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Article

Optimizing Waste Management in Costa Rica: Leveraging Agent-Based and Reinforcement Learning Models for Equitable Recycling Access

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Abstract: This study tackles waste management challenges in Costa Rica, where urban-rural disparities limit access to recycling facilities, posing barriers to national sustainability goals. By analyzing optimal facility placements, this research aims to improve accessibility and streamline waste management using Agent-Based Modeling (ABM) and Reinforcement Learning (RL). Integrating geospatial and demographic data, it forecasts recycling behaviors across Costa Rican provinces, with RL identifying cost-effective facility locations to boost recycling rates. Findings reveal **notable accessibility gaps**—urban centers like **San José achieve a 56% accessibility rate**, whereas **rural areas, such as Puntarenas, fall below 30%**. Strategic placements could elevate **Cartago's recycling rate to 27.38%**, and RL optimization indicates a **53.4% potential rise in recycling** and a **12% decrease in landfill reliance** in accessible areas. These outcomes underscore the need for **region-specific investments** in waste infrastructure, suggesting that **AI-enhanced waste categorization** and **community engagement** could further progress Costa Rica's sustainable waste management.

Keywords: Agent-Based Modeling (ABM); Reinforcement Learning (RL); waste management infrastructure; geospatial analysis; urban-rural disparities; cost simulation

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Introduction

Effective waste management and recycling systems are essential for addressing global environmental challenges associated with rising waste generation, particularly in **developing nations** where **urban-rural disparities** complicate sustainable practices. This global push, fueled by the **United Nations Sustainable Development Goals (SDGs)** for responsible consumption (SDG 12) and climate action (SDG 13), underscores the need for **efficient, equitable waste systems** [1]. Despite Costa Rica's reputation as a **sustainability leader in Latin America**, the nation faces significant **waste management challenges** due to infrastructural gaps and financial constraints. Such urban-rural divides are also evident in other global contexts, where disparities in infrastructure and resource allocation underscore the need for **tailored, inclusive policies** to advance sustainable development [2]. These challenges are common in developing countries, where effective **circular economy practices** in waste management remain underdeveloped, especially in the face of inadequate **recycling infrastructure** and **open dumping practices** [3]. Studies have highlighted the critical role of **Geographic Information Systems (GIS)** in mapping recycling facility access, especially for strategic management of **plastic waste** in the Global South, suggesting GIS-based approaches as transformative in **reducing plastic pollution** [4]. Social dynamics and internet access have also been shown to play a crucial role in fostering **waste-sorting behaviors** in rural areas, supporting sustainable practices [5]. Urban centers like **San José benefit from dense recycling networks**, while rural areas such as Limón and Guanacaste suffer from limited access, resulting in disparities in

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recycling participation rates across the country [6]. This study addresses these critical gaps in Costa Rica's waste infrastructure, aiming to bridge the **rural-urban divide by strategically improving recycling accessibility**.

The objectives of this research are fivefold: first, to evaluate current accessibility of recycling facilities across Costa Rican provinces using **geospatial and demographic data**; second, to simulate the effects of adding recycling facilities in underserved regions to quantify accessibility improvements; third, to **predict recycling rates** across provinces under enhanced infrastructure scenarios using **Agent-Based Modeling (ABM)** and **Reinforcement Learning (RL)**; fourth, to assess the **economic feasibility of waste management initiatives** through a cost simulation model that integrates ABM, RL, and Monte Carlo methods; and fifth, to recommend **optimal waste management strategies** using RL to align with Costa Rica's sustainability goals. **In a context where economic constraints often pose barriers to sustainable practices, a risk assessment framework based on fuzzy synthetic evaluation can help prioritize and address key financial and operational risks, aiding decision-makers in implementing resilient waste management strategies** [7].

The study's methodology combines **spatial analysis** with **ABM and RL**, providing **dynamic insights** into infrastructure needs and potential **recycling behavior changes**. ABM is increasingly valued in **environmental management** for exploring **human-environment interactions** and evaluating policies through **scenario-based simulations** [8]. By simulating diverse recycling patterns and optimizing **policy recommendations in real time**, this research offers a comprehensive framework for **equitable waste management**. Similar applications of RL combined with ABM have proven effective in exploring complex social dynamics, as seen in **[9]**, which demonstrates how reward structures within an agent-based model can shape collective behaviors, providing valuable insights for policy development in adaptive systems.

To assess the economic feasibility of these strategies, the study integrates a **cost simulation model** that combines ABM, RL, and Monte Carlo methods. This economic model accounts for **setup and maintenance costs for recycling facilities**, **operational expenses**, and **processing fees**, incorporating variability to reflect uncertainties across regions. **Sensitivity analyses** applied within both ABM and RL models further enhance robustness, allowing results to be adaptable across varied **population densities** and **facility layouts**. Through this integrated framework, the research advances waste management by providing a dynamic assessment of **recycling accessibility**, **policy optimization**, and **cost impact**, contributing valuable insights toward Costa Rica's **sustainability and cost-efficiency goals**.

