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Developing a GIS-based model to quantify spatiotemporal pattern of home appliances and e-waste generation—A case study in Xiamen, China

Yupeng Liu [a,b,*], Lulu Song [a,b], Wanjun Wang [a,b], Xiaomei Jian [a,b], Wei-Qiang Chen [a,b,c]

[a] Key Lab of Urban Environment and Health, Institute of Urban Environment, Chinese Academy of Sciences, Xiamen, Fujian 361021, China
[b] Xiamen Key Lab of Urban Metabolism, Xiamen, Fujian 361021, China
[c] University of Chinese Academy of Sciences, Beijing 100049, China

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ABSTRACT

The growing amount of electronic waste (e-waste) poses considerable risks to the environment and human health, especially when treated inadequately. However, it is difficult to assess the significance of these issues without quantitative understanding of spatiotemporal patterns of e-waste generation. This paper proposes a new model to estimate in-use stock of electric household appliances (HAs) and e-waste generation at the level of 1 km × 1 km grids by coupling geographic information system (GIS) and material flow analysis (MFA). We took Xiamen, a rapidly urbanized city in China, as a case and the results showed that demands for HAs increased from 1980, peaked in 2016, and then declined. In-use HAs exhibited a logistic growth and significantly increased in both spatial extent and intensity. E-waste generation kept rising until 2019, and its spatial center expanded outward from downtown to suburban areas. Our study highlights that a dynamic and spatial model is useful for designing effective policies for e-waste management by providing spatiotemporal details of e-waste types and generation magnitudes and explicitly recognizing generation hotspots in cities.

1. Introduction

Household appliances (HAs), which refer to devices or equipment designed to perform a specific task, have entered innumerable homes and are essential in our lives (Chen and Graedel, 2015; Daigo et al., 2014; Haberl et al., 2019; Pauliuk and Müller, 2014; Rao and Baer, 2012). For example, refrigerators help keep food fresh, and air conditioners make homes cool in summer while warm in winter. At the end of their service lives, obsolete HAs are discarded and consequently become e-wastes (Baldé et al., 2017).

E-waste refers to all items of electrical and electronic products that have been discarded by their owners (Baldé et al., 2017; He et al., 2006; Yang et al., 2008). It covers a wide range of categories, such as temperature exchange equipment (e.g., refrigerators, air conditioners), monitors (e.g., TVs, screens of laptops), and cleaning machines (e.g., washing machines and clothes dryers) (Baldé et al., 2017; He et al., 2006; Liu et al., 2006). The inadequate disposal of e-wastes contaminates air, water, and soil, and results in serious environmental and health issues in cities (Liu et al., 2006; Zhang et al., 2011), countries (Dwivedy and Mittal, 2012; Li et al., 2019; Oguchi et al., 2008; Song et al., 2013; Steubing et al., 2010; Tong et al., 2018), even around the world (Baldé et al., 2017; Breivik et al., 2014; Hertwich et al., 2019; Li et al., 2013). These issues are hindering efforts to achieve many sustainable development and goals (SDGs), such as "good health and well-being", "clean water and sanitation", "sustainable cities and communities", and "responsible consumption and production".

Understanding both magnitudes and spatiotemporal distributions of obsolete HAs is important for e-waste management. At the global level, the import and exports trades with international trade statistics were usually used to explore e-waste generation and their international flows (Baldé et al., 2017). In 2016, 44.7 million metric tonnes of e-waste was generated in the globe, and most of them came from Asia (18.2Mt), Europe (12.3Mt), and Americas (11.3Mt) (Baldé et al., 2017). Discarded HAs (including refrigerators, air conditioners, washing machines, color TV sets, and personal computers) were predicted to keep increasing and would exceed 300 million units in the 2030 s (Habuer et al., 2014; Zhang et al., 2012). At national level, both imported/exported HAs and domestically produced products and sales were important factors to estimate HAs' stocks based on the material flow analysis (MFA) (Duan et al., 2016; Gu et al., 2016; Zeng et al., 2016). A weibull or logistic function was further used to simulate service-time of these HAs and predict their obsoletes (Zeng et al., 2016). However, these existing data

* Corresponding author at: Institute of Urban Environment, Chinese Academy of Sciences, No. 1799, Jimei Road, Xiamen 361021, China.
E-mail address: ypliu@iue.ac.cn (Y. Liu).

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sources are usually based on aggregated national or provincial statistics but can not depict detailed spatiotemporal patterns of e-waste at the city- and grid-levels, hindering efforts to understand its generation, identify major sources, and optimize corresponding dismantling capacity and local transportation network.

