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Understanding the trade-offs of national municipal solid waste estimation methods for circular economy policy

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ABSTRACT

Policies embracing circular economy concepts have taken hold in national legislation around the world. As the number of governments and organizations adopting circular economy policies increases, so does the need for accurate and timely measurement of material resource flows. Since many countries do not have access to centrally reported municipal solid waste (MSW) data, estimation and modeling are critical in evaluating circular economy policy effectiveness. The purpose of this paper is to examine three modeling approaches estimating national MSW data in the United States, including industry-based material flow analysis, waste-extended input-output modeling, and aggregated regional waste reporting. We establish five criteria to guide the analysis through the context of policy monitoring (data quality, flow totality, update frequency, sensitivity to disruption, and product granularity) and use these criteria to analyze and score each model. We then use a literature search to identify five, internationally-implemented options for circular economy policy and determine the data and modeling components that are most helpful in evaluating policy effectiveness. Finally, we provide a crosswalk of the model scores and policy needs to inform the suitability of model selection by policy type. We found that data quality and update frequency are identified as critical components for evaluating circular economy policies within the models evaluated, and can both be fulfilled by aggregated regional waste reporting. Flow totality, sensitivity to disruption, and product granularity requirements vary by both model and policy types. While none of the evaluated models satisfy the combination of requirements for any of the five policies, industry-based material flow analysis offers flow totality for extended producer responsibility, landfill bans, and recycling rate target policies that typically require it. The waste-extended input-output model can provide disruption sensitivity and product granularity as needed for policies like minimum recycled content and market restrictions. Policy developers in areas where strong centralized data collection is not an option should design policy action(s) with modeling tradeoffs in mind, including the potential hybridization of modeling approaches that may provide the most accurate national MSW estimates.

1. Introduction

The idea of a closed-loop material system was first introduced in 1966 by the American economist Kenneth Boulding in his realization that Earth should be viewed as a spaceship where resources are not unlimited and must be viewed from a cyclic perspective (Boulding, 1966). The Brundtland Report of 1987 effectively embraced the loop affirming the need at an international level by calling for the pursuit of sustainable development, emphasizing the need for a system-wide, international approach focused on trade, capital, and technology flows rather than leaving individual countries to develop such alone (Brundtland, 1987). As policy to support sustainable development evolved, it stimulated additional data and new measurement tools such as life cycle assessment (LCA) (International Organization for Standardization, 2006) and material flows analysis (MFA) to support them.

The current-day concept of circular economy (CE) as the embodiment of a closed-loop system has gained international traction in recent years. Although there is no standardized definition for the term "circular

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economy" (Kirchherr et al., 2017), common principles have emerged: closed-loop cyclicality, regenerative systems, and minimization of waste (Cramer, 2022). The 2020 United States' Save our Seas 2.0 Act supports these principles by defining CE as "an economy that uses a systems-focused approach and involves industrial processes and economic activities that—(A) are restorative or regenerative by design; (B) enable resources used in such processes and activities to maintain their highest values for as long as possible and (C) aim for the elimination of waste through the superior design of materials, products, and systems (including business models)." It embraces the need to shift from the model in which resources are extracted, manufactured into products, and then become waste to one in which consumption is decoupled from economic growth (EMF, 2022). A CE approach strives to reduce overall use and resource intensity of materials, and "recapture 'waste' as a resource to manufacture new materials and products" (USEPA, 2021). This approach to materials management is being embraced by a growing number of countries around the world (Fitch-Roy et al., 2021; Cramer, 2022).

China is recognized as the first country to have incorporated CE into national policy; after the China Circular Economy Promotion Law of 2008, other national governments followed suit (Bening 2021, Fitch-Roy et al., 2021). Among them, South Korea's 2016 Framework Act on Resource Circulation, Italy's 2017 'Towards a Model of Circular Economy for Italy', France's 2018 Circular Economy Roadmap, and India's 2019 National Resource Efficiency Policy (OECD, 2021). The European Union (EU) introduced the Circular Economy Action Plan (CEAP) in March 2020 (EU, 2020). Japan announced its Partnership on Circular Economy in March 2021 (Japanese Partnership for Circular Economy, 2022), and Chile advanced South American CE efforts by adopting the Roadmap for a Circular Chile in July 2021 (Chile Ministry of Environment, 2021).

Before governments can effectively manage resource use, material use and management must be accurately measured. As the number of nations and governments adopting CE policies increases, so does the need for accurate and timely material-specific measurement of resource flows. While data gathering in related research is focused on public perception of CE, this paper is focused on the measurement and estimation of municipal solid waste (MSW) generation and management for use in evaluating national policy effectiveness (Almulhim and Abubakar 2021). Governments and organizations with centralized waste reporting requirements of sufficient scope, such as the EU, are in a better position to track efficient material use and evaluate the effectiveness of implemented CE policies (EU, 2011). However, countries without centralized material reporting mandates are at a disadvantage for understanding and improving the circularity of material flows. For example, the United States has a centralized or federally mandated data repository for reporting and tracking nationally defined hazardous waste, but a similar system is not used for non-hazardous solid waste (USEPA, 2022). While the mandated hazardous waste data are important for knowing what is generated and managed, as well as protecting human health and the environment from their hazards, their specificity and low volumes are insufficient for broad CE considerations. Data describing the higher volumes of non-hazardous solid waste, including MSW, can be more beneficial for CE policy because these waste streams encompass the broader materials flowing through an economy. If MSW data are unavailable for a country, it becomes necessary to develop a means to estimate the information.

1.1. Approaches to estimate MSW generation and management

For this study, MSW consists of post-consumer items such as appliances, tires, batteries, newspapers, books, magazines, containers and packaging, food wastes, yard trimmings, and miscellaneous organic wastes collected from residential, commercial, and institutional sources (e.g., businesses, schools, hospitals, etc.). The materials associated with these products include paper, glass, metals, plastic, textiles, rubber, wood, and others. The end-of-use management pathways for these materials refer to a variety of disposal and recycling methods for MSW, including but not limited to landfilling, combustion with energy recovery (municipal waste energy), mechanical recycling, composting, and anaerobic digestion, with new pathways continuing to emerge to address specific material challenges (USEPA, 2022a). While others may include Construction and Demolition (C&D) Sector materials (Superti et al., 2021), C&D waste is excluded here because of how it is managed within the target location of this study.

