
GDP	Gross domestic product
GWP	Global warming potential
AD	anaerobic digestion
PCA	Principal component analysis
CHP	combined heat and power
ANAMMOX	Anaerobic ammonium oxidation
LCA	life cycle assessment

1. Introduction

Global warming is mainly attributed to the increase in greenhouse gas (GHG) emissions, impairing not only the whole ecosystem, but also the social and economic system (Wang et al., 2016). By the end of 2019, China accounts for about 27% (1.41×10^{11} t CO_2-eq) of world's GHG emissions, which is equal to the sum of the United States, India, Russia, and Japan. As a result, China is facing greater pressure on carbon emission reduction. In 2015, at the Climate Conference in Paris, China promises to reach the peak of carbon emissions around 2030. Furthermore, in September 2020, China proposed to achieve carbon neutrality before 2060 to mitigate the extreme effects of climate change. According to statistics in most developed countries, the wastewater treatment industry accounts for 1-2% of their total GHG emission, ranking among the top ten carbon emission industries (Li, 2022). However, this proportion was seldom reported in developing

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countries, such as China. Identifying the carbon emission characteristics helps to clarify the most emitted process, thus delivering more efficient mitigation pathways.

To date, several investigations have provided limited information to understand GHG emission from WST industry in China, such as energy-water nexus in cities/regions (Liao et al., 2020); direct CH_4/N_2O emissions (Bao et al., 2014, Wang et al., 2011); energy-related or life-cycle GHG emissions at full-scale wastewater treatment plants (WWTPs) (Bao et al., 2016); GHG emissions based on different sludge treatment and disposal ways (Feng, 2019, Chen and Kuo, 2016) etc. Although the existing reports have estimated the CH_4 and N_2O emission from wastewater treatment sector (Kumar et al., 2021, Wei et al., 2020), the data is unreliable and inadequate for most developing countries, including China. Besides, no holistic study has reviewed these works to understand the complete picture of GHG emission from China's wastewater treatment system, and uncertainty GHG inventories from each research also make it a challenge to fully evaluate the GHG emission.

When accounting GHG emission from WWTPs at city/province/country level, emission factors (EFs) approach reported by various organizations, such as Intergovernmental Panel on Climate Change (IPCC), Danish Center for Environment and Energy, United States Environmental Protection Agency (USEPA), and Emissions Database for Global Atmospheric Research (EDGAR) etc. (Xi et al., 2021), is conducted. Among them, the IPCC method is the most used, but there is a high degree of uncertainty associated with the huge differences. This is because the IPCC method is roughly calculated by per capita emissions, lacking the data accuracy. Cai et al. (2015) also concluded that the emission factor of anaerobic process is significantly lower than the default value of IPCC, resulting in a lower underestimated value of GHG evaluation. According to Hartley (2018), the selection of wastewater treatment technology is the biggest factor affecting GHG emission, and Xi et al. (2021) proposed that operational data integrated methods (ODIM) that calculate local emission by different treatment processes was more accurate than IPCC approach when evaluate GHG emission at city level. Therefore, it is necessary to use detailed calculation models to quantify GHG emission accurately.

In this study, a model of ODIM combined with IPCC method will be used to evaluate direct CH_4 and N_2O from a total 5,282 WWTPs in 660 cities, covering six commonly used wastewater treatment processes. Then, suitable strategies for GHGs control will be proposed after identifying which processes or sources have higher GHG emission amounts. Furthermore, the spatial distribution analysis and the effects of regional development characteristics, the WWTP scale and operational technology on GHG emission will be analyzed.

2. Methodology

2.1 Data source and system boundary

The base year used in this study was 2017. Information of wastewater treatment characteristics, such as total nitrogen (TN), chemical oxygen demand (COD), electricity and chemical consumption, and used biological treatment technology in 4,205 WWTPs can be obtained by the Statistical Yearbook of Urban Drainage (SYUD, 2018). There were six commonly used biological wastewater treatment processes at WWTPs in China, including anaerobic-anoxic-oxic (AAO), anoxic oxic (AO), oxidation ditch (OD), sequencing batch reactors (SBR), membrane bioreactor (MBR), biofilm. City development characteristics, such as gross domestic product (GDP), population density, daily water consumption, investment, were found from Statistical Yearbook of Urban Construction (SYUC, 2017). Hong Kong, Taiwan, Macao and marine environments are excluded due to the lack of information. Besides, the regional power grid baseline emission factor of six regions in 31 provinces was collected by the Ministry of Ecological Environment (MEE, 2017).