2. Literature Review

2.1. Current State of Waste Management

Costa Rica faces significant challenges in waste management, with pronounced regional differences due to socioeconomic and infrastructure variability. In the **Metropolitan Area**, the waste generation rate is approximately **0.59 kg per person per day**, with **55.9%** of the waste stream being organic [10]. In contrast, **Guácimo** reports a slightly lower rate of **0.55 kg per person per day**, composed of **35% recyclable materials**, **45% biodegradable waste**, and **20% destined for landfills** [11]. These discrepancies highlight the **47% share of national waste produced in urban centers like San José**, which strains existing infrastructure. The recent closure of the **Los Pinos landfill** in Cartago has exacerbated the need for alternative solutions. Developing accurate leachate movement models tailored to Costa Rica's tropical environment is essential for improved landfill management [6].

To tackle these challenges effectively, it is essential to analyze the regional distribution of waste types, as detailed in **Table 1**.

Table 1. Regional Waste Generation Rates and Composition.

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Region	Waste Generation Rate (kg/person/day)	Organic Waste (%)	Recyclable Waste (%)	Landfill-bound Waste (%)
Metropolitan Area	0.59	55.9	-	-
Guácimo	0.55	45	35	20

2.2. Landfill Capacities and Regional Waste Management Practices

Data from the Ministry of Health indicates that **1,282,057 tonnes** of waste were directed to landfills in 2021, with only **9.6% deemed recoverable**. This highlights considerable shortcomings in Costa Rica's waste management systems, as merely **3.9%** of the waste was recycled, **2.7%** composted, and **2.4%** co-processed [12,13]. Urban centers, particularly San José, generate a significant share of organic waste—approximately **58%**—which emphasizes the urgent need for expanded composting and organic waste treatment facilities [14]. Currently, **94% of the nation's solid waste** is deposited in landfills, posing substantial environmental challenges. The situation is exacerbated in rural areas where waste collection infrastructure remains inadequate, underlining the critical need for robust policy measures to reduce landfill dependence and address these regional disparities [15,16].

Table 2 provides a detailed breakdown of waste sent to landfills by category, illustrating the limited recovery potential and highlighting areas where improvements could yield significant benefits.

Table 2. Waste Recovery and Disposal Rates.

Year	Total Waste (Tonnes)	Recoverable (%)	Recycling (%)	Composting (%)	Co-Processing (%)
2021	1,282,057	9.6	3.9	2.7	2.4

2.3. Costa Rica's Recycling Challenge: A Global Perspective

Costa Rica's recycling rate remains low at **9.6%**, with **83.8% of waste diverted to landfills**. In comparison, **Germany** and **South Korea** boast recycling rates of **69.3% and 50%**, respectively, due to strong policy frameworks and high public participation [13]. Costa Rica could benefit by adopting similar strategies, such as **mandatory recycling quotas** and **deposit return schemes**, which have driven success in other countries.

Table 3 presents a comparative overview of recycling rates in Costa Rica and other countries, highlighting the gaps in infrastructure and regulatory support that Costa Rica could address.

Table 3. Global Recycling Rates and Contributing Factors.

Region/Country	Recycling Rate (%)	Key Contributing Factors	References
European Union	46% (2020)	Varies across member states; strong policies and infrastructure	[17]
Germany	69.3% (2024)	Stringent waste separation, strong regulations	[18]
United States	21% (2024)	State-level variations, mixed public participation	[19]

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Japan	20% (2023)	Meticulous waste sorting, but lower recycling infrastructure	[20]
Brazil	4% (2024)	Driven by informal sector, lack of formal infrastructure	[21]
South Korea	69% (2023)	Public involvement, advanced waste sorting systems	[22]
Sweden	50% (2024)	High integration of Waste-to-Energy (WtE) technologies	[23]
Costa Rica	9.6%	High landfill dependency, minimal recycling infrastructure	[13]

2.4. Government Initiatives and Policies

The Costa Rican government has introduced key initiatives, such as the **Environmental Health Route policy** and the **National Circular Economy Strategy**, to increase the national recycling rate to **25% by 2033**. These initiatives include specific targets, such as a **10% reduction in per capita waste generation by 2025**, enhanced public education on recycling, and development of new processing facilities in underserved areas [24]. Additionally, **Law No. 9786**, targeting single-use plastics, supports these goals by enforcing restrictions and promoting sustainable alternatives [25,26].

Table 4 summarizes the primary government initiatives and their objectives, illustrating the Costa Rican government's multifaceted approach to addressing waste management challenges.

Table 4. Government Initiatives and Goals.

Initiative	Goal	Target Year	Reference
Environmental Health Route Policy	Increase recycling rate to 25%	2033	[24]
Environmental Health Route Policy	Ensure regular garbage collection in 34% of the territory	2023	[24]
Environmental Health Route Policy	Reduce per capita waste generation by 10%	2025	[24]
National Circular Economy Strategy	Promote circular economy practices	Ongoing	[25,26]
Law No. 9786 (Law to Combat Plastic Pollution and Protect the Environment)	Drastically reduce single-use plastic usage and promote sustainable alternatives	2019	[27]

These initiatives underscore Costa Rica's commitment to waste management reform through policy innovation, infrastructure development, and public engagement.