In this big data era, various geolocation-based data from social media are of great help to address this challenge (Xu et al., 2015). With these new spatially explicit data, the methods of analysis have also been advanced recently (Chen and Liu, 2021; Liu et al., 2019; Yeow and Cheah, 2019). Among them, combining geographic information system (GIS) with MFA is one of the popular methods (Breunig et al., 2018; Han et al., 2018; Kleemann et al., 2017; Reyna and Chester, 2014; Tanikawa et al., 2015; Tanikawa and Hashimoto, 2009). GIS can serve as both data container and processor to spatialize materials pattern (Han and Xiang, 2013), assist materials accounting (Meinel et al., 2009), and depict interregional flows (Kleemann et al., 2017; Marcellus-Zamora et al., 2016; Reyna and Chester, 2014; Tanikawa et al., 2015; Tanikawa and Hashimoto, 2009). In these cases, the GIS-based MFA model has shown promise in material stocks and flow characterization and great potential for quantifying e-waste generation over time and across space. Understanding these spatiotemporal patterns of e-waste generation help the optimization of e-waste recycling system by explicitly recognizing the primary source areas and excluding the marginal areas and optimization of logistic network (Liu et al., 2019) .

Based on new data sources and advanced methodologies, we proposed a spatially explicit model combing GIS with the stock-driven MFA to quantify spatiotemporal patterns of in-use HAs and estimate the generation of both e-waste and secondary materials. Using this new model, we aim to answer the following questions: (i) what are the spatiotemporal characteristics of in-use HAs and e-waste generation within a city? (ii) what are the mechanisms of HAs demand and obsolete generation? and (iii) how GIS-based MFA model help to optimize e-waste management system and its logistic network?

2. Materials and methods

2.1. Framework

A GIS-based model combined with stock-driven MFA was proposed in this study to simulate stock and flow of HAs and to estimate e-waste generation over time and across space (Fig. 1). The fundamental unit of the GIS-MFA model is the residential community, which is a basic unit of living for urban residents in Chinese cities. A residential community usually takes 1,000–100,000 m^2 land, contains one or more buildings in the contiguous locality with a clear boundary, lives hundreds to thousands of households at the neighborhood level. Therefore, we estimated HAs stocks for each residential community first, and then aggregated them from neighborhood level to urban accounts based on a bottom-up approach. For estimating HAs flows, we recognized three main processes that could generate demand and obsolete of HAs, including "new house", "living quality improvement", and "replacement" (Fig. 1). In the "new house" process, we assumed that home decoration in newly built communities would generate demands and inputs of HAs (Fig. 1). For existing communities, dwellers would also ask for purchasing new HAs to improve their living quality and thus generated HAs inputs, which denoted as the "living quality improvement" process (Fig. 1). The "replacement" process represented the renovation of HAs because the old ones were at the end of their service lives and therefore generated both inputs and outputs of HAs (Fig. 1). Finally, stocks and flows of four primary constituent materials in HAs, including plastic, iron, copper, and aluminum, were estimated by total units of HAs and corresponding materials intensities (Fig. 1).

2.2. Stocks and flows quantification

2.2.1. In-use HAs stock

In-use HAs stock is estimated by multiplying the total number of households in each community and the average ownership of in-use HAs per household:

$$HAS_m^t = \sum_i F_{i,n}^t \times AI_m^t \tag{1}$$

where *HAS* is the total unit of in-use HAs in the community *i* for type *m* at year *t*, *F* is the total number of households in the community *i* (year of built $n < t$), *AI* is the average ownership of in-use HAs per household for type *m* at year *t* (Fig. S1). *AI*'s value refers to the urban–rural-weighted ownership of in-use HAs per household (Fig. S1 and Fig. S2).

2.2.2. Has demands and inputs

Three processes could generate HAs demands and inputs, including "new house", "living quality improvement", and "replacement":

$$HAI_m^t = HAI\_new_m^t + HAI\_imp_m^t + HAI\_rep_m^t \tag{2}$$

where *HAI* is total HAs input for type *m* at year *t*, *HAI_new* represents HAs input by purchasing new HAs from newly built communities and home decoration, *HAI_imp* represents HAs input for living quality