The system boundary for accounting GHG emissions in this study only considers the wastewater treatment and preliminary sludge treatment at WWTPs, as shown in Fig.1. The main GHGs produced during WST are mainly CO_2, CH_4 and N_2O, with global warming potential (GWP) of 1, 25 and 298. According to Koutsou et al. (2018), on-site GHG emissions are mainly direct N_2O and CH_4 from microorganisms in the secondary sedimentation tank, while off-site GHG emissions are related to the consumption of energy and chemicals. Therefore, this study quantified on-site from biological processes and off-site GHG emissions from the consumption of electricity and chemicals, as shown in Eq. (1):

$$GHG_{WWTPs} = \sum_{i=1}^{5,282} GHG_{N_2O} + GHG_{CH_4} + GHG_{electricity} + GHG_{PAM} \tag{1}$$

Besides, due to a low proportion of anaerobic digestion (AD) of nearly 3% (Zhang et al., 2017), the recovered CH_4 is not calculated in GHG emission evaluation in this study.

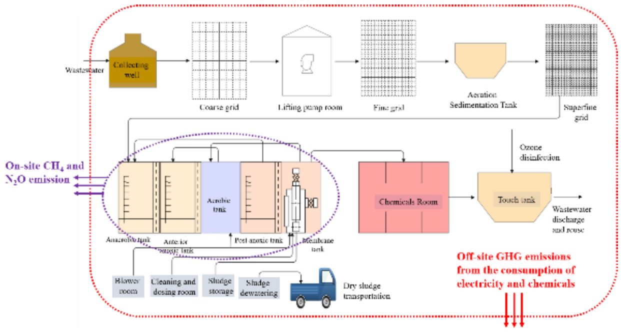

Fig. 1. System boundary at an AAO-based WWTP.

2.2 Quantification of GHG emission

Due to various wastewater treatment technologies, ODIM was established to estimate the direct N_2O and CH_4 based on different processes and practical operational data, which is obtained by the average value from over 40 real WWTPs (Xi et al., 2021). This is because ODIM is more accurate than IPCC with the consideration of variability in operating conditions and changes in the influent load.

On-site GHG emissions at each WWTP include direct N_2O (as kg N_2O/y) and CH_4 (as kg CH_4/y), as shown in Eq. (2)-(3):

$$GHG_{N_2O} = \sum_{i=1}^{5,282} TN_{removal,i} \times EF_{w1,i} \times GWP(N_2O) \tag{2}$$

$$GHG_{CH_4} = \sum_{i=1}^{5,282} COD_{removal,i} \times EF_{w2,i} \times GWP(CH_4) \tag{3}$$

where $TN_{removal}$ and $COD_{removal}$ are the removal amounts of TN (TN_{inlet} - $TN_{effluent}$) and COD (COD_{inlet} - $COD_{effluent}$) at each WWTP. EF_{w1}, EF_{w2} are the EFs of direct N_2O and CH_4 emissions from each WWTP with six kinds of biological treatment technologies (Xi et al., 2021). 44/28 is the conversion factor of kg N_2O-N into kg N_2O.

Off-site GHG emissions from the consumption of electricity (as kWh/y) and PAM used for sludge treatment (as kg/y) are presented in Eq. (4)-(5):

$$GHG_{electricity} = \sum_{i=1}^{5,282} W_i \times EF_{w3,i} \tag{4}$$

$$GHG_{PAM} = \sum_{i}^{660} C_{p,i} \times EF_{w4} \tag{5}$$

where EF_{w3} is regional power grid baseline emission factor in China (MEEC, 2017), kg CO_2-eq/kWh; C_P is the consumption of PAM at WWTPs for one year; EF_{w4} is the emission factor for PAM (1.5 kg CO_2-eq/kg) (Chai et al., 2015). Due to the lack of data, the amount of PAM consumption was only presented at city level, not at WWTP scale.

2.3 Principal component analysis

Principal component analysis (PCA) is a multivariate statistical method to investigate the correlation between multiple variables. It derives a few principal components from the original variables, thus retaining as much information of the original variables as possible and are not related to each other. In this study, several city development indicators and wastewater treatment characteristics were chosen to investigate their effects on total GHG emissions from wastewater treatment industry.