MSW estimation models can be classified broadly into two conceptual categories: "bottom-up" measurement-based models and "top-down" material balance models derived from industrial statistics. The terms top-down and bottom-up have been previously used when characterizing material measurement techniques, such as in Wuhan, China (Zhou et al., 2021). In this study, bottom-up measurement refers to models relying on data collected by field sampling or surveying of relevant material management pathway facilities, including landfills, material recovery facilities (MRFs), municipal waste-to-energy facilities, etc. In essence, bottom-up models use data from the point when a material enters the post-consumer-use phase of the material life cycle. Examples of bottom-up MSW models can be found in the United States with voluntary regional reporting efforts from state environmental organizations (SEOs) (ADEQ, 2018; MPCA, 2022; VDEC, 2019) and non-governmental organizations (NGOs) (EREF, 2016). SEOs and NGOs may conduct waste audits or waste characterization studies to determine the materials composition of various MSW management pathways. These data can be aggregated from the sub-regional/municipality level to regional/state and national estimates of MSW tonnages to guide material management policy development and implementation. However, frequent updates with this process can be time-consuming and financially intensive to maintain. Bottom-up modeling techniques are represented in Fig. 1 as funneling MSW data from end-of-use management pathways up through regional agencies and aggregated for consolidated reporting.

Conversely, top-down modeling generally relies on data from the manufacturing phase of a material's life cycle as the basis for a mass balance estimate of pathways flows, although this doesn't always need to be true if selected pathways statistics are available. Such models are consistent with the concepts of MFA (OECD, 2008) for resource productivity and usually incorporate national-level economic and consumption statistics from manufacturing sectors, import/export data, and, when available, data on pathways obtained from industries, trade associations, and local, regional, or national governments. In this way, there can be components of field sampling/waste characterization studies involved in top-down measurement, but it does not represent most data. Examples of top-down models include various waste-extended input-output (IO) models (Meyer et al., 2020; Towa et al., 2020; Tisserant et al., 2017) and the Facts and Figures describing MSW in the United States (USEPA, 2020). The use of an IO framework has grown because it describes the generation and movement of commodities throughout the sectors of an economy and can be adapted for detailed material flow analysis through various techniques (Towa et al., 2020). Top-down techniques are represented in Fig. 1 as funneling data about material production and consumption from industry and government bodies through software or IO models for estimation and consolidated reporting of MSW management.

1.2. Objectives and scope

The objectives of this paper are to: 1) qualitatively and quantitatively assess three existing approaches for estimating MSW generation and management at the national level; 2) analyze the potential data needs of five CE policy types when considering effectiveness; and 3) identify trade-offs of the MSW estimation approaches for the CE policy types. We also discuss potential harmonization of estimation approaches and suggest further research and development to enhance current estimation

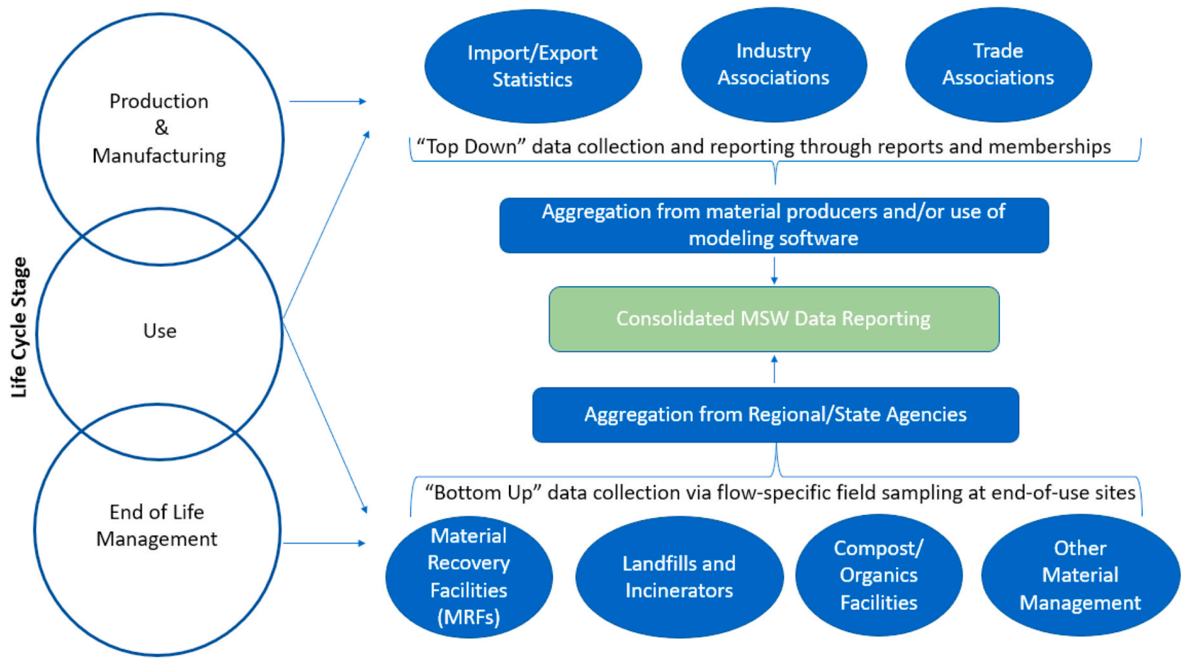

Fig. 1. Visualization of Top-Down vs. Bottom Up MSW data collection and reporting methods.

capabilities. We choose here to focus on data needs for CE policy and not the more traditional solid waste management policies. The difference between the two is that CE policy seeks to minimize materials becoming waste while solid waste management policy focuses on what happens once materials become waste.