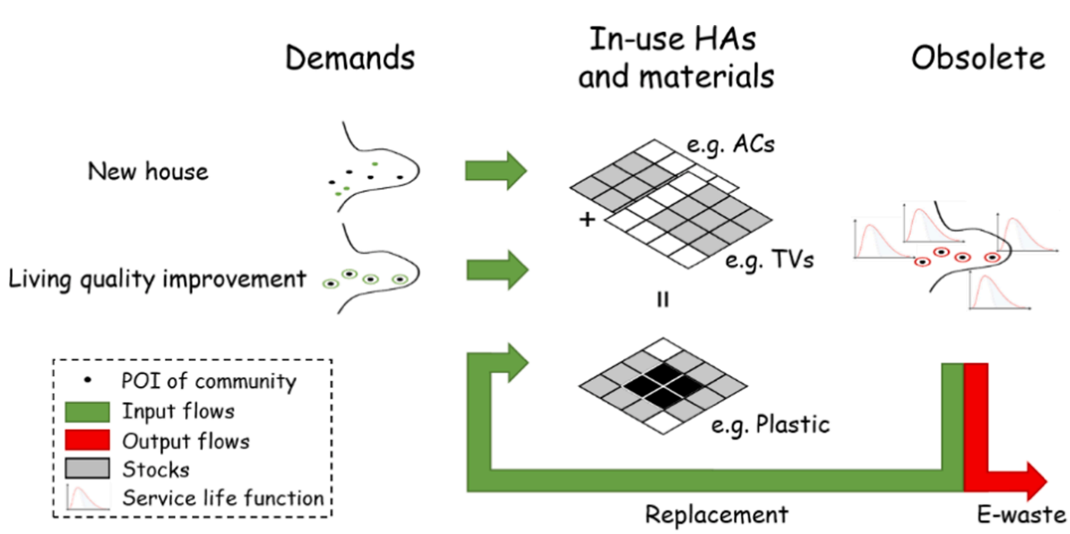

Fig. 1. A framework for simulating in-use, demand, and obsolete household appliances and stocks and flows of materials in space and across time. POI - points of interest; ACs - air conditioners; TVs - televisions.

improvement, *HAI_rep* represents HAs input for replacement of obsolete HAs.

$$HAI\_new^t_m = \sum_i F^t_{i,t} \times AI^t_m \tag{3}$$

$$HAI\_imp^t_m = \sum_i F^t_{i,n} \times \left(AI^t_m - AI^{t-1}_m\right) \tag{4}$$

$$HAI\_rep^t_m = HAO^t_m \tag{5}$$

HAI_new equals the total number of households (*F*) in newly built community *i* at year *t* (year of built $n = t$) times the average ownership of in-use HAs per household *(AI)* for type *m* at year *t* (Eq. (3)). *HAI_imp* equals the total number of households (*F*) in the existing community *i* (year of built $n < t$) times changes of the average ownership of in-use HAs per household (ΔAI) for type *m* from year *t-1* to *t* (Eq. (4)). *HAI_rep* equals to the total unit of obsolete HAs (*HAO*) for type *m* at year *t* (see in Section 2.2.3).

2.2.3. Obsolete HAs and outputs

At the end of service lives, obsolete HAs generate both output flow (HAO) and new purchase demand for replacement. We assume that a 1:1 replacement happens in the same year due to necessity and convenience of HAs in livings (Stephan and Athanassiadis, 2018).

$$HAO^t_m = \sum_i^{j=n\to t} HAI^j_{i,m} \times D^{t,j}_m = HAI\_rep^t_m \tag{6}$$

$$D^{t,j}_m = \frac{1}{SD_m\sqrt{2\pi}} \cdot e\left(-\frac{[(t-j) - Mean_m]^2}{2SD^2_m}\right) \tag{7}$$

HAO equals HAs input (*HAI*) in the community *i* for type *m* at the year of purchase *j* ($n \leq j < t$) times the demolition rate (*D*) of HAs type *m* at year *t*. *D* is the demolition rate of HAs type *m*. Its value refers to a function of the average lifespan (*Mean*) and standard deviation (*SD*) of HAs type *m*. The values of the average lifespan (*Mean*) and standard deviation (*SD*) for five types of HAs are shown in Table 1. A three-year running mean is used to reduce the uncertainties due to delays of home decoration and HAs replacement.

2.3. Stocks and flows of constituent materials in HAs

Material stocks (*MS*), input flows (*MIF*), and output flows (*MOF*) are estimated by multiplying the total units of HAs and constituent material intensities:

$$MS^t_s = \sum_i HAS^t_{i,m} \times MI_{m,s} \tag{8}$$

Table 1
The average lifespan (*Mean*) and standard deviation (*SD*) of household appliances in Xiamen, China.

Household appliances (*m*)	Average lifespan (years)	Standard deviation (% of mean)	References
Refrigerator	14	10	1–7, *
Air conditioner (AC)	7	15	1–4, 6–7, *
Washing machine (WM)	12	15	1–4, 6–7, *
Television (TV)	11	20	1–4, 6–7, *
Personal computer (PC)	5	20	1–4, 6–7, *

1. (Baldé et al., 2017), 2. (Dwivedy and Mittal, 2012), 3. (He et al., 2006), 4. (Li et al., 2019), 5. (Liu et al., 2006), 6. (Oguchi et al., 2008), 7. (Yang and Kohler, 2008), * survey in local household appliances dismantling company in Xiamen, China.

$$MIF^t_s = \sum_i HAI^t_{i,m} \times MI_{m,s} \tag{9}$$

$$MOF^t_s = \sum_i HAO^t_{i,m} \times MI_{m,s} \tag{10}$$

HAS, HAI, and *HAO* are total units of in-use stock, input, and output of HAs for type *m* in the community *i* at year *t*, respectively. *MI* represents the intensity of constituent materials for HAs' type *m* (Table 2).

2.4. Study area and data compilation

We selected Xiamen, a city formerly known as Amoy as the study area, which is a livable and loveable city with lengthy seaside, Buddhist temples, art galleries, and beautiful parks (Fig. 2). Xiamen has a total of ~ 1700 km^2 area, which is comprised of several islands, and houses more than 4 million residents, resulting in a relatively high density of ~ 2400 person/km^2 (Fig. 2). The old town of Xiamen was located at the southernwest part of the Xiamen Island and the Gulangsu Island in a long history. During1980-1990 s, urban area expanded northward to the Huli district, the middle and northern part of the Xiamen Island. Since 2000 s, urban area has expanded across sea and to the mainland part of Xiamen, including the Haicang, Jimei, Xiang'an, and Tong'an districts. Rapid urbanization in Xiamen leads to massive demands for HAs and generate substantial e-wastes, which poses considerable pressure on the environment and human health.