The general procedure if PCA is shown as the following:

a. Indicators contributing both positively and negatively to the GHG emission need to be standardized by Eq. (6)-(7):

$$\frac{X_i - X_{min}}{X_{max} - X_{min}} \times 100\% \tag{6}$$

$$\frac{X_{max} - X_i}{X_{max} - X_{min}} \times 100\% \tag{7}$$

b. The raw data matrix will then be reorganized with each row representing a provincial district and each column representing a different city developing index. Then, the new data matrix, X, is normalized to have zero mean based on its number of columns, m.

c. The covariance matrix R is reconstructed based on the following equation 8:

$$R = \frac{1}{m-1} X^M X \tag{8}$$

where M is the conjugate transpose operator.

d. Singular-value decomposition (SVD) decomposition is performed on R, which is presented in Eq. (9):

$$R = V \Lambda V^M \tag{9}$$

where Λ is the diagonal matrix of the eigenvalues of R in decreasing numerical order, and V is the matrix of the eigenvectors of R as columns.

e. Matrix N is constructed by selecting the first "α" columns of V corresponding to the first principal eigenvalues. It is then used to transform the original space of variables to the reduced dimension subspace:

The columns of matrix N are the selected eigenvectors and are called loadings. The W matrix is the reduced subspace of the original variable space, and its vectors are called scores.

3. Results and discussion

3.1 GHG emissions quantification

According to the carbon emission database, the total GHG emission of China in 2017 was estimated to be 9.34 billion tons CO_2-eq. From calculation, the total GHG emission from China's WST industry was estimated to be 34.18 Mt CO_2-eq, which accounted for 0.4% of total emission. The reason why the relative lower proportion of GHG emission in wastewater industry than that of developing countries may be attributed to the industrial structure in China (Guo et al., 2019). Fig.2 presents the reported national GHG emission from the wastewater treatment industry worldwide ((Koutsou et al., 2018; Nayeb et al., 2019; Shrestha et al., 2022; Noyola et al., 2016; Hall et al., 2011; Singh et al., 2017)). In sum, the total GHG emission in China was quite higher than other countries, but the emission intensity in China (0.37 kg CO_2-eq/capita/day) was quite like 0.36 in Nepal (Shrestha et al., 2022). This value in Greece was relatively lower than that in China because the system boundary considered the GHG emission from sludge disposal and wastewater discharge (Koutsou et al., 2018). Besides, other differences may be due to the variance in used EF value.

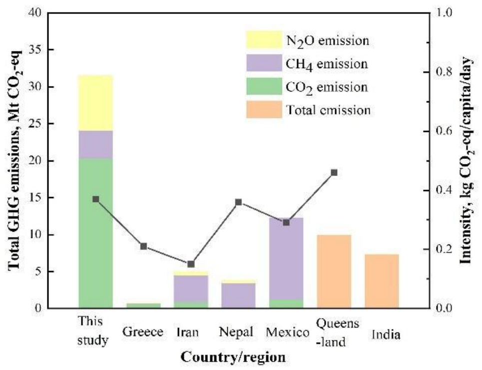

Fig.2. Comparison of total GHG emissions and emission intensity in different countries/regions.

Almost 64.5% of GHG emissions (20.3 Mt CO_2-eq per year) was from off-site GHG emission, and 99.3% off-site GHG emissions were due to electricity consumption. Electricity consumption mainly comes from the upgrading pumping stations, aeration system and sludge reflux etc. For example, aeration accounts for 45-75% of total energy costs (Rosso et al., 2008). This means that it is efficient to control aeration conditions to save energy, and it was reported that 22% of off-site emission will be reduced by modifying extended aeration process conditions (Yapıcıoğlu, 2021). Moreover, with the increase in the clean energy utilization process in China (Zhang et al., 2021), the wastewater treatment industry can also effectively reduce the reliance on electricity consumption. Besides, Zeng et al. (Zeng et al., 2017) assumed that the GHG emission may decrease by 32.2% if all WWTPs operate efficiently. Therefore, it is urgent to improve WWTPs efficiency to achieve GHG reduction in the future. In contrast, the off-site GHG emission from PAM consumption was relatively low, but accurate dosing during wastewater treatment could avoid nearly 95% of them (Li et al., 2022).

