TECHNICAL BRIEF

WasteWise: A Decision Support Tool for Selecting Circular Bioeconomy Business Models

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November 2025

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Acknowledgments

This work was carried out under the CGIAR Multifunctional Landscapes Program with support from the CGIAR Food Frontiers and Security Program. We would like to thank all funders who support this research through their contributions to the CGIAR Trust Fund (www.cgiar.org/funders). We also acknowledge UMWELT Design LLP for the tool's user interface design, and Mr. Andoh Amponsah and Mr. Desmond Ayertey for consultancy support in data collection.

Citation

Somorin, T.; Yadav, S.; Nartey, E. G.; Ghosh, S.; Taron, A.; Gebrezgabher, S. 2025. *WasteWise: a decision support tool for selecting circular bioeconomy business models*. Colombo, Sri Lanka: International Water Management Institute (IWMI). CGIAR Multifunctional Landscapes Program; CGIAR Food Frontiers and Security Program. 22p.

About Multifunctional Landscapes

Multifunctional Landscapes is a CGIAR Science Program that aims to enhance the resilience, productivity, and sustainability of agricultural landscapes by integrating diverse land uses, ecosystem services, and livelihood strategies. The initiative supports evidence-based policies and innovations that balance food production with climate adaptation, biodiversity conservation, and social inclusion. By working with local communities, governments, and partners, it promotes landscape-level approaches to managing natural resources for long-term ecological and economic benefits. To learn more about the CGIAR Research Portfolio, please visit www.cgiar.org/cgiar-research-porfolio-2025-2030/

Front/Back Cover Photo Credit: Lindsay Bird/CBC.

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Acronyms and Abbreviations

AD	Anaerobic Digestion
BCR	Benefit-to-Cost Ratio
CAPEX	Capital Expenditure
CBE	Circular Bioeconomy
CH_4	Methane
ERP	Electricity Recovery Potential
FWI	Food Waste Index
GHG	Greenhouse Gas
GIS	Geographic Information System
IRR	Internal Rate of Return
LHV	Lower Heating Value
MCDA	Multi-Criteria Decision Analysis
MCA	Multi-Criteria Assessment
MCDM	Multi-Criteria Decision-Making
MSW	Municipal Solid Waste
NRP	Nutrient Recovery Potential
OFMSW	Organic Fraction of Municipal Solid Waste
OPEX	Operating Expenditure
PBP	Payback Period
POME	Palm Oil Mill Effluent
RRR	Resource Recovery and Reuse
ROI	Return on Investment
SDG	Sustainable Development Goal
TOPSIS	Technique for Order of Preference by Similarity to Ideal Solution
WaCT	Waste Wise Cities Tool
WFD	Waste Flow Diagram
WMPSS	Waste Management and Circular Economy Policy Support System

1. Context

Organic waste, from agriculture, food processing, municipal sources, and other bio-based industries, is one of the fastest-growing waste streams globally. According to a World Bank report, cities are expected to generate approximately 2.2 billion tonnes of municipal solid waste (MSW) per year by 2025, up from 1.3 billion tonnes in 2012 (World Bank, 2018). The biodegradable fraction accounts for more than 50% of the MSW stream in low- and middle-income countries and is a significant liability.

Other organic waste streams, such as crop residues, agro-industrial by-products, and food-processing effluents, are rarely accounted for in official statistics, meaning the true scale of organic waste generation is considerably higher. When poorly managed, it becomes a significant source of greenhouse gases (GHGs), particularly methane, which is over 80 times more potent than carbon dioxide over a 20-year horizon. Additionally, organic waste contributes to water and soil pollution, the spread of pathogens, and the loss of valuable nutrients that could otherwise support food and energy systems.

Food waste alone also illustrates the magnitude of the challenge. In 2022, an estimated 1.05 billion tonnes of food were wasted across households, food service, and retail, equivalent to 132 kg per person per year, with households accounting for approximately 79 kg per capita. This squandered food is responsible for roughly 8–10% of global GHG emissions, occupies nearly 30% of the world's agricultural land, and represents an economic loss of more than US $1 trillion annually, even as 783 million people face hunger and 150 million children under five experience stunting due to chronic under-nutrition (FAO, 2019; UNEP, 2024).

Such statistics underscore the untapped potential for resource recovery and reuse (RRR) through circular bioeconomy (CBE) solutions (Otoo & Drechsel, 2018). Proven RRR pathways include composting, which recycles nutrients back into agriculture; anaerobic digestion, which generates biogas and nutrient-rich digestate; biochar production, which sequesters carbon and improves soil fertility; and emerging innovations such as alternative proteins and insect-based feeds.

Selecting the most suitable valorization pathway, however, is far from straightforward. Decision-makers confront multiple and often conflicting trade-offs while grappling with data gaps and uncertainties. Reliable global information on waste flows remains inconsistent, and the absence of accessible, comparable tools often leads to sub-optimal investments or the underutilization of promising RRR options. *WasteWise* was developed to respond to this need. It is a multi-criteria decision support system tool that provides a user-friendly, data-driven platform for assessing the feasibility and selecting context-appropriate CBE business models. Users can modify inputs, test scenarios, analyze trade-offs, and visualize data through an interactive dashboard. Designed for application, *WasteWise* enables planners and policymakers to make evidence-based, transparent, and locally relevant decisions to accelerate the transition to sustainable, circular resource management.

1.1. Aim and Objectives

To enable informed and evidence-based decision-making for CBE transitions by providing a user-friendly, data-driven decision support tool that guides the feasibility assessment and selection of context-appropriate technologies and business models.

Specifically, *WasteWise* enables local planners and decision makers to:

- Estimate resource (waste) potential and conduct rapid assessment of suitable sites and locations for RRR interventions using spatial and non-spatial datasets.
- Identify suitable valorization technologies - with their objective assessment (technical, economic, and environmental feasibility).
- Apply multi-criteria decision-making methods to rank CBE business models across technical, financial, social, market, environmental, institutional, and health dimensions.
- Modify inputs, test scenarios, analyze trade-offs, and visualize data via a user-friendly interface and an interactive dashboard.