2.5. Waste Management Innovation Index

The Waste Management Innovation Index offers a comprehensive comparison of waste management practices globally, assessing each country's progress in technological advancements, policy innovation, public engagement, infrastructure development, and sustainability impact. This index highlights areas where Costa Rica's waste management practices fall short compared to leading countries globally, as shown in Table 5.

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Table 5. Waste Management Innovation Index.

Country	Technological Advancements	Policy Innovation	Public Engagement	Infrastructure Development	Sustainability Impact	Overall Index Score	References
Germany	High	High	High	High	High	9/10	[28]
United States	High	High	High	High	Moderate	9/10	[29]
Japan	High	High	High	Moderate	Moderate	8/10	[20]
Brazil	Low	Low	Low	Low	Low	3/10	[30]
South Korea	High	High	High	High	High	9/10	[31]
Sweden	High	High	High	High	High	9/10	[32]
Costa Rica	Low	Moderate	Moderate	Low	Low	4/10	[33]

The index underscores Costa Rica's need for improvement in technology and infrastructure, with Germany, South Korea, and Sweden serving as models for advancing Costa Rica's waste management practices.

2.5. Innovative Waste and Water Management Initiatives in Costa Rica

The **Costa Rican Electricity Institute (ICE)** has unveiled a significant **biogas initiative** aimed at addressing the country's mounting **waste management crisis**. This ambitious project, planned for roll-out over the **next five to six years**, focuses on converting **organic waste**, which constitutes **53%** of the nation's waste stream, into **renewable energy**. **ICE's executive president, Marco Acuña**, highlighted the success of an existing **biogas facility at La Uruca**, which generates **140 kilowatts** of energy from landfill gas, feeding directly into the **national power grid**. This biogas initiative aligns with the Ministry of Health's **"Waste to Energy"** strategy, targeting the development of regional waste-to-energy centers throughout Costa Rica. However, **municipal engagement and infrastructure challenges** remain significant hurdles, underscoring the need for strengthened partnerships for comprehensive implementation. As a **medium-term solution**, ICE's biogas project promises to reduce dependency on landfills, alleviating the environmental strain on the heavily impacted **Greater Metropolitan Area** [34].

3. Methodology

3.1. Data Collection

The methodology involved collecting **geospatial** and **demographic data**. Geospatial data included shapefiles of Costa Rica's **provincial boundaries** and the locations of existing and potential **recycling facilities**, sourced from previous research [35]. These shapefiles were processed using GeoPandas in Python, ensuring alignment with the Coordinate Reference System (CRS) for accurate spatial analysis. To refine province-specific analyses, the recycling facility data was filtered to include only facilities within each provincial boundary.

Demographic data, collected from official sources, included **population totals** and **average household sizes** for each province, as shown in **Table 6 [36]**. This data enabled estimation of household numbers, essential for scaling spatial analyses and aligning simulation results with actual population distributions.

Table 6. Population and Average Household Size per Province.

Province	Population	Average Household Size
Guanacaste	412,808	3.3
Alajuela	1,035,464	3.13
Cartago	545,092	3.2
Heredia	479,117	3.1
Limón	470,383	3.2
San José	1,601,167	3.1
Puntarenas	500,166	3.4

For provinces lacking specific household location data, **simulated household points** were generated within provincial boundaries using the population and household size data from Table 6. This simulation applied **Equation 1**, which calculates the total number of households in each province:

$$\text{Total Households}=\frac{\text{Population}}{\text{Average household size}}$$

The simulated households were incorporated into the spatial analysis, allowing for the evaluation of their proximity to both existing and potential recycling facilities. This ensured a more precise representation of **recycling accessibility** across Costa Rican provinces.

3.2. Distance Calculations and Household Count in Distance Ranges

For both actual and simulated households, the **straight-line (Euclidean) distance** to the nearest existing or proposed recycling facilities was calculated. This distance measurement is standard in Geographic Information Systems (GIS) for assessing **geographic proximity** between points, commonly applied in infrastructure and accessibility studies [37].

These distances were categorized into **five intervals**: 0-5 km, 5-10 km, 10-20 km, 20-50 km, and >50 km. These intervals were selected to represent significant levels of accessibility to recycling centers. To count the number of households within each distance range, an **indicator function** was applied, assigning a value of 1 if a household's distance did_idi falls within a specified range [X,Y] and 0 otherwise. The total household count for each range [X,Y] was calculated using **Equation 2:**

$$\text{Households in Range (X-Y Km)}=\left(\sum_{i=1}^{n}\text{I}x \leq d_i < \text{Y}\right)\times\text{Scaling Factor}$$

where:

- di represents the distance of household i to its nearest facility.
- `IX≤di<Y is an` **indicator function** equal to 1 if did_idi is within the range [X,Y], and 0 otherwise.
- n is the total number of sampled households.
- The **scaling factor** is applied in provinces where household samples were used, to approximate the total population within each distance range.

3.3. Expanded Agent-Based Model for Recycling Rate Prediction

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This model simulates **provincial recycling rates** by generating randomized data within predetermined ranges for each province, facilitating the analysis of recycling rate patterns and the assessment of potential impacts of improved accessibility to recycling facilities.