This study builds on prior MSW modeling studies, including those of Chowdhury (2009) and Zhou et al. (2021). Like Chowdhury's work, we contrast existing waste generation and recovery data for their quality and usefulness. We differ from Chowdhury's work in a few key ways intended to highlight the novelty of our efforts and further the conversation around fit-for-purpose data. We apply our analysis to CE policy as opposed to traditional solid waste management planning and, in doing so, introduce a new set of data needs in terms of quality, scale, and availability. In addition to MFA-based modeling, we consider recently published approaches for estimating MSW statistics in the United States, including IO modeling and voluntary bottom-up data collection via regional reporting. With respect to Zhou et al. we focus on approaches to generate MSW estimates at the national scale in the United States, which is much broader than MSW estimation at the city level in Wuhan, China. Because the United States lacks mandatory bottom-up MSW sampling and reporting, our focus remains on top-down modeling and voluntary bottom-up reporting. Thus, our research is applicable to countries with a more diverse use of material management pathways and to those without mandated centralized MSW reporting.

2. Methods

Our approach to this work is to use a combination of literature review, data quality assessment, and policy assessment to synthesize an understanding of potential tradeoffs to consider when attempting to satisfy MSW data needs to support CE policy. We use a case study of the United States since it lacks national MSW data reporting requirements despite having one of the world's largest material footprints. To minimize subjectivity throughout the process, we introduce well-defined criteria to guide assessment activities. Since the purpose of this work is not to select a "best" modeling approach, but instead to further discussions of fit-for-purpose data, we feel this approach is sufficient.

As outlined in Table 1, we consider a bottom-up measurement approach through a literature review of United States state-based

Table 1
Modeling approaches categorized.

Modeling Approach	Top vs. Bottom
Industry-based Material Flow Analysis (IMFA)	Top Down
Waste-extended Input Output (WEIO)	Top Down
Regional Data Reporting	Bottom Up

reporting (regional data reporting) and two top-down approaches (industry-based material flow analysis (IMFA) and waste-extended input-output (WEIO) modeling) in the scope of this study. We selected the United States as the area of focus due to its continued expansion of CE principles and policies at the national level, and its simultaneous lack of mandatory non-hazardous waste reporting requirements and related need for MSW estimation methods (USEPA, 2021, Save Our Seas 2.0 Act, USEPA, 2009).

We developed a critical assessment of the three model approaches listed in Table 1 using five criteria: data quality, flow totality, update frequency, sensitivity to disruption, and product granularity. We selected these criteria based on our understanding of the strengths and limitations of the Industry-based Material Flow Analysis (IMFA) model currently used to estimate MSW in the United States, as a baseline for evaluating against other estimation methods. Data quality (DQ) assessment was carried out quantitatively while all other criteria were evaluated qualitatively as described below.

2.1. Quantitative model assessment: data quality analysis

Our study adapted the DQ assessment method for life cycle inventory data developed by Edelen and Ingwersen (2016) for application to selected waste models. This method scores individual data points from 1 (highest) to 5 (lowest) for five indicators: flow reliability (how trustworthy is the data or information source?), temporal correlation (how recent is the data?), geographic correlation (how well does the data represent the area of study, the United States?), technological correlation (are current technologies reflected?), and data collection methods (is the data representative of the entire market?). For the scope of this paper, ideal geographic resolution is national, whereas state/regional data are within one level and municipalities/sub-regions are within two levels of resolution. The scoring matrix provided by Edelen and Ingwersen for the criteria is available in Tables 1–1 of Supporting Information (SI).

The average/arithmetic mean of these five indicators provides the DQ score for a given data source. Table 2 lists data classification by score range.

For the purposes of this study, we define DQ scores classified as Medium to High (i.e. numerical value less than 3.5) as meeting acceptable quality standards. Application of this method to each model is described below.

2.1.1. IMFA data quality analysis

We selected the Facts and Figures model published by USEPA as the IMFA evaluated in this study, with underlying data for the year 2018 (i. e. the most recent data published) used as the basis for the DQ analysis. Some data describing plastics in the model are claimed as confidential business information (CBI) by the industry source, which required evaluation by the intermediary data collector following instructions provided by our project team. The IMFA model uses a mass balance equation to calculate generated MSW and to estimate tonnages of materials managed through various pathways including recycling, composting, other food management, combustion with energy recovery, and landfilling/residuals. In this model, recycling rates are identified by two calculation methods based on data availability by product from top-down data suppliers (See Fig. 1). In the first calculation method, recycling tonnages are provided from states or industry groups and divided by tonnages of generated material. In the second calculation method, an industry reported recycling rate is applied to the tonnage of generated material to calculate tonnage of materials recycled. Each of these factors (tonnage of recycled material, tonnage of generated material, and recycling rate) were individually scored using the data quality methodology.

After scoring individual data sources with an arithmetic mean, we applied a max value approach to find overall DQ scores by material type. When any two data points were added, subtracted, multiplied, or divided, we adopted the maximum value of the component DQ scores for the product of the individual data points. This approach reflects the logic of significant figures – the data for a specific product category should only be as certain as its least certain data source. The complex nature of the Facts and Figures model (i.e., each product has its own calculation methodology, over 4000 data points to score) does not lend itself well to simple averages of DQ scores. The max value approach ensures that low-scoring data sources carry through the analysis and are clearly reflected in final category scores. Even though the IMFA model presents data by product, we present DQ results for the selected IMFA model at the material level since materials are the focus of CE.

2.1.2. WEIO data quality analysis

To evaluate waste estimates generated by WEIO modeling, we selected The United States Environmentally Extended Input Output (USEEIO) model. USEEIO currently calculates commercially generated MSW and includes DQ scoring using the method of Edelen and Ingwersen. Ideally, waste estimates for a given year would be calculated based on the industry waste intensities (kg waste material per dollar of BEA industry output) for that year and the corresponding industry outputs. However, annual waste intensity data is not typically available, and USEEIO waste intensity data is based on a single year (2014) and assumed to be constant for other years. The derivation of the USEEIO waste intensity satellite table is described in Meyer et al. (2020). For this study, we calculated USEEIO waste estimates using 2018 industrial outputs reported by the Bureau of Economic Analysis (BEA, 2022).

Table 2
Data quality scores and classification.