1.2. Who can use this tool?

The tool is designed for a wide range of stakeholders involved in planning, implementing, or investing in circular and resource recovery initiatives, particularly municipal authorities, entrepreneurs, practitioners, and policymakers in data-scarce contexts.

Specifically, *WasteWise* enables the following stakeholders:

- *Local and national planners* – municipal authorities, urban development agencies, and regional authorities responsible for waste management planning and policy design.
- *Entrepreneurs and social enterprises* that want to identify viable business models and assess their investment potential.
- *Researchers and technical consultants* – universities, think tanks, and consultancy firms that require a robust framework for feasibility studies, policy analysis, or project appraisal.
- *Community-based organizations and cooperatives* – interested in small-scale resource recovery or waste-to-value initiatives.

1.3. What are the key outcomes?

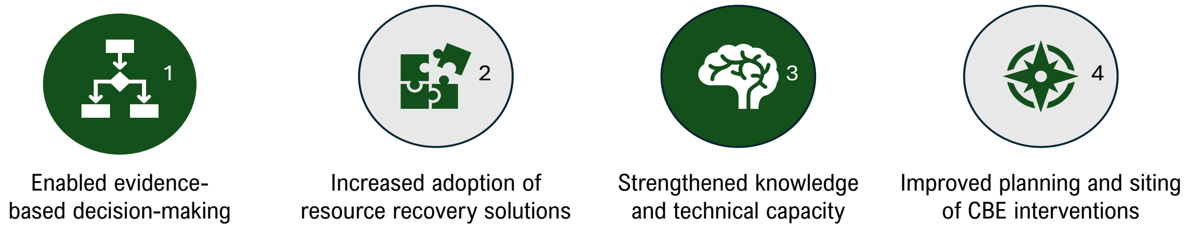

Figure 1 *– WasteWise key outcomes*

WasteWise delivers several outcomes: *i)* it supports evidence-based decision-making through multi-criteria evaluation and transparent ranking of business models; *ii)* it fosters collaboration by connecting diverse data and stakeholder perspectives; *iii)* it builds knowledge and technical capacity, and *iv)* it provides clear guidance to accelerate the uptake of circular and resource-recovery solutions (Figure 1).

2. Tool Architecture

WasteWise[1] decision support system tool integrates user-defined inputs with advanced data processing and a multi-criteria decision analysis method to guide the selection of CBE business models. Its architecture combines four interlinked components (Figure 2):

- User perspectives and inputs
- Backend data integration
- Multi-Criteria decision-making method
- Data visualization and outputs

2.1. User Perspectives & Inputs

Users begin by defining key inputs that frame the analysis. These inputs ensure that the tool captures local priorities and context from the outset. Because waste data are often scarce and unreliable, the developers have embedded key baseline datasets[2] directly into the tool, so users only need to supply a minimum set of essential inputs to run a scenario.

To run a scenario, the user provides the following minimum sets:

- **Location** – Geographic area or site of interest, which enables the tool to draw on spatial datasets such as population and potentially provide a suitable site for RRR.
- **Waste type** – Specification of the organic waste stream to be analyzed (e.g., agricultural residues, food waste, livestock manure).
- **Value-added product of interest** – The specific marketable product expected from the chosen valorization pathway, for example, nutrients, energy, treated water, etc.
- **RRR objective** – The intended purpose of the CBE intervention. This selection guides how the tool ranks CBE models—whether for financial returns, social benefits, environmental impact reduction, etc.

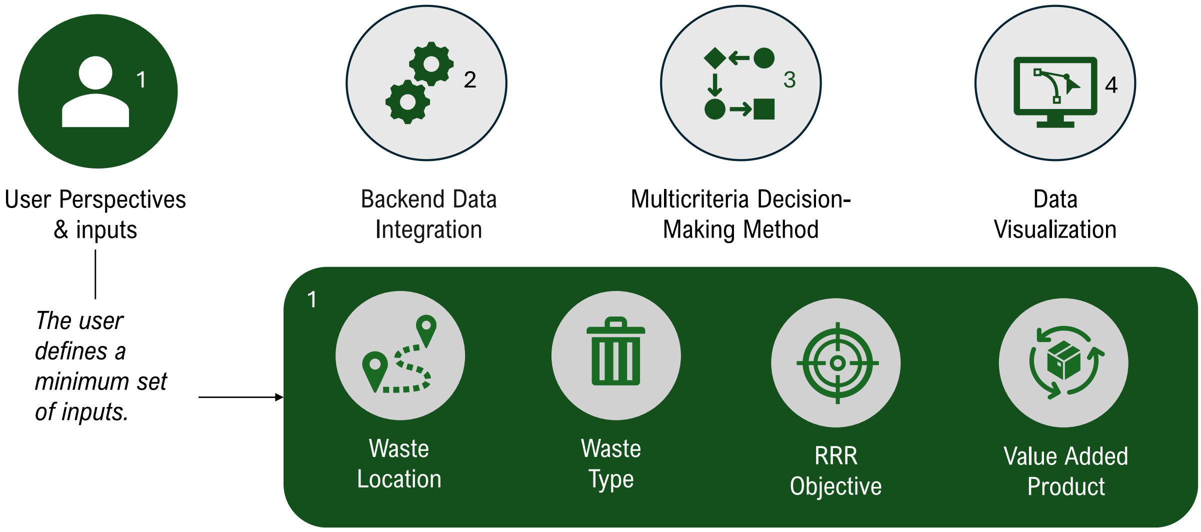

Figure 2 *– WasteWise tool architecture and minimum user-defined inputs*

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[1] WasteWise builds on methods described by Somorin et al. (2023) and prior work by Otoo et al. (2016).

[2] Additional functionality aimed at allowing users to upload or enter their own local data, which will then be validated within the tool's framework before being integrated into the analysis.

Within the RRR objective, the user can set the relative importance of key evaluation criteria and assign percentage weights to focus areas such as technology, people, environment, finance, institutions, and market (Figure 3). This ensures that the ranking reflects users' perspectives, local priorities, and broader policy goals, and that trade-offs between various factors are transparently captured in the assessment or feasibility study.