To characterize spatiotemporal dynamics of HAs and materials, GIS was used to process data from various sources. The geo-referenced points of communities were collected from https://www.metrodata.cn/metrodatateam (Fig. 2b). The built year and household numbers for each community were collected from commercial real-estate websites (e.g., Lianjia, Fang.com). Average ownership of in-use HAs per household and constituent material intensities for five types of HAs were collected from statistics and local surveys. The GIS-MFA model was run from 1970 to 2019 in Xiamen with a ten-year spin-up.

3. Results and discussion

3.1. Temporal changes of HAs' stocks and flows

Total HAs demands (inputs) in Xiamen increased from 1980, peaked in 2016, and then declined in the following years until 2019 (Fig. 3). The new house process dominated the total HAs demands before 2000, followed by the living quality improvement process (Fig. S3). After 2000, demands from the replacement of obsolete HAs increased rapidly (Fig. 3) and finally took more than half of the total demands (Fig. S3).

The reverse U-shaped tendency of HAs inputs resulted in a logistic growth of in-use HAs stocks in Xiamen during 1980–2019 (Fig. 3). From 1980 to 1990, the increase in in-use HAs stocks was steady but slow (Fig. 3). After 1990, in-use HAs stocks increased rapidly and reached more than 4 million units in 2010 (Fig. 3). During 2010–2019, in-use HAs stocks declined slightly first, but increase again soon and finally

Table 2
Materials intensities for typical household appliances in Xiamen, China.

Household appliances (*m*)	Iron (kg/unit)	Copper (kg/unit)	Aluminum (kg/unit)	Plastic (kg/unit)
Refrigerator*	38.6	4.0	3.0	9.0
Air conditioner (AC) *	19.5	4.9	4.0	14.6
Washing machine (WM) *	5.0	0.4	0.3	16.0
Television (TV) *	1.4	0.6	0.4	3.5
Personal computer (PC) *	11.0	3.0	2.0	1.0

* Survey in local household appliances dismantling company in Xiamen, China.

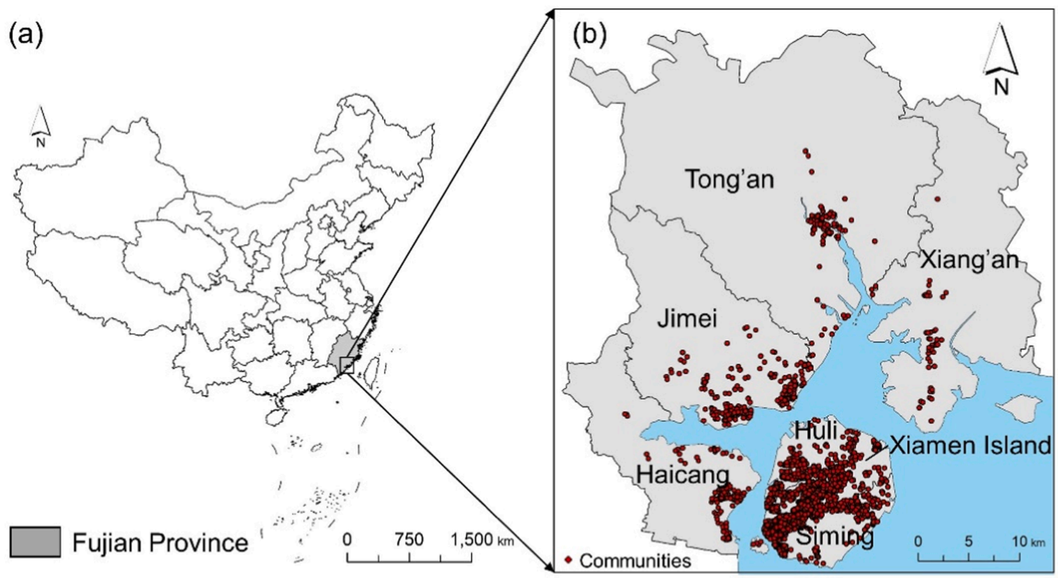

Fig. 2. The study area in Xiamen, Fujian Province, China. Dots represent residential communities in Xiamen.