According to Fig. 3, a color change from light pink to dark pink indicates the GHG emission volume at the provincial level (Mt/y), and the pie charts represent the percentage of different stages of the wastewater treatment industry. Overall, the spatial distribution of GHG emission of wastewater treatment industry was basically in line with the development process of urban wastewater treatment facilities in China. In particular, the Hu line clearly distinguishes between high emission areas and low emission areas, with higher GHG emission in the east, accounting for approximately 76.4% of total emission. Among six regions, North China emitted the most GHG emissions (9.62 Mt CO_2-eq), followed by 6.62 Mt, 5.80 Mt and 4.36 Mt in East China, and Central China, respectively. Most provinces located in Northern regions accounted for a higher proportion of CH_4 and N_2O emission, which may be attributed to higher EF_{grid} and relatively low discharge standards. Five provinces emitted almost 37.3% of GHG emission in these regions, with the order: Shandong (3.42 Mt) > Guangdong (2.51 Mt) > Jiangsu (2.40 Mt) > Zhejiang (2.38 Mt) > Hebei (2.06 Mt). The GHG emission of other provinces in these three regions ranged from 0.012 Mt CO_2-eq (Tibet) to 1.56 Mt CO_2-eq (Sichuan). Fig.3 also illustrates the amount and proportions of different types of GHGs, and their decomposition trends mainly like that of total GHG emissions. Generally, the on-site N_2O emission was twice higher than direct CH_4 emission. This is because N_2O from the activated sludge tanks at WWTPs is the dominant source of GHG emissions (Parravicini et al., 2016), while CH_4 generated by sludge AD could be further recovered. So, controlling direct N_2O emission at WWTPs seems more important.

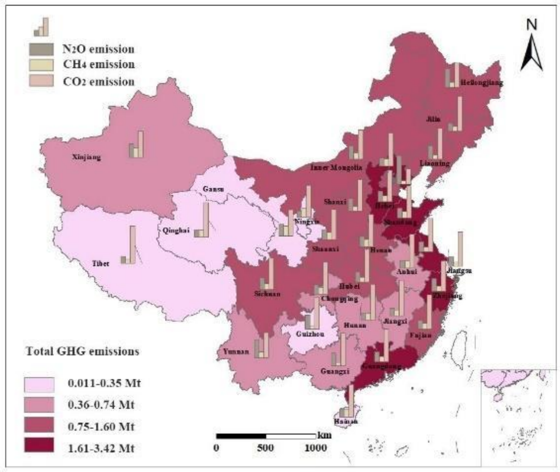

Fig.3. Total and decomposition of GHG emission from China's wastewater treatment industry in each province.

3.2 Influential factors of GHG emission

3.2.1 Effect of regional characteristics and development

Regional urbanization rate, area, population size, and GDP may have significant influence on GHG emission of 31 provinces in China, which is similar with the results by Wei et al. (2020), who found the correlation between sludge production and these factors. Pearson correlation analysis was used to analyse the effects of per capita GDP, urbanization rate, population size and area on total provincial GHG emission. Correlation coefficients with higher than 0.75 (with p < 0.01) indicates a strong positive correlation (Fig 4. (c) and (d)), while fitting the degree of urbanization rate and area (Fig. 8. (a) and (b)) was not enough to prove their relevance. The main reason might be the relatively concentrated urbanization rate (45-65%) and area (smaller than 500,000 km^2) of most provinces. Both GDP and population size had strong positive correlation with total GHG emission from China's wastewater treatment industry, the higher population size and per capita GDP are, the higher GHG emission is. Population size (R^2 = 0.9073) exhibited a more significant effect on GHG emission than GDP (R^2 = 0.8866). For example, the population of Jiangsu and Sichuan was approximately the same (just over 80 million), but the GHG emission of Jiangsu was nearly 1.22 times more than that of Sichuan.

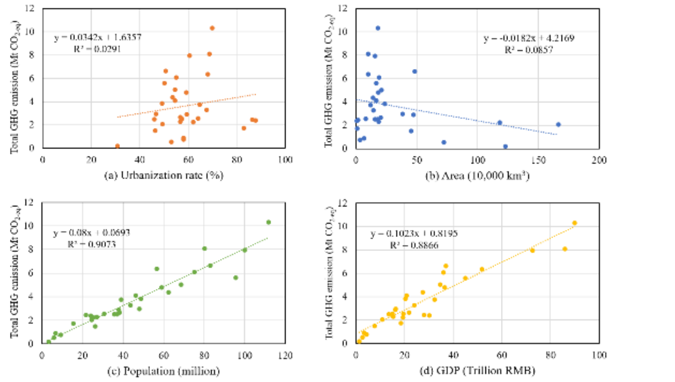

Fig.4. Linear correlation analyzing between total GHG emission and urbanization rate (a), area (b), population (c) and per capita GDP (d) of different provinces in 2017.