Data Score	Data Classification
$x < 1.5$	High
$1.5 \leq x < 2.5$	Medium-High
$2.5 \leq x < 3.5$	Medium
$3.5 \leq x < 4.5$	Medium-Low
$x = 5$	Low

2.1.3. Regional reporting-based data quality application

We conducted a review of United States state environmental agency websites to consolidate publicly available regionally reported data for MSW generation and recycling, using 2018 as the baseline year. We included all 50 United States and the District of Columbia in the scope of the search and applied the max value approach discussed in section 2.1.1 during DQ analysis. For this estimation method, we scored the “data collection methods” criterion by defining market representation as the percent of gross domestic product (GDP) for the continental United States We feel GDP is the best measure because it captures the value added by material use in the form of goods and services.

2.2. Qualitative model assessment

We define the four qualitative assessment criteria as follows.

- *Flow totality* refers to inclusion of all relevant waste management pathways in the model or measurement method. A top-down model beginning with generation data and estimating pathway totals should account for the various ways that waste is managed within a geographic boundary. A bottom-up model collecting data by pathway from facilities or regions should ensure that calculated ‘generated’ waste totals include all relevant pathways in the sum.
- *Update Frequency* refers to how often updated data are available for publication under each model type, or how often the models can practically be run given the time intensity of data collection. For this assessment, annual updates are the standard for national-level waste modeling.
- *Sensitivity to Disruption* refers to how well, if at all, a model incorporates impacts of major socioeconomic events on material generation and recovery rates when they occur. For example, international export bans on plastic waste in 2018 had an immediate impact on secondary material markets (Kumamaru 2021), which were further altered by the COVID-19 pandemic and its effect on consumer behaviors. Material models which can demonstrate correlations that these real-world events and others have on national material management efforts are preferred.
- *Product granularity* refers to the level of MSW resolution by common household items that the model can report. Least granular models are models that are limited to recycling, disposal, or generation totals by material, whereas granular models offer materials management data by consumer product.

2.3. Assessment of data needs for circular economy policies

To evaluate the potential contributions and usefulness of each waste estimation model in this study, we selected five internationally employed CE policies and their typical actions. The CE policies presented in Table 3 span five continents (Fitch-Roy et al., 2021; EMF, 2023, USEPA, 2021; Chile Ministry of Environment, 2021) and a full range of product life cycle stages: production/product design, use phase/consumption, end-of-life/waste, and resource circulation (Hartley et al., 2020; Milios, 2018). The policy mix presented was also informed by Ekvall et al. (2016) and distributes policies across the three broad classifications of administrative, economic, and informative actions (Milios, 2021).

To determine which model characteristics are required for measuring the effectiveness of each individual CE policy, we conducted a literature review to analyze available policy studies for relevant mentions of each assessment criteria defined in Section 2.1 and 2.2. The

Table 3
Policy mix used for evaluation of model usefulness/applications of CE policy.

CE Policy	Life Cycle Stage	Policy Action	Classification
Minimum Recycled Content	production/ use	regulatory targets, certifications	administrative/ informative
Market Restrictions	production	regulatory bans	administrative/ informative
Extended Producer Responsibility	use	taxes/fees	economic
Landfill/disposal Bans	end-of-life	regulatory bans	administrative
Recycling Rate Targets	end-of-life	regulatory targets	administrative

specific terms and keywords used for the literature search are summarized in Table 4.

For the literature review, we identified 39 initial sources across the five policies listed in Table 3 using Elsevier's ScienceDirect search engine (Elsevier 2022) and original regulatory documents from various governments embracing CE in policy-making. Search terms by CE policy were formulated as "<CE policy name> and circular economy" or "<CE policy name > effectiveness". If the journal search failed to provide multiple sources, we reviewed policy documents directly from regions and nations mentioned in relevant peer-reviewed papers. After reviewing the initial sources for relevance, 22 sources remained for the analysis. Each relevant literature source was evaluated by whether or not the source authors demonstrated evidence of considering each of our five model criteria listed in Sections 2.1 and 2.2. Team members independently rated sources on a "yes" or "no" basis for each criteria, and when members disagreed on a criterion rating, we discussed and re-evaluated the source as a team until a consensus could be reached. For each CE policy, a final yes/no was awarded for each criterion based on the majority response for all sources included for a policy. Example determinations and justifications for the model criteria relevant to determining Minimum Recycled Content (MRC) policy effectiveness can be found in S.2–1.

3. Results

3.1. Model assessment

Table 5 presents the results of the model assessment and outlines fulfillment of each assessment criteria (as defined in 2.1 and 2.2) for

Table 4
Literature review search terms by policy type.

CE Policy	Search Terms
Minimum Recycled Content (MRC)	minimum recycled content circular economy minimum recycled content policy minimum recycled content effectiveness minimum recycled content
Market Restrictions (MR)	market restrictions circular economy market restrictions recycled material market ban circular economy effectiveness market ban circular economy
Extended Producer Responsibility (EPR)	extended producer responsibility extended producer responsibility circular economy extended producer responsibility effectiveness
Landfill/Disposal Bans (LB)	landfill ban policies landfill ban circular economy disposal ban policies disposal ban circular economy landfill ban policy effectiveness
Recycling Rate Targets (RRT)	recycling rate policy effectiveness recycling rate calculation recycling rate circular economy policy national recycling rate target circular economy recycling rate circular economy policy effectiveness

Table 5
Criterion scoring results for assessment of selected waste modeling approaches.

Assessment Criteria	MSW Estimation Method		
	IMFA	WEIO	Regional
Data Quality	No	Yes	Yes
Flow Totality	Yes	No	No
Update Frequency	No	No	Yes
Sensitivity to Disruption	No	Yes	Yes
Product Granularity	Yes	Yes	No

each of the three MSW modeling approaches selected for evaluation in this study. Table 6 presents a detailed break-down of quantitative DQ scores by common material types for each model for both MSW generation and recycling where available, where Generated Tonnage includes the estimated or reported volume of materials generated in the waste stream and Recycled Tonnage includes the estimated or reported volume of materials recycled in the waste stream. Subsequent sections provide the rationale for how each model was scored.