3.3.1. Simulation Approach

The simulation estimates recycling rates by generating random data points following a **normal distribution**, using **mean (μpi)** and **standard deviation (}σpi)** values from real-world data. Each province undergoes **100 iterations** to capture variability in recycling behavior, ensuring statistically realistic outcomes based on **normal distribution sampling** [38]. Using the np.random.normal() function, the simulation calculates recycling rates for each province, producing datasets for analysis and validation.

To obtain the **average recycling rate (R¯pi)** for each province, the simulation applies **Equation 3**:

$$\bar{R}_{pi} = \frac{1}{n}\sum_{j=1}^{n} R_{pij}$$

Where:

- $\bar{R}_{pi}$ represents the **average recycling rate** for province i,
- n is the number of **simulations**,
- R_{pij} is the recycling rate from the j-th simulation for province i.

This approach ensures a statistically robust measure of the typical recycling rate, reflecting variability across iterations.

3.3.2. Validation Against Real Data

The simulated recycling rates were validated by comparing them to **official recycling data** for each province. Any discrepancies were addressed through parameter adjustments, aligning the simulated results with real-world performance and enhancing predictive reliability [39].

3.3.2. Recycling Rate Calculation

To assess recycling accessibility, a **proximity-weighted formula** was used to calculate the **recycling rate (RRpi)** for each province, accounting for both existing and potential recycling facilities. The calculation applies **Equation 4**:

$$RR_{pi} = \frac{H_{\text{existing}} + H_{\text{potential}}}{H_{\text{total}}}$$

Where:

- $H_{existing}$ Households within a certain radius of existing facilities,
- $H_{potential}$ Households within a certain radius of potential facilities,
- H_{total} is Total number of households in the province.

This **GIS-based accessibility analysis** evaluates infrastructure distribution and its impact on recycling rates, providing insights into how strategic facility placement can improve provincial recycling performance.

3.4. Sensitivity Analysis of Recycling Accessibility Model

The sensitivity analysis extends the **proximity-weighted formula** from Section 3.4, evaluating how variations in key parameters impact **recycling accessibility** using an **Agent-Based Model (ABM)**. It examines three variables: **household coverage near existing facilities (Hexisting)**, coverage near potential facilities (Hpotential), and **proximity adjustment factors**. Hexisting assesses

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accessibility within defined distance ranges (e.g., 0-5 km, 5-10 km), while Hpotential simulates additional coverage from varying site counts (e.g., 5, 10, 15, 20).

Proximity adjustment factors alter distance thresholds to simulate improved accessibility, while scaling factors (e.g., 1.0, 1.2, 1.5) adjust household counts to reflect potential population density changes. Using spatial data, the analysis identifies configurations that **maximize accessibility** by testing these variables across multiple scenarios.

4. Q-Learning Approach for Waste Management Optimization

4.1. Waste Management Optimization Model and Architecture

The **Q-learning-based reinforcement learning (RL) model** was developed to optimize waste management strategies across Costa Rica's provinces. It simulates **interventions and policies** that affect key waste management metrics, focusing on improving **recycling rates**, reducing **landfill reliance**, and enhancing **biogas production capacity**. By evaluating the impact of **distinct actions** across provincial contexts, each with specific baseline metrics, the model serves as a **decision-making tool** within a broader waste management framework.

The **Q-learning algorithm** enables the agent to learn optimal policies over time by receiving feedback on **state changes** following actions. The model includes **12 discrete actions**, representing specific interventions. Examples include:

- **Action 0**: Increase the recycling rate by **5%**.
- **Action 1**: Improve **waste-to-energy (WtE) technology**, increasing WtE investment by **10%** and reducing landfill dependence by **2%**.

Each action adjusts **state variables** such as recycling rates, landfill usage, emissions, and bioenergy production, reflecting their **multi-faceted impacts**. The state space is initialized with **province-specific baselines**, such as current recycling rates and landfill dependence, to simulate real-world conditions. This approach demonstrates the **flexibility of Q-learning** in optimizing complex, multi-variable systems. Similar applications of Q-learning have been effective in minimizing **carbon emissions** in recycling line challenges [40] and improving **human-robot collaboration** in waste management processes [41].

By integrating **provincial baselines and intervention strategies**, the model provides a robust framework for data-driven optimization of Costa Rica's waste management goals.

4.2. Dataset and Model Initialization

The model's dataset comprises **25 variables** representing key aspects of waste management, including **waste generation**, **landfill capacity**, **recycling efforts**, **public engagement**, and **bioenergy production**. These variables, normalized between **0 and 1**, ensure computational efficiency and are derived from **official studies** and **national reports**, ensuring relevance to Costa Rica's waste management context. Key variables and their ranges, outlined in **Table 7**, encompass environmental and social metrics vital for simulations, complementing the data discussed in **Section 3.1**.

Table 7. Key Variables in the Waste Management Model.