Additionally, the user can set or adjust key parameters to tailor the feasibility analysis for a specific waste treatment plant. These include:

- **Waste collection efficiency** – the percentage of available waste that can be collected.
- **Plant capacity factor** – the expected operating efficiency of the plant (for example, average output as a percentage of its design capacity).
- **Plant scale** – the intended size of the facility (small, medium, or large) based on projected waste flows and market demand.
- **Expected operational life of plant** – the planning horizon, such as 5, 10, or 20 years, for which the plant is expected to operate.
- **Truck capacity** – the size and type of collection vehicles (manual, small, medium, or large).
- **Fuel type** – the type of fuel or energy source for transport (e.g., gasoline, diesel, LPG, natural gas, hydrogen, or no fuel for manual collection).
- **Average distance** – the typical transport distance from the waste source to the plant. This feature uses a radius (in km) from the chosen plant location to the waste source.

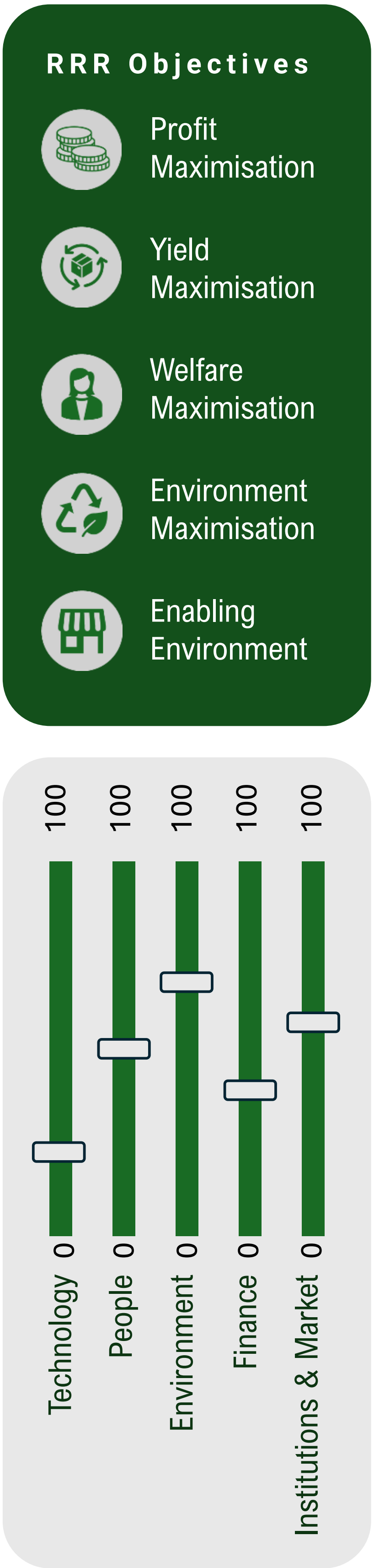

***Figure 3**–User-adjusted parameters*

These features allow *WasteWise* to reflect local infrastructure, operational conditions and logistical constraints, ensuring that the tool's recommendations on technology choice and business model are realistic and context-specific.

2.2. Backend Data Integration

A key feature of the *WasteWise* backend is its seamless integration of spatial and non-spatial datasets, enabling the generation of location-specific insights for resource recovery. This integration allows the tool to link waste composition and technology performance data with real-world geographic and socio-economic conditions. Behind the interface, multiple datasets feed into the analysis. This includes calculated parameters derived from user inputs and default databases, as well as geospatial datasets, such as population density and waste availability maps.

The spatial layer combines multiple data sources to map the location and quantity of organic waste across the value chain, from production through harvest and transport, to processing, marketing, and consumption. This ensures that only feedstocks with significant, spatially verified availability are considered when recommending technologies and business models. The model includes:

- **Remote sensing and GIS datasets,** e.g., land use, population density, urban road networks, water bodies, and administrative boundaries[3].

- **Secondary data sources**, for example, national statistics on crop residues, population data, market waste, slaughter waste, and faecal sludge.

The non-spatial component provides the composition and quality characteristics of waste streams. It also captures diverse indicators such as GHG emissions, feedstock costs, and labor requirements.

2.2.1. Waste Information

The backend includes an extensive waste information database that characterizes a wide range of organic waste streams used in RRR. Current categories cover agricultural residues, organic fractions of MSW, livestock manure, and faecal sludge, with market waste and slaughter waste to be incorporated in upcoming versions (Table 1). For each waste type, the database provides detailed proximate and ultimate analysis, including moisture content, volatile matter, ash, and elemental composition (carbon, hydrogen, oxygen, nitrogen, and sulfur).

It also documents key energy and nutrient parameters, such as the C/N ratio and suitability for composting, as well as lower heating values (LHV) for bioenergy applications. Additionally, it provides theoretical methane (CH_4) yield, biogas yield, and methane content, enabling a rapid assessment of anaerobic digestion potential. Concentrations of nutrients (total nitrogen, phosphorus, and potassium) relevant for soil amendment products are also included. Other waste information includes feedstock cost, bulk density, and potential landfill gas emissions data. The data structure enables automatic matching of user inputs with the most suitable CBE technologies, whether for bioenergy or composting, ensuring that technology options are tailored to the specific type, quality, and availability of local organic waste. Waste information is linked to the spatial availability of resources in each country, so that only waste types and datasets relevant to the user's selected country are displayed.

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[3] Work is ongoing to include ground truth/field observations to validate remote sensing outputs and capture context-specific information such as seasonal variation.