PCA was used to analyse the effects of regional development characteristics, such as population density, construction land, investment, daily water consumption and sewer pipeline density on GHG emission. According to the results, 57.6% of the input data's variation could be explained by the first two principal components (PC1 and PC2), and PC1 has a bigger influence on GHG emission than PC2. According to Fig.5, population density, investment and construction land had positive correlation with GHG emission, while daily water consumption and sewer pipeline density showed negative effects. The data of most non-first-tier cities with less development is mainly concentrated on the original point, presenting a vertical strip distribution, which means they are basically unaffected by these factors. In contrast, in most developed cities, such as Beijing (BJ), Chongqing (CQ), Wuhan (WH), Chengdu (CD), Shenzhen (SZ) and Guangzhou (GZ), are far away from the coordinate X axis, indicating that construction land and investment influenced significantly on GHG emission. This is mainly because there are more WWTPs in metropolis with more construction land, in highly developed cities with higher investment. It is interesting that Hanzhong (HZ') is a medium-size city, but the investment was quite large, resulting in higher correlation between affecting factors and GHG emission. On the Y axis, Ningdong (ND) and Sanya (SY) were most affected, which is mainly attributed to their location and industrial structure.

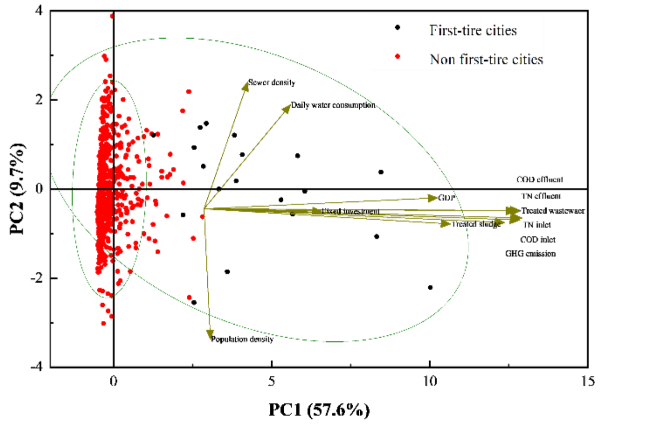

Fig.5. Principal component analysis.

3.2.2 Effect of operational conditions

The effects of influent and effluent quality on total GHG emission are presented in Fig.6. As mentioned above, off-site GHG emission accounted for 90.58% of total emission, so the effects of four indexes on these two categories are similar. The higher $COD_{influent}$, $TN_{influent}$, $COD_{effluent}$, and $TN_{effluent}$ concentration, the higher total and off-site GHG emission. Similarly, the highest on-site GHG emission is obtained with the largest and $TN_{influent}$, but $COD_{influent}$ ranged from 0.4-0.6 Mt emitted more on-site GHGs than the two groups with higher $COD_{influent}$ (0.6-0.8 Mt and 0.8-1 Mt). When effluent COD is in the range of 0.4-0.6 Mt and TN in the range of 0.1-0.2 Mt, the highest on-stie GHG emission was generated. This means that stricter discharge standards with higher discharge quality have limited influence on on-site GHG emission. Besides, all indexes exhibited low direct but high indirect GHG emission due to more complicated sources of indirect GHG emission (energy and chemical consumption, sludge transportation and disposal).

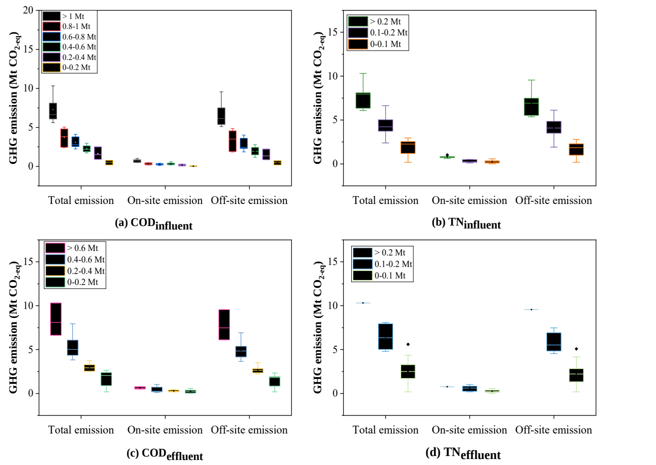

Fig.6. The relationship between GHG emission and $COD_{influent}$ (a), $TN_{influent}$ (b), $COD_{effluent}$ (c), and $TN_{effluent}$ (d).