Data Category	Variable	Value/Range	Source/Notes
Waste Generation	Total Waste Generated (Urban)	47% of national waste from San José	[42]
	Total Waste Generation Rate (Urban)	0.59 kg per person per day	[10]

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	Total Waste Generation Rate (Rural)	0.55 kg per person per day	[11]
	Daily Solid Waste Generation	3,982 tons per day	[413
Landfill Capacity	Landfill Dependence	94% of solid waste to landfills	[15]
	Recovery Rate from Landfills	9.6%	[12]
	Landfill Emissions	1,195,300 - 1,502,700 tonnes CO_2e	[44]
Plastic Waste	Annual Plastic Waste	1.45 million tons (12% plastic)	[35]
	Daily Plastic Waste Generation	50 tons per day	[34]
	Plastic Bottle Production	600 million annually	[35]
Recycling and Recovery	Recycling Rate (Current)	1%	[13]
	National Recycling Target	25% by 2033	[24]
	CO_2e Emissions Avoided by Recycling	-17,500 to -21,600 tonnes CO_2e	[13]
Public Engagement	Ecoins Program Registered Users	46,162 (2023)	[45]
	Ecoins Program Collection Sites	520 (2023), projected 1,127 by 2030	[13]
Bioenergy	Biogas Production Capacity	140 kW from organic waste	[46]
	Daily Biogas Production	412.5 cubic meters	[47]
Economic Indicators	PAYT (Pay-as-You-Throw) Effectiveness	13% waste reduction	[48]

4.3. Q-Learning Configuration

The **Q-learning algorithm** employed a learning rate (**α=0.1**) and a discount factor (**γ=0.99**) to balance **immediate and long-term rewards**. An **epsilon-greedy strategy** with decay (**ϵ=1.0**) facilitated exploration during early training and increased exploitation as learning progressed. The **Q-value updates**, governed by **Equation 5**, allowed the agent to refine its decision-making:

$$Q(s,a) \leftarrow Q(s,a) + \alpha \left[\mathrm{Re}\,ward + \gamma \max_{a'} Q(s',a') - Q(s,a) \right] (1)$$

where:

- Q(s,a) is the expected cumulative reward for taking action a in state s,
- α controls how quickly the model updates beliefs,
- γ factors future rewards, and
- max⁡a′Q(s′,a′) is the maximum expected reward for the next state.

The **reward function** (Equation 6) aligned with Costa Rica's waste management goals, penalizing **landfill emissions** and **water pollution** while incentivizing improvements in **recycling rates**, **facility accessibility**, **public engagement**, and investments in **waste-to-energy (WtE) technologies**. This function prioritized actions that contributed most to sustainability metrics.

$$\text{Reward} = 0.5 \times \text{Landfill Dependence} + 2.0 \times \text{Recycling Rate} - 0.3 \times \text{Landfill Emissions} + 1.5 \times \text{Facility Accessibility} + 1.2 \times \text{WtE Investment} + 1.0 \times \text{Biogas Production Capacity}$$

To ensure model robustness, a **sensitivity analysis** was conducted on key hyperparameters, including $\boldsymbol{\alpha}$, γ, and $\boldsymbol{\epsilon}$, as well as reward weights for **recycling** and **landfill reduction**. Using a custom **WasteManagementEnv class**, these parameters were systematically varied across multiple episodes. Results, summarized in **Table 8**, identified the most effective configurations for optimizing **recycling rates** and **landfill reliance**.

Table 8. Tested Parameter Values for Sensitivity Analysis of the RL Model.

Parameter	Values
Learning Rate (α)	0.05, 0.1, 0.2
Discount Factor (γ)	0.9, 0.95, 0.99
Exploration Rate (ε)	1.0, 0.5, 0.1
Epsilon Decay Rate	0.99, 0.995, 0.999
Recycling Weight	1.5, 2.0, 2.5
Landfill Weight	-0.3, -0.5, -0.7

4.3. Cost Simulation Methodology for Provincial Waste Management

The cost simulation integrates **Agent-Based Modeling (ABM)**, **Reinforcement Learning (RL)**, and **Monte Carlo simulations** to evaluate waste management feasibility across Costa Rica. **ABM models waste flows** (1.5 tons per household annually) and facility expenses, while RL optimizes strategies for recycling rates, landfill reduction, and biogas production. Monte Carlo simulations refine cost projections across 100 iterations, introducing variability in electricity, fuel, and operational costs to highlight cost-effective solutions.

Table 9 summarizes the key cost parameters used, including facility setup, maintenance, and processing expenses, providing a comprehensive overview for decision-making.

Table 9. Key Cost Parameters for Waste Management Operation.

Cost Category	Cost (USD)	Source/Notes
Electricity (Industrial Rate)	\$0.1088 per kWh	Based on ICE tariff for industrial consumption of up to 8,100 kW [49]

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Gasoline Price	$1.39 per liter		[50]
Unit Collection Costs	$22.65 per ton		[51]
Final Disposal Costs	$18.81 per ton		[51]
Recycling Transportation (General)	$14.50 per ton (approx.)		[52]
Operational Costs for Recycling	$27.00 per ton		[53]
Recycling Facility Setup Costs	$300,000 - $500,000		[53]
Maintenance Costs (Annual)	$10,000 - $15,000		[53]
Labor Costs (General Workers)	$500 - $800 per month	Average salary for workers at recycling centers (estimated).	
Waste Processing Costs	$32.00 per ton		[51]

5. Results

5.1. Accessibility of Households to Recycling Facilities Across Provinces

The analysis reveals that **adding potential recycling facilities** significantly increases household coverage across Costa Rican provinces, particularly in underserved areas (**Supplementary Table 1** provides facility counts/locations by province; **Supplementary Table 2** details household accessibility by distance). This expansion is strategically illustrated in **Figure 1**, which visually represents the distribution of both existing and potential recycling facilities, highlighting key placements aimed at improving accessibility and filling service gaps across Costa Rica.