***Table 1–Current categories and types of organic wastes included in* WasteWise**

Waste Categories	Waste Types
Organic Fractions	Food Waste OFMSW Market Waste Faecal/Fecal Sludge
Livestock Waste	Cattle/Cow Dung Poultry Litter Swine/Pig Slurry Sheep Manure Goat Manure Chicken/Poultry Manure
Agricultural Crop Residues	Palm Kernel Shells Palm (Empty Frond Brunch) Switch Grass Sugarcane Bagasse Rice Husk Rice Straw Wheat Straw Coconut Husk/Fiber Coconut Shell Maize/Corn Cob Corn Stover Corn Stalk Cotton Stalk Cottonseed Husk Coffee Husks Shea Husks Sorghum Bagasse Mango Pits Mango Peel Cassava Peels/Residues Maize/Corn Stalk Yam Residues Plantain Trunks/Stem Sorghum Stalk Cowpea Shells Groundnut Shells Millet Husk Oil Palm Fiber Soyabean Husk Cocoyam Straw Maize Husk Pepper Residues Tomato Residues
Agro-ind. Waste	POME - Palm Oil Mill Effluent
Slaughter Waste	Animal Blood Meat & Bone Meal
Forestry Residues	Wood Chips Forest Residues Wood/Saw Dust

The spatial filtering ensures that the technology recommendations remain context-specific and grounded in nationally available feedstocks.[4] For example, when a user selects a waste category and defines the geographic area, the system automatically retrieves the relevant waste data and links it to spatial estimates of waste availability for the selected country (and district):

- **Waste quantity estimates** – The tool calculates annual waste generation (in metric tonnes per year, wet basis) using spatial data combined with typical generation rates.

- **Collected waste and area coverage** – the potential waste quantities are then derived by applying the user-defined collection efficiency. The selected radius determines both the coverage area (*in square kilometers*) and the distance covered.

- **Technology assignment:** Wastes are classified as dry, moist, or highly moist to guide technology choice (e.g., dry wastes for combustion/pyrolysis).

- **Resource potential indicators** – Depending on the user's selected value-added product, the tool estimates either the energy recovery potential—for example, LHV, theoretical methane yield, and electricity recovery potential from bio-solids, biogas, or bio-oil—or nutrient recovery potential, such as total nitrogen and potassium content. This allows users to focus the assessment on the specific resource streams that align with their CBE objective.

2.2.2. Technology Data Structure

The technology database underpins *WasteWise* by capturing multiple operational parameters for each resource recovery option.

Each technology record contains:

- **Performance and efficiency** – electricity balance (produced minus consumed) in kWh per tonne of waste and overall conversion efficiency (%).

- **Economic indicators** – capital expenditure (CAPEX) and operating expenditure (OPEX) per tonne of waste; detailed breakdown of capital costs (land preparation, equipment, installation, land costs, miscellaneous) and operating costs (utilities, labor, maintenance, feedstock/inputs, miscellaneous).

- **Resource requirements** – land and water use per tonne of waste, labor needs (persons per tonne), and fuel or energy inputs.

- **Technology profiles** – information that supports ranking by system efficiency, cost factors, and technology readiness.

All the data enables the tool to compare RRR/CBE technologies on a consistent annual basis, assessing trade-offs among multiple objectives. They provide the quantitative backbone for MCDA when matching available waste feedstocks to the most suitable technologies, ensuring that recommended interventions are feasible and contextually appropriate.

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[4] Crop residues are derived from the main cash commodities with the highest residue generation potential.

2.2.3. Multi-Criteria Decision-Making Method (MCDM)

The tool embeds a robust multi-criteria decision-making framework (Figure 4) to compare and rank alternative CBE business models for any selected waste stream. Rather than relying on a single metric, it integrates several factors, including technical, economic, social, and environmental considerations, into a single, transparent feasibility index.

At the core of the approach are seven evaluation domains (technical, financial, social/people, market, environmental, institutional, and health), each comprising around 30 performance criteria (Table 2). These range from technology maturity, operational reliability, and resource recovery potential, through to payback period, return on investment, job creation potential, gender and youth inclusion, policy support, and buyer confidence. Environmental indicators capture net greenhouse gas emissions, biodiversity and pollution risks, as well as energy, land and water use efficiencies.

For each business model, performance scores for these criteria are either pulled from the backend database or calculated from user-defined inputs. Objective indicators such as electricity or nutrient recovery potential, or economic returns, are normalized on a common 1–5 scale and combined with the weights assigned by the user or derived through expert judgment. This yields composite scores for each domain that classify feasibility, e.g., low, moderate, high, or very high—making trade-offs explicit.

To integrate these diverse dimensions into a single decision, the tool applies MCDM techniques, notably the Analytic Hierarchy Process (AHP) to structure and weight the criteria, and TOPSIS to rank the alternatives based on their closeness to an “ideal” solution. The result is a single closeness coefficient that expresses the overall feasibility of each technology or business model, typically interpreted as low (<0.3), medium (0.3–0.6), or high (>0.6) and ranked accordingly.

This process highlights not only the top-ranked option but also the reasons behind its performance across various domains. In practice, it reveals, for example, that technologies with substantial financial and people-centered benefits—such as high job creation and favorable returns—tend to score highest overall. In contrast, options such as passive landfilling without gas recovery consistently score lowest. By making these trade-offs transparent, the MCDM framework enables decision-makers to select CBE solutions that best align with local priorities and needs

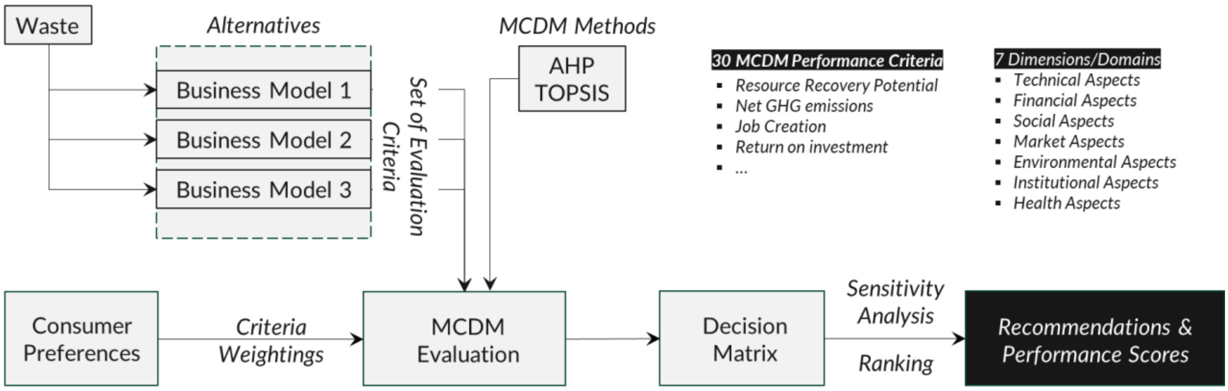


Figure 4*–Multi-Criteria Decision-Making Method*

Table 2−WasteWise evaluation domains, indicators, and assessment scales.