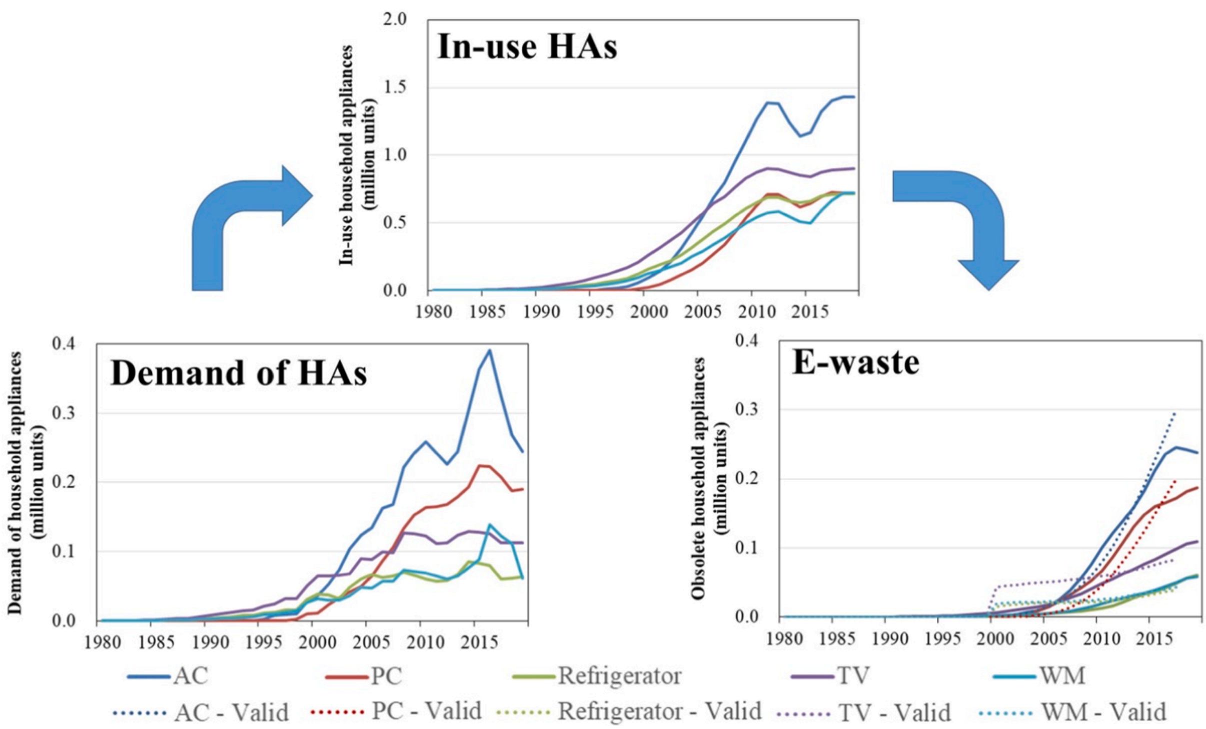

Fig. 3. Temporal dynamics (solid lines) of in-use, demand, and obsolete household appliances (HAs) in Xiamen, China. Dotted lines represent cross-validations of e-waste generation based on survey data in Xiamen's urban statistics and estimated methods based on Gu et al., 2016 and Zeng et al., 2016. AC - air conditioner; PC - personal computer; TV - television; WM - washing machine.

peaked at about 4.5 million units in 2019 (Fig. 3). A trade-off between the decrease in average ownership of in-use HAs (Fig. S1 and Fig. S2) and the increase in demands from newly built communities and home decoration led to the fluctuation of in-use HAs stocks between 2010 and 2015 (Fig. 3).

The rapid growth of e-waste generation has occurred since 2010, but growth patterns varied among five types of HAs with acceptable errors (TV: +3.82%, Refrigerator: +0.09%, WM: +0.16%, AC: −3.76%, PC: +10.79%) (Fig. 3). Specifically, obsolete refrigerators, WMs, and TVs kept increasing until 2019 (Fig. 3). Obsolete PCs showed a logistic growth and began to saturate at the level of about 0.2 million units per year (Fig. 3). Obsolete ACs have exceeded 0.2 million units per year since 2015, peaked at about 0.25 million units in 2017, and then declined slightly (Fig. 3). Both the peak of HAs inputs during 2014–2016 and the relatively shorter life spans of in-use PCs and ACs (5 ~ 7 years) than other types of HAs resulted in the saturation trend of e-waste generation in recent years. Consequently, total e-waste generation in Xiamen reached 0.65 million units in 2019 (Fig. 3), which contained about 20,000 tonnes of secondary materials, including 51% of iron, 32% of plastic, 10% of copper, and 7% of aluminum (Fig. S4).

3.2. Spatial patterns of HAs' stocks and flows over time

The spatial center of main HAs demands and related materials input flows generated at the downtown area (the southwest part of the Xiamen Island) before 1990 and then moved to the suburban area of Xiamen (the middle part of the Xiamen Island) (Fig. 4 and Fig. S6). The movement of the spatial center of main HAs demands indicated that fast outward growth of urbanization and a trend toward saturation of old city development (Fig. 4 and Fig. S6). During 2000–2010, the Haicang district, as a new developing urban center on the mainland part of Xiamen, showed strong HAs demands and increased materials input flows due to the construction of new residential communities and transportation infrastructures (e.g., the Haicang Bridge connects the old city on the Xiamen Island and new developing urban center on the mainland part of Xiamen) (Fig. 4 and Fig. S6). After 2010, strong HAs demands and related materials input flows expanded widely to the other areas on the mainland part of Xiamen, including Jimei, Tong'an, and Xiang'an, where were listed as key construction areas by the government (Fig. 4 and Fig. S6).