In **Alajuela**, potential facilities increase **0-5 km access from 23.1 million to 34.7 million households** and add **9.2 million households within 10-20 km**, effectively reducing travel distances and enhancing service reach. **Cartago** benefits from new facilities, with an additional **8,550 households within 0-5 km** and expanded **20-50 km coverage reaching 52,700 households**.

For **Guanacaste**, where population density is lower, potential facilities reduce the **median access distance from 8.7 km to 6.3 km**, benefiting **2,719 households**. **Heredia** gains improved access for **74,258 households within 20-50 km**, addressing gaps in suburban areas, while **Limón** shows expanded **0-5 km access from 29,363 to 44,045 households** and **10-20 km access for 29,363 households** with the addition of new facilities. **Puntarenas** shows unique coastal distribution patterns, with potential facilities adding **47,250 households within 5-10 km**, easing the load on current sites and improving inland service.

In **San José**, coverage is extensive, with **0-5 km access rising from 26,114 to 46,895 households** and **20-50 km access expanding to serve 250,694 households**, enhancing both suburban and semi-urban reach. In summary, strategically placed facilities would significantly improve accessibility in **Alajuela, Cartago, and San José**, while **Limón, Puntarenas, and Guanacaste** would benefit from increased coverage in intermediate and rural areas. This expanded network of facilities is designed

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to reduce regional accessibility disparities and support a balanced recycling infrastructure across Costa Rica.

Figure 1 visually represents the distribution of both existing and potential recycling facilities across Costa Rica's provinces, demonstrating strategic site placement to enhance accessibility and fill current service gaps.

Figure 1. Geographic Distribution of Existing and Potential Recycling Facilities Across Key Provinces.

Caption:Figure 1 shows the distribution of existing (green circles) and potential (purple crosses) recycling facilities across the provinces of Limón, Puntarenas, Alajuela, Guanacaste, San José, Heredia, and Cartago in Costa Rica. Existing sites meet current needs, while potential sites target areas with gaps.

5.2. Simulated Recycling Rates Across Provinces

The **simulated recycling rates** reveal substantial regional differences across Costa Rica, influenced by **infrastructure density, geography**, and **public engagement**. **Table 10** shows average recycling rates and variability, with **Cartago** leading at **27.38%**, driven by well-distributed facilities that promote widespread participation. **San José** follows with **22.29%**, benefiting from dense urban infrastructure, while **Heredia** (17.82%) has high urban participation but limited reach in peripheral areas. **Limón** (12.83%) and **Puntarenas** (7.69%) face challenges due to geographic constraints and sparse facility coverage, while **Alajuela** exhibits the highest rate variability (**2.88%**), reflecting a pronounced urban-rural divide. **Guanacaste** (12.50%) similarly experiences limited access outside main towns due to its rural character.

Table 10. Simulated Recycling Rates and Variability Across Costa Rican Provinces.

Province	Average Recycling Rate (%)	Standard Deviation (%)	Key Observations
San José	22.29	1.52	Dense urban infrastructure supports high recycling rates; outskirts less covered.

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Heredia	17.82	1.34	Concentrated in urban areas; peripheral regions underserved.
Cartago	27.38	1.50	Highest recycling rate, with well-distributed facilities supporting broad engagement.
Limón	12.83	1.46	Coastal focus leaves inland areas significantly underserved.
Puntarenas	7.69	1.42	Lowest rate; elongated geography complicates facility distribution.
Alajuela	19.64	2.88	High variability due to urban-rural divide.
Guanacaste	12.50	1.38	Sparse infrastructure limits access outside major towns.

This analysis emphasizes the importance of **strategic facility placement** to improve recycling rates and enhance equitable access, especially in underserved rural and suburban areas. **Figure 2** visually depicts the recycling rate distribution across provinces, highlighting regional variability and the distinct challenges faced by provinces with lower rates.