Domains	*WasteWise* Indicators	Assessment	Scale	1	2	3	4	5
Technical	Technology Maturity & Readiness Level	Subjective	Scale (1-5)		x			
	Technology Compatibility Index	Subjective	Scale (1-5)		x			
	Operational Reliability Score	Subjective	Scale (1-5)		x			
	Resource Recovery Potential	Objective	Product Yield/t waste		x			
	Technology Complexity Score	Subjective	Scale (1-5)		x			
Environmental	Net GHG emissions	Objective	kg CO_2/eq./t waste				x	
	Odor Pollution Risk	Subjective	Scale (1-5)				x	
	Noise Pollution Risk	Subjective	Scale (1-5)				x	
	Biodiversity Impact Score	Subjective	Scale (1-5)				x	
	Waste Diversion Rate	Subjective	Scale (1-5)				x	
	Water Use Efficiency	Objective	L/t waste				x	
	Land Use Efficiency	Objective	L/t waste				x	
	Energy Use Efficiency	Objective	L/t waste				x	
Institutional	Policy and Institutional Support Score	Subjective	Scale (1-5)					x
	Regulatory Compliance Ease	Subjective	Scale (1-5)					x
	Financial & Incentive Mechanisms Score	Subjective	Scale (1-5)					x
	Land Access & Tenure Security Score	Subjective	Scale (1-5)					x
Social	Job creation potential	Subjective	Scale (1-5)			x		
	Social Acceptance Score	Subjective	Scale (1-5)			x		
	Gender & Youth Inclusion Index	Subjective	Scale (1-5)			x		
Market	Market Demand Potential Score	Subjective	Scale (1-5)					x
	Market Accessibility & Inclusiveness Score	Subjective	Scale (1-5)					x
	Price Competitiveness Score	Subjective	Scale (1-5)					x
	Market Infrastructure & Distribution Score	Subjective	Scale (1-5)					x
	Standards, Certification & Buyer Confidence Score	Subjective	Scale (1-5)					x
	Tech. After-Sales Service & User Support Score	Subjective	Scale (1-5)					x
Economics	Payback period (PBP)	Objective	years	x				
	Return on Investment (ROI)	Objective	%	x				
	Internal rate of return (IRR)	Objective	%	x				
	Benefit-to-Cost Ratio (BCR)	Objective	Ratio	x				
Health	Occupational Health and Safety Score	Subjective	Scale (1-5)				x	
	Health Mitigation Capacity Index	Subjective	Scale (1-5)				x	

[1] Profit Maximization, [2] Yield Maximization, [3] Welfare Maximization; [4] Environment & Health Maximization; [5] Enabling Environment

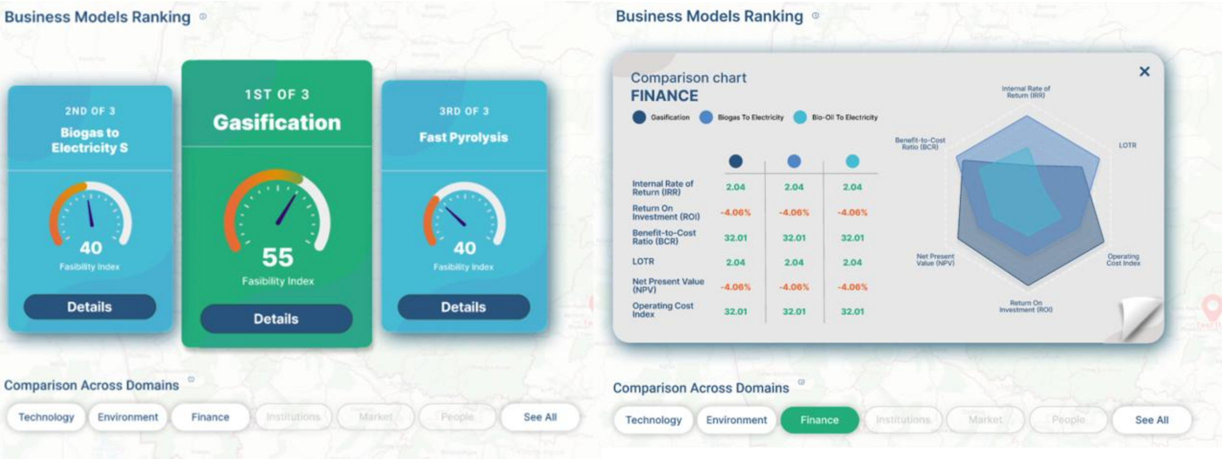
2.2.4. Data Visualization and Outputs

Another key strength of the *WasteWise* platform lies in its ability to communicate complex analytical results through clear, interactive visualizations (Figure 5). These visual outputs help users not only interpret technical findings but also explore alternative business scenarios and understand the implications of selected resource recovery pathways.

Spatial visualizations present the geographic distribution of waste resources and processing options. Using high-resolution GIS layers, the tool displays maps of feedstock availability, waste flow density, and potential/suitable treatment plant locations. Users can visualize waste-generation hotspots and track the spatial relationships between biomass resources and infrastructure, such as roads, settlements, and water bodies. This provides a strong evidence base for decisions on site selection and logistics planning. Non-spatial visualizations complement these maps by showing the financial, technical, and environmental performance of competing technologies or business models.

Users can explore dynamic dashboards that display cumulative cash flows, GHG emissions, and the energy or nutrient recovery potential of each technology. Comparison charts and radar diagrams summarize multi-criteria decision analysis scores across key domains, including finance, environment, technology, and social considerations. The combined spatial and non-spatial visualizations enable *WasteWise* to transform technical analysis into accessible insights, supporting evidence-based decisions for CBE investments and planning.