Continuous HAs inputs ensured that in-use HAs and materials stocks kept increasing in both spatial extent and density (Fig. 4, Fig. S5 and S6). In the 1980 s, only the downtown area owned many in-use HAs and materials stocks (Fig. 4 and Fig. S6). From 1990 to 2000, more HAs and materials stocks were accumulated in the suburban area than those in the downtown area due to the rapid development of new economic and technological districts (e.g., Xiamen Hi-tech Industrial Development Zone was established in 1990) (Fig. 4 and Fig. S6). After 2000, in-use HAs and materials stocks not only kept increasing in the downtown area but also proliferated in the suburban area and new developing urban centers on the mainland part of Xiamen (Fig. 4 and Fig. S6).

The spatial extent and magnitude of e-waste generation showed roughly a 10-year delay to the HAs input (Fig. 4). Before 2000, e-wastes generated merely in the downtown area (Fig. 4). Then, the spatial center of e-waste generation moved to the suburban area during 2000–2010 due to the rapid urbanization and industrialization that started from the 1990 s (Fig. 4). After 2010, the spatial extent of e-waste generation expanded outward followed a further urban expansion and cross-island development in Xiamen since the new century (Fig. 4).

3.3. Advances and uncertainties of the model

The GIS-based MFA model performed well in characterizing spatio-temporal patterns of in-use stock of HAs and e-waste generation in 1 km $\times$ 1 km grids. Based on the degree of spatial detail, the state-of-the-art MFA models could be divided into three categories: non–, quasi-, and spatially explicit models. Non-spatial models have been widely used in analyzing, simulating, and predicting time-series changes of HAs for a city (Liu et al., 2006; Zhang et al., 2011), a country (Agency, 2001; Habuer et al., 2014; Li et al., 2019; Steubing et al., 2010; Zhang et al., 2012), even globe (Baldé et al., 2017). As a significant update, combining GIS makes MFA be a quasi-spatially explicit model. It enables MFA to quantify heterogeneous patterns of HAs stocks (Fig. 4 and Fig. S5) and various contents of materials flow within a city (Fig. S6). In this close coupling approach, GIS is treated not only as a data container but also as a processor participates in processing material stocks and flows. The spatiotemporal maps of HAs' stock and e-waste generation predicted by the GIS-based MFA model are key foundation for further designing local recycling facilities and optimizing management system (see in Section 3.5).

The uncertainty analysis of the model mainly focuses on the dependence of HAs' demands and abandonment and the effect of technological innovation. In the model, HAs' demands mainly come from three sources, including the newly built communities and home decoration, living quality improvement, and replacement of obsolete HAs (Fig. 1). For demands from newly built communities and home decoration, we assume every new apartment would be sold in the year of built and thus generates demands for purchasing new HAs. This assumption makes HAs demands in a newly built community release in the year of built and hence results in an overestimation. Therefore, we used a three-year running mean to reduce this uncertainty. In the using stage, the ownership of HAs could be affected by the family's income and personal preference. For example, a family lives in an apartment with two bedrooms and one living room (it is the most popular style of apartment in Chinese cities). In that situation, we could assume that the number of air conditioners in this family is less than four – one for the living room and two for the bedrooms. In most cases, this family shares only one refrigerator and washer machine. However, the numbers of in-use TVs and PCs could vary based on the status of income, job, and personal preference, and therefore have greater uncertainties than other types of HAs. For estimating quantities of obsolete HAs and e-waste generation, we used the normal distribution function to estimate the discarding probability of in-use HAs, which can avoid a potential overestimation of Weibull distribution since a product could last longer in developing countries than in developed countries because people repair products more often (Baldé et al., 2017). Moreover, the service lifespan of HAs is another critical parameter to estimate e-waste generation. Extending or shorting one year of service life leads to changes in $\pm$ 6420 units of obsolete refrigerators, $\pm$36300 units of obsolete ACs, $\pm$6950 units of obsolete WMs, $\pm$12300 units of obsolete TVs, and $\pm$ 41300 units of obsolete PCs per year in Xiamen, which take about 1%, 6%, 1%, 2%, and 7% of annual e-waste generation for each HAs type, respectively.

Technological innovation can speed up the turn-over rates of HAs and alter types and proportions of constitution materials. To benefit from the technological innovation and falling prices of HAs, customers change HAs regularly and often before it breaks. For example, TV broadcasting switch from analog to digital single makes many customers choose to upgrade their TVs and obsolete older ones even if they do not break (Baldé et al., 2017). These technical upgrades accelerate switch-over rates of HAs, shorten replacement cycles, and finally affect the estimation accuracy of discarding probability by a normal or a Weibull distribution function. Meanwhile, technological innovation can also affect the simulation accuracy by altering constituent materials in HAs. For example, the popular style of TV set has changed from the cathode ray tube (CRT) to light-emitting diodes (LED) in recent years that leads to a significant decrease in iron intensity. These changes ask for a more detailed inventory of constituent materials that should be assimilated into this model according to the sub-classification of HAs and alternative materials.