Although the GHG emission at WWTPs was calculated by various wastewater treatment technologies, the electricity consumed at each WWTP was quite different. Moreover, the WWTP scale may also affect the GHG emission. Therefore, the relationship between various scales and technologies of WWTPs and the GHG emission intensity at WWTPs was studied, as shown in Fig. 9. The results indicated that there was no statistically significant difference between GHG emission intensity at WWTPs and scale with the capacity larger than 10,000 t/d, but the GHG intensity for WWTPs with scale < 10k m^3/d is nearly twice higher than other scales. This may be attributed to indirect emissions or electricity consumption by fluctuations in influent loading and the lack of continuous monitoring (Xi et al. 2021). However, from analysis of mean value, the larger WWTP scale (smaller than 40,000 t/d), the lower the GHG emission intensity. In contrast, technology selection affects greatly on the intensity of GHG emission, and the mean intensity of six technologies is in the order: AO (0.776 kg CO_2-eq/m^3) > SBR (0.636 kg CO_2-eq/m^3) > MBR (0.603 kg CO_2-eq/m^3) > biofilm (0.502 kg CO_2-eq/m^3) > AAO (0.373 kg CO_2-eq/m^3) > OD (0.371 kg CO_2-eq/m^3). The result is quite different from the study reported by Bao et al. (2016), they found that the total GHG emission from a SBR-based WWTP was 53.07% (m^3 treated wastewater) higher than an AO-based WWTP, which may be attributed to higher electricity intensity of SBR. Moreover, Liao et al. (2020) found that AAO-MBR technology has the highest total GHG emission intensity (0.79 t CO_2-eq/m^3 wastewater), primarily due to its large electricity intensity required. This reason may be because AAO and OD are the most used technologies at most WWTPs with larger scale in China, resulting in relatively lower GHG emission intensity, which can be proven by He et al. (2019). They found that the energy consumed from different methods are influenced greatly by the treatment capacity, and SBR is more efficient at small-scale WWTPs (<10×10^4 m^3/d), with energy consumption of 0.128-0.424 kWh/m^2, while oxidation ditch and AAO has better performance at medium-scale (10-20×10^4 m^3/d) and large-scale WWTPs (>20×10^4 m^3/d), consuming 0.126-0.434 kWh/m^3 and 0.141-0.473 kWh/m^3, respectively. Based on the above, it is efficient to choose suitable treatment capacity at WWTPs with various technologies to obtain less GHG emission intensity. Besides, when building new WWTPs, it is necessary to investigate actual treatment capacity, aiming to choose suitable wastewater treatment methods to reduce GHG emission.

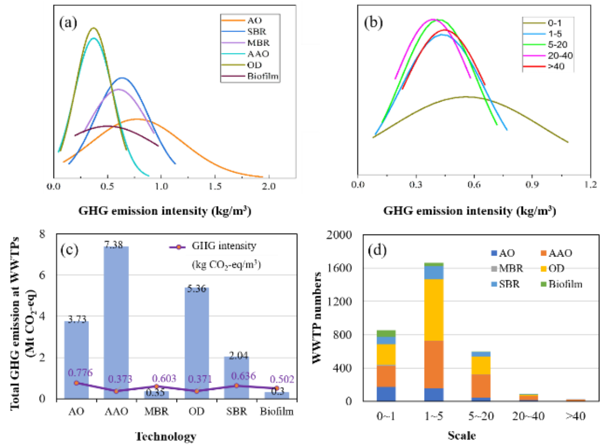

Fig.7. The distribution curve of GHG emission intensity from WWTPs: different technology (a), different scale (b); the total GHG emission and emission intensity of six technologies (c); the distribution of WWTPs with six technologies of different scales (d).

4. Challenges

4.1 Energy sufficient technologies may cause more GHG emission

With the continuous improvement of sustainable WWTPs, various technologies, such as advanced anaerobic digestion, turbine engine or fuel cell, and combined heat and power (CHP), were proposed to achieve the goal of energy self-sufficiency. However, this energy self-sufficient or ever output WWTPs, such as Strass, they may not realize 'carbon neutralization', because more N_2O emission is generated by anaerobic ammonium oxidation (ANAMMOX) process. For example, De Haas compared six different processes with life cycle assessment (LCA) and found that A/O released the least GHG emission, with 86 kg CO_2-eq/mL wastewater, while the side stream of ANAMMOX emitted the highest GHG emission (De Haas, 2018). Although new technologies bring some benefits, such as energy self-sufficiency, if the problem of N_2O emissions cannot be solved, this model is far from being "environment-friendly". Therefore, how to solve the N_2O problem in terms of technology development in the future is the next step of ANAMMOX.