3.1.1. IMFA modeling

As shown in Table 6, the IMFA model scores low in quality for generation by material due to aging data. Industry sources have routinely published reports containing the data used in the IMFA model since its inception. However, the frequency and granularity of those data have decreased over time. This results in the IMFA approach relying on decades-old data, where necessary, to estimate waste and recycling statistics by material. Further, since 5% of all data points comprising those reports are uncited assumptions, reliability becomes a concern. Because 75% of all data points in the model are calculation-based (i.e., industry data used as factors in equations estimating material composition and total flow, rather than totals directly reported from industry), a low score in reliability from an assumption in an early calculation step carries through and reduces all subsequent calculation scores. Thus, not all data sources are low quality in calculating material generation with the IMFA model, but all materials evaluated have at least one low-scoring or uncited source that carries through the analysis. Despite recycling estimates by material scoring higher in quality than generation, we determined that the IMFA model does not meet the defined modeling criteria for Data Quality. More detail on DQ scoring by material and product is provided in Tables 1 and 2.

Regarding qualitative model assessment criteria, the mass balance equation used by the IMFA model in this study provides flow totality by considering generation, landfilling, recycling, composting, and combustion with energy recovery (USEPA, 2020). Because landfilling/disposal is calculated as the remainder of other estimated pathways from generation, all MSW generated under the model is accounted for in treatment/management pathways. Note that the landfilling pathway should be seen as landfilling and other disposal, because the total theoretically includes litter, combustion without energy recovery, and other pathways not currently accounted for in the model. Ultimately, this means the IMFA model may be over-reporting landfilling as a percentage of total MSW managed. Because this study did not compare absolute MSW tonnages estimated for any pathway across the various models, we are unable to comment on the range of uncertainty in the estimated values. However, prior studies suggest that current IMFA models are substantially underestimating MSW generation (Chowdhury, 2009, Zhou et al., 2021).

Because some industry sources lack annual reporting, we do not consider the IMFA model to be frequently updatable. Additionally, we classified the model as not sensitive to disruption due to the influence of older data. Because it takes top-level product production and population data and estimates material generation and management pathways across the lifecycle, only national-level variations in production will appear to change recycling totals, etc. Ultimately, a model referencing decades-old data is unlikely to reflect real-time market events that

Table 6
Data quality assessment results.

	IMFA		WEIO		Regional Data Reporting	
	Generated Tonnage	Recycled Tonnage	Generated Tonnage	Recycled Tonnage	Generated Tonnage	Recycled Tonnage
Paper	Low	Low	Medium	n/a	n/a	Medium
Plastic	Low	Low	Medium	n/a	n/a	Medium
Glass	Low	Medium-High	Medium	n/a	n/a	Medium
Metal	Low	Low	Medium	n/a	n/a	Medium
Textiles	Low	Medium-Low	Medium	n/a	n/a	Medium
Organics (Yard Waste)	Low	Medium	Medium	n/a	n/a	Medium
Overall Tonnage	n/a	n/a	Medium	n/a	Medium-High	Medium-High

impact the waste and recycling industries. The model does fulfill product granularity by considering four product categories (durable goods, non-durable goods, containers and packaging, and other wastes) with 29 sub-categories (USEPA, 2020).

3.1.2. *WEIO modeling*

The IO-based estimates are derived from a single methodology and have uniform DQ across all materials (Table 6), unlike the IMFA model whose calculation methodologies and data sources vary by product type and material. The composite DQ score of "medium", although satisfying this study's minimum level of quality, is driven by a few key factors. The data are from a single characterization study performed in a single sub-region in 2014. This corresponds to scores of "medium-high" for temporal and geographical correlation. The data also merit a score of "medium-high" for technological correlation because of variance in the multi-site sampling results. The reliability of the data is considered "medium-low" because the data are described by the provider as being sub-regional estimates derived from statistically meaningful sampling instead of sampling all sub-regional sites. Finally, the data collection method is scored as "low" because data from selected sites in a single region (i.e., one state that represents 14.3% of total GDP) are used to estimate waste generation at a national scale.

Regarding qualitative criteria, the WEIO model included in this study lacks flow totality because it only accounts for waste generation and not waste management in the waste satellite account model. Including waste management in the WEIO model is an interesting challenge because waste management pathways are sub-industries within the Waste and Remediation Services Industry (BEA industry 562000). This could be remedied by either introducing waste management through the waste satellite table or examining the physical flow of materials associated with purchases in the IO tables (Towa et al., 2020). For update frequency, the principles of the WEIO model are well-known and the model itself is implemented as part of a framework for automated data processing and model generation. However, while the economic component of the model can be updated annually, the waste satellite table is static in its current form because it is based on a single study from 2014. For this reason, we classified the WEIO model as "No" under update frequency. We classified the model as "Yes" in reflecting disruption sensitivity because the overall output of waste generation is tied directly to annual economic data by sector and therefore sensitive to market factors. More investigation is necessary to determine the impact of economic disruptions on waste generation factors. The WEIO model inherits the 68 products tracked in the highly granular waste characterization study.

3.1.3. *Regional data reporting*

Unlike the IMFA and WEIO models, the regional reporting model uses data directly from bottom-up, state-based reports with limited augmentation. The collected data are summarized with regional sources in Tables 1–3. Because these regional reports generally do not offer waste generated by material type, there are no DQ scores assigned ("n/a") to the material categories for generated tonnage in Table 6. Table 7 presents the assigned scores across each of the five model evaluation criteria. Aggregated state-reported generation data voluntarily reported for 2018 (i.e., all MSW materials) scores "medium-high" overall for DQ, which is an average of all component scores in Table 7. This score is bolstered by a "high" temporal correlation (score of 1) given the data are from the desired 2018 reporting year and hindered by a "low" reliability (score of 5) because the state waste reports often do not cite data sources or the confidence of their statistics. Note that there is likely room for improvement with reliability if the data can be disaggregated and accessed at the highest level of resolution for reporting. Data collection scores a "medium" for total generated waste because the data were obtained from 19 states representing 46.4% of total GDP.

Aggregated state-reported recycling also scores "medium-high" for the same reasons as aggregated generation. Twenty states reported overall recycling totals for 2018, representing 48.1% of GDP. Recycling tonnage disaggregated by material was reported by 13 states, or 26.8% of GDP, and scores "medium-low" for data collection. The materials presented in Table 6 are among the most-reported materials, but due to the lack of standardized waste reporting in the United States, many states also offered data for various materials not listed. For example, two states reported household hazardous waste and used oil as discrete categories. This does not necessarily mean that these materials are unaccounted for in other states "miscellaneous" materials or "other" materials categories, but that very few states choose to report on these individually. Due to lack of standardization, it is difficult to estimate how many states may have access to less-commonly reported materials.