3.4. Model's future

Based on the degree of spatial detail, our GIS-based MFA model still belongs to the quasi-spatially explicit category. Lack of one or more variables that is a function of space or can be related to spatial processes (e.g., materials exchanges between neighbors) becomes the main barrier to obstruct the evolvement from a quasi-spatially to spatially explicit model. A spatially explicit MFA model should, theoretically, describe HAs flows from local to another place (e.g., transporting e-waste from a demolishing building to a formal dismantling factory). However, these flows or processes are usually generated every day or month, and therefore mismatch with the annual or decadal estimation of e-waste generation by the service life model. These non-negligible spatiotemporal flows interfere with the accuracy of stock and flow estimations of HAs.

Furthermore, the forecasting capacity should be incorporated into the model and be used to create processes of e-waste generation on space. Fortunately, previous studies have widely demonstrated the mechanisms of HAs' demand and abandonment and revealed main drivers, including social factors, such as the change in population and its lifestyle and economic factors (e.g., GDP and income) (Bergsdal et al., 2007; Hu et al., 2010a; Hu et al., 2010b; Müller, 2006; Yang and Kohler,

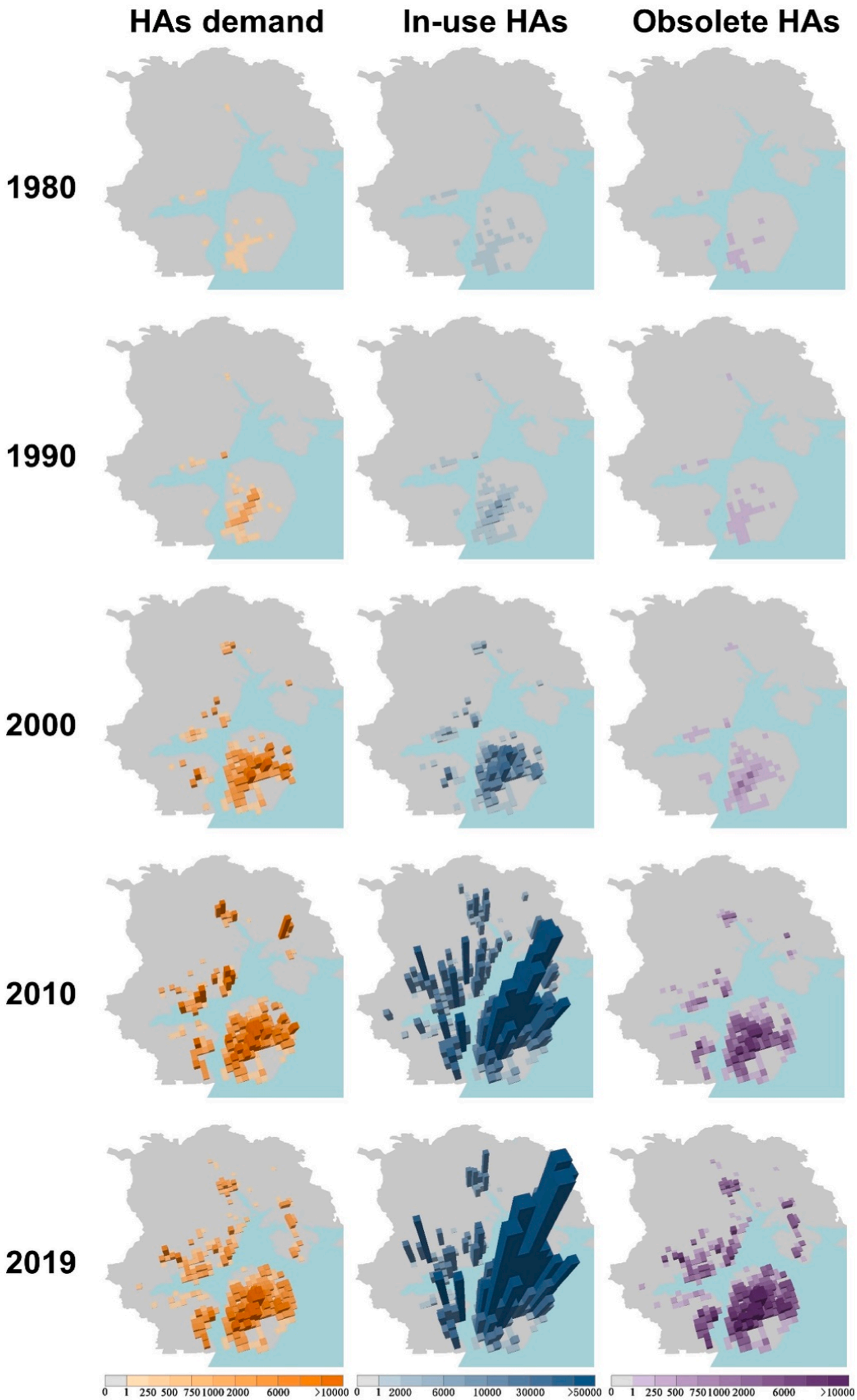

Fig. 4. Spatiotemporal demand, in-use, and obsolete household appliances in Xiamen, China.