4.2 Stricter discharge standards may increase more GHG emission

In recent years, more and more high "local discharge standards" have come out. For example, the government in Shenzhen city has just announced that the water quality of main rivers should meet the requirements of surface water IV (COD≤30, BOD≤56, P≤0.3, NH3-N≤1.5 etc.) by 2025. Generally, the stricter discharge standard means better water quality. However, when increasing nitrogen removal (especially smaller than 5 mg N/L), the amount of total GHG emissions could also significantly increase, while no clear growth on GHG release with phosphorus removal. According to Foley et al. (Foley et al., 2010), daily GHG emissions of different process and treatment standards ranged from 0.25 to 0.6 t CO_2-eq/ML, which was attributed to the nitrogen removal rate. Moreover, more chemical agents such as polyaluminium chloride (PAC) and PAM for dewatering, have been widely used in WWTPs to achieve better water quality, which not only increase GHG emission, but also produce more the sewage sludge for wastewater treatment per unit (Wang, 2018).

5. Conclusion

This paper proposed a model of ODIM combined with IPCC method to accurately estimate GHG emission from high-population density cities in wastewater treatment industry, using China as a case study. In 2017, the national GHG emission from total 4,205 WWTPs was 34.18 Mt CO_2-eq, with an emission intensity of 0.37 kg CO_2-eq/capita/day. Compared with developing countries, the proportion of GHG emission from China's wastewater treatment industry was relatively low, but the emission intensity is relatively similar. The system boundary and the unification of accounting methods will be the important premise and foundation for the future international comparison. Due to nearly 64.5% of GHG emissions being generated from electricity consumption, the mitigation strategies should be energy source shift, improved aeration, and recovered CH_4 utilization etc. According to the Hu Line, the total GHG emissions in Eastern China was approximately four times higher than that in the Western China. PCA indicated that GDP and the treated volume of wastewater had strong positive correlations to the total GHG emissions in most first-tier cities. Due to the EFs for direct CH_4 and N_2O in this study were used the average values of reported studies, but still lacking accuracy. The differences in EF are affected by various regions and operational conditions at WWTPs, so more detailed EF analysis and scenario analysis should also be further investigated. These future studies may help to formulate specific policies for GHG emission reduction with the consideration of local conditions.

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Declaration of interest statement

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper. All authors read and approved the final manuscript.

Reference

BAO, Z., SUN, S. & SUN, D. 2014. Characteristics of direct CO2 emissions in four full-scale wastewater treatment plants. Desalination and Water Treatment, 54, 1070-1079.

BAO, Z., SUN, S. & SUN, D. 2016. Assessment of greenhouse gas emission from A/O and SBR wastewater treatment plants in Beijing, China. International Biodeterioration & Biodegradation, 108, 108-114.

Chai, C.Y., Zhang, D.W. & Yu, Y.L. et al. 2015. Carbon footprint analyses of mainstream wastewater treatment technologies under different sludge treatment scenarios in China. Water, 7, 918-938.

CHEN, Y. C. & KUO, J. 2016. Potential of greenhouse gas emissions from sewage sludge management: a case study of Taiwan. Journal of Cleaner Production, 129, 196-201.

DE HAAS, D. W. 2018. The energy versus nitrous oxide emissions nexus in wastewater treatment systems. IWA Nutrient Removal and Recovery Conference. Brisbane, Australia.

FENG, Q. 2019. Camparasion of GHG emission in different sewage treatment processes (in Chinese). Sichuan Building Materials, 45.

FOLEY, J., DE HAAS, D., HARTLEY, K. & LANT, P. 2010. Comprehensive life cycle inventories of alternative wastewater treatment systems. Water Res, 44, 1654-66.

HALL, M. R., WEST, J., SHERMAN, B., LANE, J. & DE HAAS, D. 2011. Long-term trends and opportunities for managing regional water supply and wastewater greenhouse gas emissions. Environ Sci Technol, 45, 5434-40.

Hantoko, D., Kanchanatip, E., Yan, M., Lin, J. & Weng, Z. C. 2018. Co-gasification of sewage sludge and lignite coal in supercritical water for h2 production: A thermodynamic modeling approach. Energy Procedia, 152, 1284-1289.

He, Y., Zhu, Y. & Chen, J. et al. 2019. Assessment of energy consumption of municipal wastewater treatment plants in China. Journal of Cleaner Production, 228, 399-404.

KOUTSOU, O. P., GATIDOU, G. & STASINAKIS, A. S. 2018. Domestic wastewater management in Greece: Greenhouse gas emissions estimation at country scale. Journal of Cleaner Production, 188, 851-859.