The inconsistency in pathway reporting supports classifying flow totality as a 'No'. While a portion of regions provided very detailed materials management data across flows, the intent of this characterization is to analyze aggregated regional reporting as a method for estimating national MSW management. Thus, most regions would need to report on all waste management pathways to provide sufficient information to generate national material flows.

Unlike the IMFA and WEIO models, the regional reporting model fulfills the update frequency criterion. Regions that do report often provide data annually, as observed when accessing archives and prior-year reports during the review of state environmental websites. Additionally, the regionally-reported data are generally a consolidation of

Table 7
Summary of regionally aggregated data quality scores.

Data Category/Flow	# States	GDP Represented (%)	Reliability	Temporal	Geographic	Technological	Data Collection	Avg.	Score
2018 Recycling tons	20	48.1	5	1	2	1	3	2.4	Medium-High
2018 Recycling by Material	13	26.8	5	1	2	1	4	2.6	Medium
2018 Disposed tons	19	46.4	5	1	2	1	3	2.4	Medium-High
2018 Total Generated tons	19	46.4	5	1	2	1	4	2.6	Medium

facility-based data from sub-regions making them a better reflection of market disruptions. Changes to the market should be reflected in the generation and recycling totals aggregated at the regional level if regional agencies are leveraging reliable sub-regional data. This underscores the need for DQ scores to be integrated at the highest resolution of reporting (sub-regional or individual facilities). Finally, no region was identified in this analysis to have reported materials management data by product, resulting in a classification of 'No' for product granularity.

3.2. CE policy data needs assessment

To determine which model characteristics are required for measuring CE policy effectiveness, we cross-walked the five model assessment criteria with the needs of five circular economy policy actions: minimum recycled content, market restrictions, extended producer responsibility, landfill bans, and recycling rate targets. Table 8 summarizes the results from this analysis, with detailed process notes for an example policy included in Tables 2–1.

The MRC results reflect four examples. Given the importance of data quality to decision-making, we are not surprised for this to be important for minimum recycled content policies. We did not find flow totality to be a requirement when evaluating the effectiveness of minimum recycled content policies. For example, California legislation AB 478 (An act to amend Sections 14506.7, 2021) sets MRC levels for several materials based on recycling rates alone, with no consideration of what happens to non-recycled materials during end-of-life. Update frequency is a requirement for MRC to comply with the annual monitoring requirements as discussed in three of the four sources. The remaining source does not discuss monitoring frequency and does not influence this result. We also found that sensitivity to disruptions is considered a requirement for MRC modeling given that availability of recycled content can fluctuate with disruptive events and impact the effectiveness of MRC actions. Finally, product granularity is important to MRC analysis because the recycled content targets are typically set on a product-by-product basis.

We identified three examples of market restrictions (MR) for our study. Again, DQ is a required criterion for monitoring policy effectiveness because of its importance to decision making. As with MRC, flow totality is not a requirement for monitoring the effectiveness of MR for two of the three examples. In both the ban of plastic bags in Australia and the ban of secondary plastic imports in China, the focus was only on a material or product of interest in limited flows and did not consider total management of the materials when analyzing the policy implementation. In contrast, the ban on secondary copper imports in China described in the third example was intended to address the domestic copper life cycle and considered all management pathways associated with it. The copper and plastic bag examples suggested an annual monitoring cycle, supporting the need for update frequency. The plastics ban example did not offer sufficient information to assess this criterion. Since the MR examples focus on creating change through material markets, sensitivity to major market disruptions, including MR policies, is necessary when monitoring effectiveness. We concluded the product granularity criterion is a requirement for monitoring MR effectiveness depending on the nature of the ban. For example, the bans on secondary copper and plastic bags included product specificity while the ban on secondary plastic imports was only applied at the broad material level.

We identified four examples of extended producer responsibility (EPR) from the literature. DQ is again required to support policy-related decision-making, including "technical information from waste management operators … to facilitate the eco-design" of products under EPR schemes (Republic of France, 2018). Unlike MRC and MR actions, understanding the totality of waste flows for monitoring EPR effectiveness is important to three of the four examples. For example, Quebec has completed multiple MSW and recycling characterization studies in direct support of its EPR programs (EPRC 2017). Like MRC and MR actions, update frequency of modeling is required given the publication of yearly reports and regular industry collaboration in three of the four implemented policy examples. The need for market disruption sensitivity is less clear. One example linked effectiveness and monetary penalties under the EPR program—suggesting that models must take economic changes into account. The other three examples were either not sensitive to disruption or did not address effectiveness. Product granularity is important for EPR, as all four examples implemented schemes on a product-by-product basis.

We identified three examples of landfill bans (LB) in the literature review. As with the other actions, DQ is an important characteristic for action tracking and assessment. For example, the EU Landfill of Waste Directive 2018/850 directly references the need for precise MSW reporting rules to "ensure the reliability of data" in assessing the result of the landfill bans (EU, 2018). While one of the three examples did not require flow totality, two identified the need to prevent waste from landfill and incineration suggesting that a holistic understanding of material destinations is required for action evaluation (EU, 2018; Scharff, 2014). One directly mentioned prioritizing the waste hierarchy, which also suggests that a total understanding of "end-of-life" material flows is necessary to understand shifting material management strategies (EU, 2018). Two of the three examples referenced annual data reporting or the need to routinely evaluate negative effects of the policy, resulting in a classification of 'yes' for update frequency. None of the examples referenced sensitivity to disruption or augmenting the landfill ban policies around significant market disruptions. Product granularity is deemed not important for LB action analysis because two of the three examples focused on overall MSW bans. However, one study evaluated a wood pallet-specific landfill ban, suggesting that product-specific bans can be utilized (Buehlmann, 2009).

Finally, we identified eight examples of recycling rate targets (RRT) for this analysis. DQ is important for all eight. As summarized by Michigan's recycling rate calculation guidance, "it is important to calculate the rate with the highest level of accuracy possible" (MDEQ).

Table 8
Summary of CE policy data needs assessment and crosswalk with model applicability.