2008). However, existing predictions of e-waste generation merely focus on the country and city levels. To explicitly understand where is the hotspot of e-waste generation in the future, country- or city-level prediction of e-waste generation should be further scaled down in finer spatial scales. Two potential approaches could help to achieve this goal, they are the similarity-based and the dynamic model-based scaling approaches. The similarity-based scaling methods seek scaling relations of material stocks between the city level and more detailed levels (e.g., community or individual building level) based on the example statistical or empirical regressions. These statistical (or empirical) relations refer to urban spatial planning, detailed information of population and income for communities, and another socioeconomic status. Dynamic model-based scaling methods proceed deductively with mechanism analysis and emphasize processes (Wu, 1999). For example, the land use/cover changes (LUCC) model could be coupled with the MFA-GIS model to predict the birth and decay of communities in cities and simulate population dynamics. With the prediction capacity, the MFA-GIS model should be more useful for understanding the mechanisms of materials stocks and flows and designing effective policies for e-waste management.

3.5. Policy implications for e-waste management

The spatial features of in-use HAs and e-waste generation are key information to design recycling facilities planning and optimize the e-waste management system. In Xiamen, many spatial hotspots of e-waste generation have revealed in Fig. 4. For example, the Siming district, as the old city and downtown area of Xiamen, had the highest e-waste generation rate (or density, >6,000 even >10,000 unit per km^2), followed by the Huli district (1,000 ~ 6,000 unit per km^2), where was a new economic and high-tech district developed since 1990s. After 2010, many local hotspots occurred on the mainland part of Xiamen due to the new developing plan by the government (Fig. 4). These hotspots are potentially key areas for planning local recycling facilities or logistic centers. Meanwhile, potential quantity of e-wastes generated in next few years could further be predicted by the model, which provides temporal information to help plan corresponding dismantling or transportation capacity. Both these spatial and temporal dynamics of e-wastes can certainly support a city-level management planning.

Scaling-up to regional and national levels, China now has established a formal recycling system followed by a provincial territory-based approach to dismantle e-waste by local companies and facilities (Tong et al., 2018; Yu et al., 2010). However, this system is now facing a deficit which is the recycling cost of e-waste from the certified recyclers higher than the dismantling subsidy from the government (Tong et al., 2018). Toward this problem, a spatially explicit model helps to characterize spatial patterns of in-use HAs and e-waste generation over time and provides two potential optimization schemes for improving the e-waste recycling management through optimization of the spatial distribution of recycling capacity and improvement of transportation efficiency of recycling network. The first scheme aims to optimize current provincial territory-based and self-sufficient dismantling capacity by creating a spatially explicit inventory of e-waste generation. Based on detailed spatial patterns of e-waste generation, cross-regional recycling companies could be established to collect e-waste across provinces according to the trade-off between transportation cost and dismantling subsidy. For the second scheme, detailed flows of e-waste transportation could bridge the gap between e-waste generation and local recyclers and form a hierarchical transportation network at the country level (Tong et al., 2018). The development of advanced equipment and new technologies, such as cheaper digital chips for monitors and expanding coverage of the internet of things (IoT), are of great help to monitor e-waste transportation, understand the network of materials flows, and finally improve transportation efficiency and lead to cost declining.

Theoretically, this model could further be used in any cities or regions which the government or stakeholders have interest in. Spatiotemporal patterns of HAs' stock and e-waste predicted by the GIS-based model contributes in two key processes in e-waste management. The first is to help the government or stakeholders to create detailed maps of e-waste generation, which is the foundation to recognize primary source areas and exclude the marginal areas. The second is to help design a new or optimize the existed logistic network and treatment facilities based on the trade-off between dismantling benefit and transportation cost. Further spatial analysis (e.g., service-radius of facilities, shortest-path of transportation) could be conducted based on these maps of e-waste generation and facilities' distribution and finally support decision-making in waste management.

4. Conclusions

A new model was proposed to combine GIS with MFA in this study and be used to estimate stocks and demands of HAs and e-waste generation over time and across space. Based on the good performance of the GIS-MFA model, it is the first time to have the capacity to map stocks and demands of HAs and e-waste generation in 1 km × 1 km grids. Detailed spatiotemporal patterns of in-use HAs and e-waste generation are essential information to optimize the network of recycling facilities and their treatment capacities. Using this GIS-MFA model at the broader extents, even the national scale, could further guide updates of the current provincial-based and self-sufficiency e-waste management system in China by explicitly recognizing the primary source of waste generation and characterizing the magnitude and direction of waste flows across space.

Declaration of Competing Interest

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.

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Appendix A. Supplementary material

In-use household appliances intensities, spatiotemporal patterns of household appliances and constitute materials.

Supplementary data to this article can be found online at https://doi.org/10.1016/j.wasman.2021.10.039.

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