KUMAR, A., THANKI, A., PADHIYAR, H., SINGH, N. K., PANDEY, S., YADAV, M. & YU, Z. G. 2021. Greenhouse gases emission control in WWTS via potential operational strategies: A critical review. Chemosphere, 273, 129694.

Li, L., Wang, X., Miao, J., Abulimiti, A., Jing, X., & Ren, N., 2022. Carbon neutrality of wastewater treatment-a systematic concept beyond the plant boundary. Environmental Science and Ecotechnology, (3), 7.

LIAO, X., TIAN, Y., GAN, Y. & JI, J. 2020. Quantifying urban wastewater treatment sector's greenhouse gas emissions using a hybrid life cycle analysis method - An application on Shenzhen city in China. Sci Total Environ, 745, 141176.

MEE, Ministry of Ecological Environment. 2017. http://www.tanjiaoyi.com/article-25419-1.html

NAYEB, H., MIRABI, M., MOTIEE, H., ALIGHARDASHI, A. & KHOSHGARD, A. 2019. Estimating greenhouse gas emissions from Iran's domestic wastewater sector and modeling the emission scenarios by 2030. Journal of Cleaner Production, 236.

NOYOLA, A., PAREDES, M. G., MORGAN-SAGASTUME, J. M. & GÜERECA, L. P. 2016. Reduction of Greenhouse Gas Emissions from Municipal Wastewater Treatment in Mexico Based on Technology Selection. CLEAN - Soil, Air, Water, 44, 1091-1098.

PARRAVICINI, V., SVARDAL, K. & KRAMPE, J. 2016. Greenhouse Gas Emissions from Wastewater Treatment Plants. Energy Procedia, 97, 246-253.

ROSSO, D., STENSTROM, M. K. & LARSON, L. E. 2008. Aeration of large-scale municipal wastewater treatment plants: state of the art. Water Sci Technol, 57, 973-8.

SHRESTHA, A., BHATTARAI, T. N., GHIMIRE, S., MAINALI, B., TREICHEL, H. & PAUDEL, S. R. 2022. Estimation of greenhouse gases emission from domestic wastewater in Nepal: A scenario-based analysis applicable for developing countries. Chemosphere, 300, 134501.

SINGH, V., PHULERIA, H. C. & CHANDEL, M. K. 2017. Estimation of greenhouse gas emissions from municipal wastewater treatment systems in India. Water and Environment Journal, 31, 537-544.

SYUC. Statistical Yearbook of Urban Construction. 2017. https://www.mohurd.gov.cn/file/old/2020/20200327/w020200327222442430525000000.xls

SYUD. Statistical Yearbook of Urban Drainage 2018. https://bbs.pinggu.org/thread-10723862-1-1.html

WANG, J., ZHANG, J., XIE, H., QI, P., REN, Y. & HU, Z. 2011. Methane emissions from a full-scale A/A/O wastewater treatment plant. Bioresour Technol, 102, 5479-85.

WANG, L. 2018. Investigation on the Sludge Yield of Municipal Wastewater Treatment Plants in Key Watershed of China (in Chinese). China water & wastewater, 34.

WANG, S., FANG, C. & WANG, Y. 2016. Spatiotemporal variations of energy-related CO2 emissions in China and its influencing factors: An empirical analysis based on provincial panel data. Renewable

Wei, L., Zhu, F. & Li, Q. et al. 2020. Development, current state and future trends of sludge management in China: Based on exploratory data and CO2-equivaient emissions analysis. Environment International, 144, 106093.

Xi, J., Gong, H. & Zhang, Y. et al. 2021. The evaluation of GHG emissions from Shanghai municipal wastewater treatment plants based on IPCC and operational data integrated methods (ODIM). Science of the Total Environment, 797, 148967.

YAPICIOĞLU, P. 2021. Minimization of greenhouse gas emissions from extended aeration activated sludge process. Water Practice and Technology, 16, 96-107.

ZHANG, Q., SMITH, K., ZHAO, X., JIN, X. K., WANG, S. Y., SHEN, J. J. & REN, Z. J. 2021. Greenhouse gas emissions associated with urban water infrastructure: What we have learnt from China's practice. WIREs Water.

Zeng, S.Y., Chen, X. & Dong, X. et al., 2017. Efficiency assessment of urban wastewater treatment plants in China: Considering greenhouse gas emissions. Resources, Conservation and Recycling, 120, 157-165.