Interactive MCDA result screens also enable users to adjust input parameters in real time, for example, waste collection efficiency or plant capacity, and immediately see how these changes affect the ranking of business models. Users can also drill down to domain-specific indicators, such as internal rate of return, benefit-to-cost ratio, and water and land-use efficiency, for each recommended business model option. In upcoming versions, the tool will incorporate uncertainty visualization, e.g., displaying confidence intervals and linking MCDA outputs to the CBE Business Model Canvas.



	●	●	●
Internal Rate of Return (IRR)	2.04	2.04	2.04
Return On Investment (ROI)	-4.06%	-4.06%	-4.06%
Benefit-to-Cost Ratio (BCR)	32.01	32.01	32.01
LOTR	2.04	2.04	2.04
Net Present Value (NPV)	-4.06%	-4.06%	-4.06%
Operating Cost Index	32.01	32.01	32.01

Figure 5–*WasteWise visualization dashboard: a) Business model ranking by feasibility index; b) Domain-specific comparison chart showing key indicators across alternative models.*

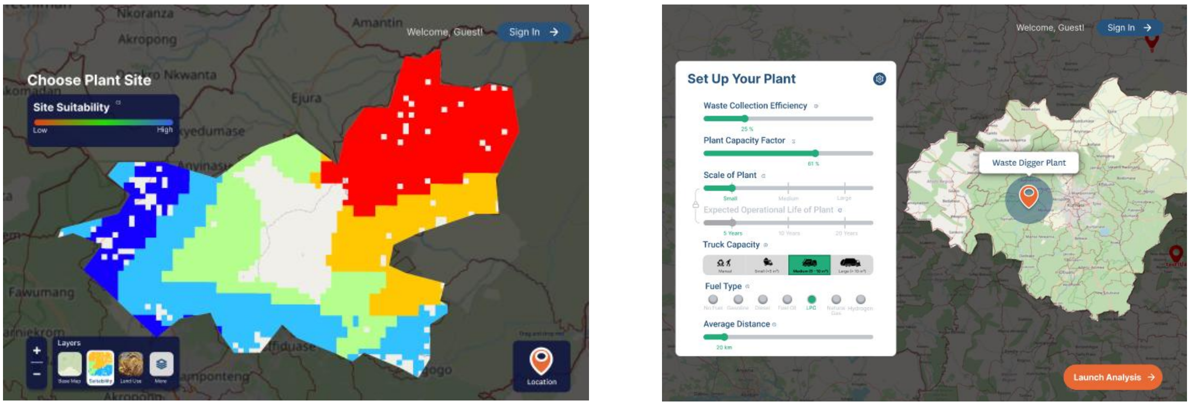
3. Performance Evaluation

3.1. Site Suitability

Site selection is a critical first step in CBE business models because it determines the long-term viability, efficiency, and community acceptance of resource recovery investments. A poorly chosen site can result in high transportation costs, feedstock shortages, conflicts with surrounding land uses, or limited access to markets. Conversely, locating facilities close to both biomass sources and demand centers strengthens market linkages, reduces distribution costs, and ensures steady uptake of recovered products.

WasteWise integrates GIS-based multi-criteria analysis with AHP and Weighted Overlay methods to identify optimal locations. Eight core spatial factors are considered: slope, elevation, agricultural production zones, proximity to settlements, proximity to surface water, road networks, electricity grids, and population density. These are further grouped into basal factors, which provide the foundational spatial context (e.g., elevation, slope, land use/land cover, administrative boundaries), and driving factors, which directly shape suitability outcomes (e.g., access to roads, electricity grids, water bodies, agricultural zones, settlements, and population density) – Figure 6.

Each factor is reclassified on a five-point suitability scale (ranging from highly suitable to unsuitable) and weighted based on expert consultation. For example, agricultural production zones and population density often carry higher weights (30% each), reflecting their importance in ensuring feedstock availability. The weighted overlay yields a composite suitability index, visualized through maps with color-coded classes (green = highly suitable, red = unsuitable). These maps guide planners in balancing environmental safeguards (e.g., avoiding water bodies and densely populated areas) with infrastructural access (e.g., proximity to roads and grids). Beyond minimizing risks, they enable a rapid assessment of suitable locations for CBE business models in each context, highlighting zones where waste resources and infrastructure converge. The result is a spatially explicit, evidence-based result that streamlines site selection and sets the stage for downstream analysis.



Waste Collection Efficiency: 25 %
Plant Capacity Factor: 61 %
Scale of Plant: Small (Small / Medium / Large)
Expected Operational Life of Plant: 5 Years (5 Years / 10 Years / 20 Years)
Truck Capacity: Medium (5 - 10 m³) (Manual / Small (<5 m³) / Medium (5 - 10 m³) / Large (> 10 m³))
Fuel Type: LPG (No Fuel / Gasoline / Diesel / Fuel Oil / LPG / Natural Gas / Hydrogen)
Average Distance: 20 km

Figure 6–*WasteWise spatial interface. (a) Site suitability mapping highlights optimal locations for plant siting based on spatial data layers. b) Interactive plant setup allows users to define operational parameters.*