Sample Circular Economy Actions		Model Criterion for Monitoring Policy Effectiveness				
		Data Quality	Flow Totality	Update Ease	Disruption Sensitivity	Product Granularity
Minimum Recycled Content	Criterion Required?	Yes	No	Yes	Yes	Yes
	Applicable Models	2,3	1,2,3	3	2,3	1,2
Market Restrictions	Criterion Required?	Yes	No	Yes	Yes	Yes
	Applicable Models	2,3	1,2,3	3	2,3	1,2
Extended Producer Responsibility	Criterion Required?	Yes	Yes	Yes	No	Yes
	Applicable Models	2,3	1	3	1,2,3	1,2
Landfill/disposal bans	Criterion Required?	Yes	Yes	Yes	No	No
	Applicable Models	2,3	1	3	1,2,3	1,2,3
Recycling Rate Targets	Criterion Required?	Yes	Yes	Yes	Yes	No
	Applicable Models	2,3	1	3	2,3	1,2,3

Model 1 = IMFA; Model 2 = WEIO; Model 3 = Regional Reporting.

While there are a variety of ways to calculate recycling rates (Arduin et al., 2019; Chile Ministry of Environment, 2021), flow totality and accounting for the entire stream of materials managed is required in all RRT examples, as is update frequency. Annual updates were the most common frequency, with one example calling for a biannual data publishing cycle. Sensitivity to disruption in modeling is also a unanimous requirement across sources because recycling rate as a performance indicator must reflect changes to the market affecting total MSW generation and recycling tendencies. For example, Florida specifically mentions the impacts that China and India's bans on imported waste have had on the growth of the recycling industry. Recycling markets "are commodity driven and subject to the ebb and flow of market demands", meaning that models tracking progress towards or effectiveness of recycling rate targets as a CE action must reflect these market dynamics (FDEP, 2019). Finally, while recycling rate targets can be applied by specific product or material, product granularity is not identified as a model requirement because recycling goals referencing total MSW generated were the standard in most sources analyzed.

4. Discussion

The common criteria to CE actions found in Table 8 are DQ and update frequency. Although quality data may seem obvious for policy analysis, the results of this work reinforce the need for improved access to data throughout material life cycles (Chowdhury, 2009). Improved data access is further supported by the need for update frequency since models can only be updated when the necessary data are available. The variability in product granularity as a requirement supports the idea that multiple simultaneous actions may be most effective (Bening, 2021; Friant et al., 2021; Syberg, 2021) because they can cover the spectrum from materials broadly to specific products. It is a bit surprising that flow totality is not a consistent requirement as the goal of CE is to maximize the value of materials in society, which would imply knowledge of material flow in all pathways. Instead, the need for flow totality in the actions analyzed here depends on the scale of the action, with actions targeting the product-level being less likely to rely on this knowledge. Sensitivity to disruptions should be important to all actions because this knowledge informs the feasibility of an intended action. For example, if secondary markets cannot support material diversion from landfills, more planning and actions will be needed to manage the diverted materials. Understanding how the criteria apply to the various CE actions provides a suitable context for framing the trade-offs among the three modeling approaches.

4.1. Identifying modeling trade-offs for CE actions

Model applicability is overlaid in Table 8 based on a comparison of the results from analyzing the models and CE actions. Although one might attempt to select regional reporting (Model 3) as the "best" option because it seemingly fulfills 19 out of 25 'nodes' in the crosswalk, the intent of this paper is not to recommend a particular model type but instead provide an understanding of the tradeoffs when selecting each type. Given no model considered in this work fully satisfies the required criteria for any of the actions, managing the trade-offs from the perspective of policy implementation will be more useful. For the sake of discussion, the selection of models will be considered as if the models evaluated here are the only available form of each model type. The limitations of the models presented here and future activities that can improve how the general model types fulfill the criteria are summarized in Section 4.2.

For MRC and MR actions, the tradeoffs based on model selection are identical because of the shared criteria requirements. If the IMFA model is used, flow totality (although not a requirement) and product granularity can be maintained, but possibly at the expense of DQ, update frequency, and market sensitivity. The IO-based model is weak on update frequency while the regional reporting model is weak on product granularity. When it comes to decision-making, data quality should not be compromised. Therefore, the main trade-off for MRC and MR policies is between product granularity and update ease/frequency. When these policies target products, they need to be analyzed for effectiveness at the product level, which supports the use of the IO-based model. However, when these policies target a "material-level," the regional reporting model should be preferred for monitoring frequency.

The tradeoffs for EPR relate to flow totality and product granularity without sensitivity to market disruption. Flow totality presents an interesting challenge because only the IMFA model provides that type of information and yet this is the model with the highest potential for DQ issues. Since the DQ scores for this model vary by material (Table 6), this tradeoff may be minimal for material models based on higher quality data. For materials with low DQ scores, additional analysis of model sensitivity and uncertainty may be necessary to improve confidence in resulting decisions. If frequent policy analysis is anticipated, the IMFA model may also be challenging because of the effort required to update it. If decision makers implementing EPR actions decide flow totality can be sacrificed to preserve DQ, the IO-based model may be the only alternative because of the lack of product granularity with regional reporting. The advantage offered by regional reporting is its update frequency.

Like EPR, LB and RRT also require flow totality and are limited in this respect to the use of the IMFA model. The two policy areas differ from EPR and each other because LB does not need models that are sensitive to disruptions or product granularity while RRT analysis does benefit from models that consider sensitivity to disruptions. After LB implementation, analyzing waste-stream impacts with the IMFA model will allow a holistic view of how MSW streams are or are not shifting away from landfills, towards recycling, or being reduced in generation volume. The best alternative for LB when DQ is a must at the expense of flow totality is again the regional reporting model for its update ease and frequency, which essentially highlights the fact the IO-based model is best suited for applications where product granularity is important. For RRT, the key tradeoff is between flow totality and sensitivity to disruption, since no model fulfills both requirements. Of the two, it's logical to assume sensitivity to disruptions is preferred since recycling rates are strongly influenced by availability and price of secondary materials. If an RRT is enacted on a material basis, negating the need for product granularity, the regional reporting model is the most attractive option in terms of update frequency. If an RRT is enacted at the product level, the IO-based model will offer the most benefit.