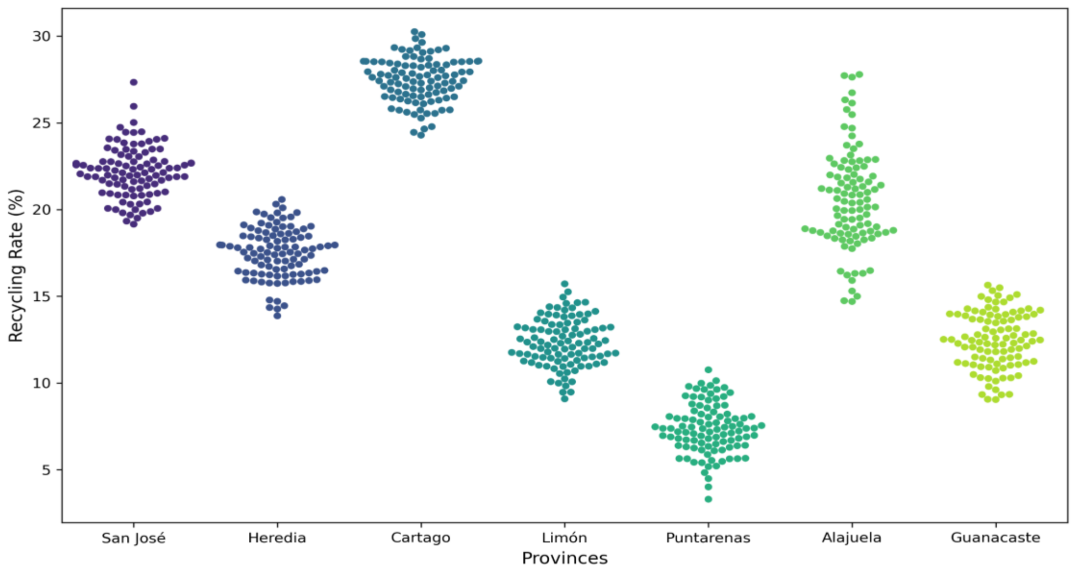

Figure 2. Swarm Plot of Simulated Recycling Rates for Costa Rican Provinces.

Caption:Figure 2 illustrates the **distribution of simulated recycling rates** for each of Costa Rica's provinces using a **swarm plot**. Each point represents an individual simulation of the **recycling rate**, and the spread of points highlights the **variability** in recycling participation across provinces. **Cartago** exhibits the **highest recycling rate**, while **Puntarenas** shows the **lowest**, with substantial disparities observed in the more **rural regions** of **Limón** and **Guanacaste**.

5.4. Sensitivity Analysis for Accessibility-Based Model (ABM)

The **sensitivity analysis** of the Accessibility-Based Model (ABM) examines how adjustments in **facility numbers, population scaling**, and **distance ranges** affect accessibility across Costa Rican provinces, highlighting distinct impacts in **rural, suburban, and urban regions**.

In rural areas like **Guanacaste**, household accessibility improves significantly with additional facilities at **10–20 km and 20–50 km** distances. **Adding 20 facilities** and applying a **scaling factor of 1.5** notably increased coverage, emphasizing the importance of facility density in sparsely populated regions. For **suburban provinces** like **Alajuela**, accessibility gains were most pronounced within **10–20 km** when **15 facilities** were added, indicating that intermediate placements effectively support suburban zones with moderate densities. In urbanized **San José**, proximity proved crucial; accessibility gains peaked within **0–5 km** distances and a **scaling factor of 1.5**, showing that densely populated areas benefit most from nearby facilities. **Limón** and **Puntarenas**, with dispersed populations, saw the greatest improvements at **20–50 km**, highlighting the need to extend reach to remote households. **Heredia** and **Cartago** also benefited from additional facilities and scaling factors within **20–50 km**, indicating the value of targeted facility placements in semi-urban areas.

Supplementary Figure 1 provides a visual representation of accessibility changes by distance range and scaling factor across provinces, while **Supplementary Table 3** details facility placement and household coverage values.

5.3. Reinforcement Learning Model for Optimizing Waste Management

The **Reinforcement Learning (RL) model** optimizes waste management strategies in Costa Rica's provinces by targeting **recycling rates, landfill reduction**, and **biogas production**. Using a Q-learning algorithm, the model tailors waste management interventions to each province's conditions and simulates their impacts on waste metrics, offering insights into the effectiveness of localized strategies.

Table 11 presents the results for each province, detailing **recycling rates**, **landfill dependence**, **biogas capacity**, and **total rewards** after 100 iterations. The results show significant regional differences, with **Cartago achieving the highest recycling rate (53.38%)**, indicating that well-optimized infrastructure can greatly enhance waste management. **Heredia and Puntarenas** also performed well with recycling rates of **47.59%** and **48.63%**, while **San José** exhibited the highest landfill dependence at **81.14%**, highlighting a need for expanded recycling facilities and urban engagement. **Limón** and **Guanacaste** also faced high landfill reliance (64.16% and 74.08%), reflecting the limited infrastructure in rural areas.

Table 11. Final Results of RL-Based Waste Management Model Across Provinces.

Province	Recycling Rate (%)	Landfill Dependence (%)	Biogas Production Capacity (%)	Total Reward
Alajuela	**32.24**	**62.88**	15.9	92.02
Limón	**41.67**	64.16	14.8	**120.35**
Cartago	**53.38**	67.76	**16.3**	119.99
Heredia	47.59	**56.73**	16.2	118.15
San José	45.43	**81.14**	15.0	87.34
Guanacaste	41.09	74.08	14.5	80.92
Puntarenas	48.63	74.98	14.8	113.87

The **total reward metric**, a measure of strategy effectiveness, peaked in **Limón (120.35)**, showing that rural areas can improve with focused interventions. **Alajuela** and **San José**, with lower rewards

(92.02 and 87.34), could benefit from additional infrastructure and targeted policies to boost recycling and reduce landfill use. These findings emphasize the value of **region-specific strategies** and demonstrate the RL model's potential to guide policy, aligning infrastructure expansion and policies to local needs.