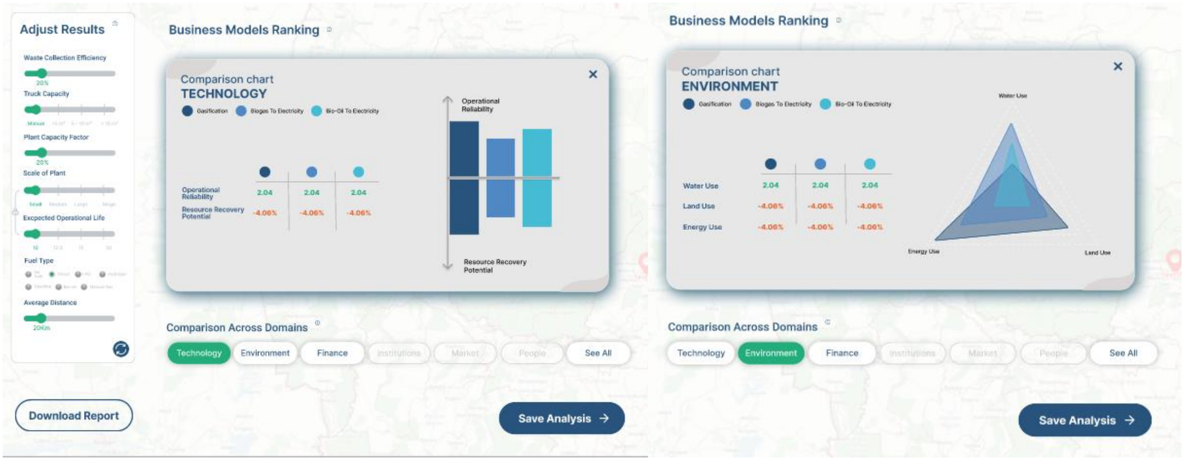
3.2. Objective Assessment

WasteWise incorporates a set of objective performance indicators to quantify the feasibility of CBE business models. These indicators are derived directly from waste and technology characteristics and data structures, ensuring a transparent and data-driven evaluation is completed before any composite or weighted scoring is applied. The tool evaluates the technical feasibility of technologies based on their capacity to convert waste into valuable bioproducts. Key objective indicators include electricity recovery potential (ERP), nutrient recovery potential (NRP), and system efficiency (Figure 7a).

ERP is derived from waste composition data, such as LHV, and is combined with technology-specific efficiency factors. NRP is estimated from the nitrogen, phosphorus, and potassium content of feedstocks and adjusted for technology efficiency. These measures provide a quantitative basis for comparing technologies across different waste streams and contexts. It also captures the performance of technologies against critical environmental metrics.

Environment metrics include net GHG emissions, which account for both process and transport emissions, as well as avoided emissions from displaced fuels and fertilizers. Additional indicators measure water use efficiency (L/t waste), land use efficiency (m²/t waste), and energy use efficiency (kWh/t waste), allowing planners to assess the intensity of resource consumption (Figure 7b). By quantifying emissions and resource footprints, the tool highlights technologies that can deliver tangible environmental benefits or, conversely, pose higher risks.

Finally, the tool assesses financial viability through standard metrics that can be calculated. These include the Payback Period (PBP), or the number of years required to recover initial capital; the Return on Investment (ROI) as a percentage of investment; the Internal Rate of Return (IRR), benchmarked against the cost of capital; and the Benefit-to-Cost Ratio (BCR), which indicates whether benefits outweigh costs, with values >1 indicating viability.



Adjust Results

Waste Collection Efficiency: 20%

Truck Capacity: Manual

Plant Capacity Factor: 20%

Scale of Plant: Small

Excpected Operational Life

Fuel Type

Average Distance: 20Km

Comparison chart
TECHNOLOGY

	● Gasification	● Biogas To Electricity	● Bio-Oil To Electricity
Operational Reliability	2.04	2.04	2.04
Resource Recovery Potential	-4.06%	-4.06%	-4.06%

Comparison chart
ENVIRONMENT

	● Gasification	● Biogas To Electricity	● Bio-Oil To Electricity
Water Use	2.04	2.04	2.04
Land Use	-4.06%	-4.06%	-4.06%
Energy Use	-4.06%	-4.06%	-4.06%

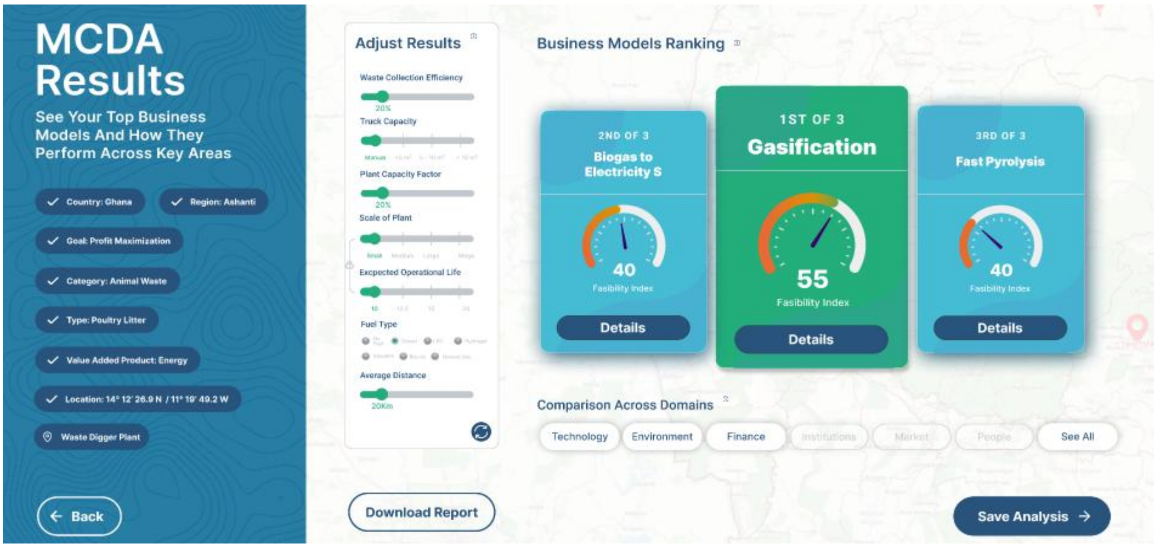
***Figure 7**–WasteWise comparison across domains. (a) The technology domain chart assesses the potential for resource recovery in business models. (b) The environmental domain chart compares models across water, land, and energy use indicators, along with other relevant indicators.*

3.3. Business Model Ranking

The final step involves integrating all domain scores using the multi-criteria decision-making framework. *WasteWise* employs AHP to structure criteria weights and TOPSIS to rank alternatives based on their closeness to an "ideal" solution. Each technology/business model is evaluated across seven domains—technical, environmental, financial, social, market, institutional, and health—comprising around 30 indicators.