4.2. Limitations, harmonization, and suggestions for further research

Ultimately, frequently published data on material movement in a circular economy will offer policymakers the ability to benchmark their progress towards recycling, materials management, and other CE goals. One aspect not considered in this work that can impact data is the ease of use each model provides based on its method of access and sophistication. For example, the WEIO model is available as a repository of R and python code and some knowledge of programming would be needed to use it. Similarly, the IMFA model is quite complex and takes time to learn to update and use. However, the three models analyzed in this work are single examples of the broader modeling approaches they represent. Understanding the limitations of these examples identified in this work and how they relate to current trends in development of the approaches can help shape a vision of how modeling can support CE policy in the future for countries that lack centralized waste data reporting.

The main limitations of the IMFA model include: key data elements that are static and lack sensitivity to disruptions; CBI data that lack transparency; and complex calculations that vary from product to product. For example, one industry might report the recycling rate while the recycling rate of another must be estimated from knowledge of generation and landfilling. This makes it difficult to compare pathways across materials and products. Given the age of the example model, these limitations are understandable and potentially rectifiable based on recent developments in MFA modeling. Lack of sensitivity can be addressed with more sophisticated application of dynamic MFA, which is a form of MFA that models how material flows shift over time in response to policies, economics, and other disruptions. This approach has been applied to numerous materials, including plastics (Lase et al., 2021; Luan et al., 2021; Millette et al., 2019), zinc (Rostek et al., 2022), and aluminum (Yang et al., 2022), and can be beneficial for policy monitoring when the necessary data are available. The example model applied several assumed product life span factors that are now treated as transient factors in current models. The need for CBI data may arise when publicly available statistics are not available, which is often the case (Millette et al., 2019; Yang et al., 2022; Mehta et al., 2022). Recent interest in predictive methods like machine learning may be a solution. Finally, the complex nature of the IMFA model is not uncommon to MFA models in general and can lead to models that vary by material.

The primary limitations of the WEIO model are aggregated product flows within industrial sectors and the use of monetary flows as opposed to physical quantities to track the movements of goods within an economy. However, given the potential for high DQ and transparency, IO-based modeling has become an increasingly preferable method for monitoring MSW management and analyzing CE policy development (Liao et al., 2015; Ruiz-Penalver et al., 2018; Sen et al., 2019; Tisserant et al., 2017; Towa et al., 2020; Tsukui et al., 2015). The best-case use in countries lacking centralized waste reporting will require model expansion through disaggregation (Towa et al., 2020) to estimate waste management by pathway (recycling totals, composting totals, etc.) to provide flow totality. Furthermore, an increase in sub-regional and regional waste characterization studies classified by industry code would further enhance waste modeling within an IO framework. The combined effect of these enhancements is that IO-based modeling may render the more laborious IMFA modeling impractical.

Since the regional reporting model provides data collected from primary sources, a main limitation is the time and resources that are needed at the sub-regional, regional, and national scales to collect data, harmonize them, and aggregate them into national estimates. For example, subregions in the U.S (e.g., cities), must be able to support the work despite the lack of direct support from the Federal Government. The result is several subregions not collecting and reporting the desired data and a large degree of variability in the data that can be collected. This is why the United States National Recycling Strategy (USEPA, 2021) includes an objective to standardize measurement and increase data collection, which has been proposed previously (Chowdhury, 2009). Note that the DQ assessment for regional reporting was implemented on the back-end of receiving data (2018). Ideally, a DQ assessment would be built into data collection models and reporting entities (states and local governments) would be asked to score their data across the five indicators when submitting. Because this was not the case for 2018 data, there are many limitations and assumptions with applying the Data Quality Assessment for Life Cycle Inventory to the State Measurement Program dataset for 2018. Flow reliability and geographic correlation are assumed to be “low” as reported by individual states.

As approaches to modeling material and waste flows continue to evolve, there is increasing interest in hybrid models that combine elements of IMFA, WEIO, and regional reporting to improve how materials are tracked and assessed throughout their life cycles. A typical hybrid model is the WIO-MFA model introduced by (Nakamura et al., 2007) to track material components within products. This concept has been further refined with physical IO modeling that uses physical flows in place of the monetary flows in the WIO model (Wachs and Singh, 2018). Another promising refinement would be the use of all three by which regional reporting data on end-of-life waste generation and management are used to bound estimates from a WIO-MFA or physical IO model that provide detail on where and how materials are applied in products within the economy.

5. Conclusions

As CE strategies are adopted by an increasing number of governments, accurate measurement of materials management activities will be key to meeting material use, recycling, and climate goals. For states/countries without mandatory centralized MSW reporting, modeling can provide estimates of material flow at the national scale. The IMFA, WEIO, and regional reporting models presented here provide nuanced trade-offs from the perspective of a decision maker evaluating the effectiveness of typical CE actions. Policy developers in areas where strong centralized data collection is not an option should design policy action(s) with modeling tradeoffs in mind. For example, policies should be implemented with longer monitoring intervals if update frequency or funding for routine data collection is an issue. Approaching the development process in this way will help maximize policy effectiveness. Another key need for decision making is high DQ. While none of the approaches we evaluated attain perfect quality when estimating material flows based on our analysis, steps can be taken to maximize DQ. The use of dynamic modeling approaches that capture sensitivities to disruptions can improve the quality of the data, as will developing more granular models for assessing CE actions implemented at the product level. Prioritizing publicly available data will also improve DQ by promoting transparency: working with communities, industries and local and regional governments to promote the need for data and encourage data sharing can improve DQ. Finally, DQ should be more readily communicated with published model results to better inform decision makers. Continued development of hybrid models like WIO-MFA and physical IO will lead to improved utility of material models for decision making. These models may still present challenges for countries because of the large data needs they entail. Dialogue on the importance of data for CE initiatives will continue to be a key need moving forward, and we undertook this analysis to assist with model development. We also anticipate that our study’s crosswalk and trade-off evaluation of MSW models and CE policies can serve as an example for decision-makers considering data-informed policy options to implement.

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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.

Data availability

Any data associated with USEPA research is made available by the Government of the United States through its open data initiative.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jclepro.2023.137349.

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