Indicators are normalized to a common 1–5 scale. Depending on the user's chosen RRR objective (e.g., profit maximization, environmental & health maximization, welfare optimization), different weightings are applied (e.g., financial = 40% for profit maximization; environment = 40% for environmental objectives). The composite "closeness coefficient" (0–1) is calculated; higher values indicate greater feasibility. This approach helps identify the top-ranked business model and explains its performance across various domains. For instance, anaerobic digestion with combined heat and power may rank highest for environmental objectives due to its high GHG mitigation, while composting may lead to a higher welfare optimization score because of its strong job creation and inclusion. In addition to the objective indicators, the framework incorporates subjective indicators that reflect context-specific priorities and stakeholder perceptions. These include factors such as policy support, market confidence, gender and youth inclusion, and community acceptance, which cannot be measured solely through quantitative data but significantly influence the success of implementation.

By allowing users to assign relative weights to these aspects, *WasteWise* ensures that rankings capture not only technical and financial viability but also the social and institutional realities that affect whether a project succeeds or fails in practice. The platform (Figure 8) presents domain-level scores and scenario comparisons in a clear, accessible manner, enabling decision-makers to explore trade-offs, test assumptions, and communicate results.



MCDA Results

See Your Top Business Models And How They Perform Across Key Areas

✓ Country: Ghana
✓ Region: Ashanti
✓ Goal: Profit Maximization
✓ Category: Animal Waste
✓ Type: Poultry Litter
✓ Value Added Product: Energy
✓ Location: 14° 12' 26.9 N / 11° 19' 49.2 W
Waste Digger Plant

Adjust Results

Waste Collection Efficiency: 20%
Truck Capacity
Plant Capacity Factor: 20%
Scale of Plant
Excpected Operational Life
Fuel Type
Average Distance: 20Km

Business Models Ranking

2ND OF 3 — Biogas to Electricity S — 40 Fasibility Index
1ST OF 3 — Gasification — 55 Fasibility Index
3RD OF 3 — Fast Pyrolysis — 40 Fasibility Index

Comparison Across Domains

Figure 8–*WasteWise MCDA results dashboard.*

4. Complementarity with Other Frameworks/Tools

WasteWise does not exist in isolation. It builds on and complements a growing family of international waste assessment and decision-support tools. Each has a different scope, target audience, and level of analytical depth. Positioning *WasteWise* among these few helps clarify its added value.

- **Multicriteria Assessment (MCA)**: WasteWise builds on IWMI's MCA framework for assessing RRR business models (Otoo et al. 2016). It further enables users to explore and visualize data.
- **WasteAware** provides a globally recognized framework for benchmarking municipal solid waste management performance (Wilson et al., 2015). *WasteWise* complements the implementation of this framework and tool by enabling feasibility studies once performance gaps and proposed interventions are identified.
- **Waste Wise Cities Tool (WaCT):** Developed by UNEP and UN-Habitat, WaCT is primarily designed to quantify MSW generation and collection rates at the city level, supporting SDG 11.6.1 monitoring. It delivers harmonized data on flows of collected vs. uncollected waste, but it does not evaluate valorization pathways (UN-Habitat, 2020). *WasteWise* complements WaCT by integrating valorization options, connecting diagnostics to actionable strategies and interventions.
- **Waste Management and Circular Economy Policy Support System (WMPSS):** WMPSS is a diagnostic and planning tool that allows countries and cities to self-assess their waste management systems. It supports high-level strategic planning. *WasteWise* further supports the translation of systemic assessments into multi-criteria feasibility analysis.
- **Food Waste Index (FWI):** The UNEP Food Waste Index provides national and global estimates of food waste at household, retail, and service levels, supporting SDG 12.3 tracking (UNEP, 2024). While FWI highlights the magnitude of the food waste challenge, *WasteWise* complements it by enabling scenario testing for converting food waste into value-added products such as compost, energy, or animal feed.
- **Waste Flow Diagram (WFD):** The WFD developed by GIZ provides a rapid visual assessment of municipal solid waste flows, especially plastic leakage risks. It is designed for rapid, low-data contexts and serves as a first-level approximation of leakage hotspots (GIZ, University of Leeds, Eawag-Sandec & Wasteaware, 2020). While *WasteWise* does not currently consider non-organic waste streams, the methodology complements WFD by providing more detailed, technology-oriented assessments, once hotspots are identified, including financial and environmental feasibility.

5. Future Work

Harnessing the RRR potential of organic waste is central to achieving global goals on climate action (SDG 13), sustainable cities (SDG 11), and responsible consumption and production (SDG 12), and calls for evidence-based planning tools that can help decision-makers prioritize the most effective, locally appropriate strategies.

WasteWise already provides a robust, data-driven platform for assessing CBE business models, and upcoming enhancements will further strengthen its analytical depth and operational relevance. Some of the upcoming features are summarised below: To ensure robustness, *WasteWise* is undergoing structured validation exercises, including pilot applications in multiple countries and stakeholder feedback sessions. Comparing model outputs with real-world case performance will provide critical feedback for improving algorithms, datasets, and indicator weighting.

Future versions will go beyond point estimates by introducing uncertainty analysis, enabling users to visualize confidence intervals around technical, financial, and environmental outputs. This will help decision-makers gauge the reliability of results under conditions of data scarcity or variability. Building on this, sensitivity functions will allow users to test how changes in key assumptions, such as waste collection efficiency, discount rates, or electricity prices, affect model rankings. These “what-if” explorations will help identify the most influential parameters in determining business model success.

Additionally, AI integration will enhance predictive analytics, automate data validation, and facilitate pattern recognition across diverse datasets. For example, machine learning algorithms can be applied to improve waste generation forecasts, optimize technology matching, and refine financial projections based on historical and contextual data. Natural language processing modules are planned to assist users in interpreting results and generating tailored policy or investment briefs from tool outputs, increasing accessibility for non-technical users.

Finally, future iterations will extend beyond feasibility assessment to support operationalization. A tailored business model canvas module integrated into MCDA outcomes will allow users to translate ranked options into actionable business models, detailing value propositions, customer segments, operations, cost structures, and revenue streams. These integrations will bridge the gap between technical feasibility and implementation, supporting planners, entrepreneurs, and policymakers in moving from analysis to investment-ready solutions and scalable CBE business models.

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