Figure 3 provides a **heatmap** visualizing these metrics across provinces, highlighting regional disparities in waste management and pinpointing areas for targeted improvements.

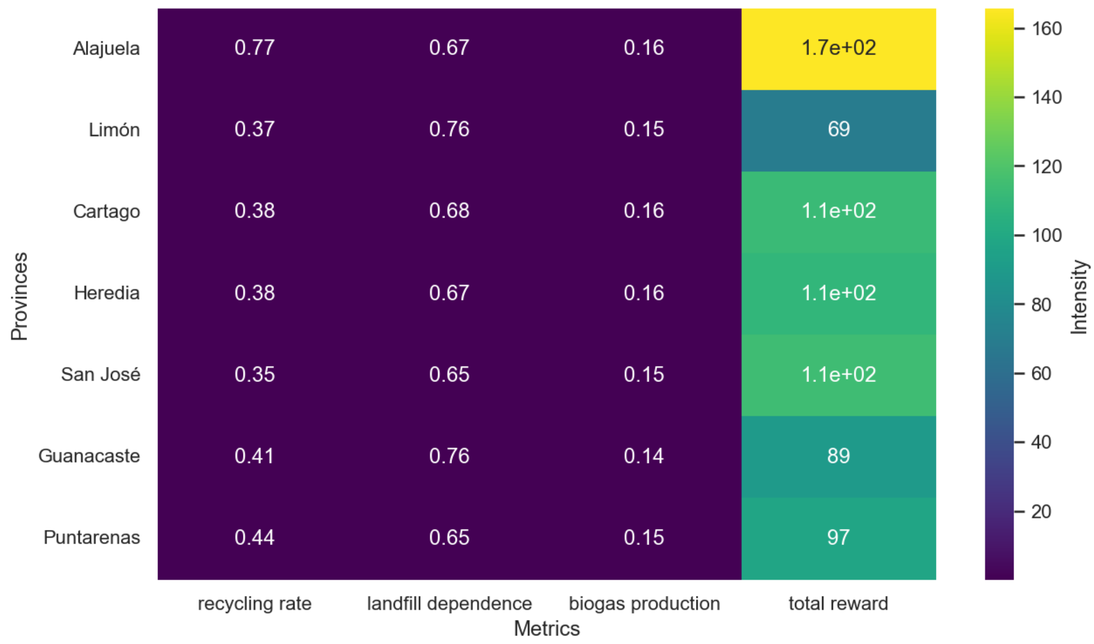

Figure 3. Heatmap of Recycling and Waste Management Metrics Across Provinces.

Caption:The heatmap illustrates key waste management metrics for seven provinces: Alajuela, Limón, Cartago, Heredia, San José, Guanacaste, and Puntarenas. The metrics include recycling rate, landfill dependence, biogas production, and total reward from recycling and waste processing activities.

5.4. Sensitivity Analysis of the RL-Based Waste Management Model

The sensitivity analysis assesses the RL model's effectiveness across Costa Rican provinces by examining **recycling rate**, **landfill dependence**, and **biogas production capacity**. The **cumulative reward metric** indicates the success of each province's waste management optimization (see **Supplementary Figure 2** for a comparison of these metrics). **Table 12** summarizes the final values, showing the model's varied impact under different regional conditions.

Table 12. Sensitivity Analysis Results of RL-Based Waste Management Model.

Province	Recycling Rate	Landfill Dependence	Biogas Production Capacity	Total Reward
Alajuela	**0.4224**	0.6488	0.159	**138.67**
Limón	0.1667	0.7416	0.148	70.01
Cartago	0.1338	**0.6976**	**0.163**	76.84
Heredia	**0.6759**	0.6873	0.162	102.89

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San José	0.3543	0.7714	0.150	83.62
Guanacaste	0.4109	0.7008	0.145	98.93
Puntarenas	0.3863	0.7098	0.148	80.90

The analysis reveals substantial regional differences. **Heredia** achieves the **highest recycling rate (67.59%)** and a relatively low **landfill dependence (68.73%)**, reflecting the benefits of local infrastructure and engagement. In contrast, **San José** shows the highest **landfill dependence (77.14%)**, highlighting a need for more recycling facilities and policy support in urban areas. **Limón** and **Guanacaste** also struggle with high landfill reliance, reflecting infrastructure limitations in rural areas.

The **total reward metric** further identifies areas of effective waste management, with **Alajuela** and **Heredia** leading at **138.67** and **102.89**, indicating significant progress. In contrast, **San José (83.62)** and **Puntarenas (80.90)** suggest room for improvement, where intensified efforts and community engagement could enhance outcomes.

5.5. Provincial Cost Simulation for Waste Management

The cost simulation results reveal significant regional cost variations in Costa Rica's waste management, driven by **setup, maintenance, and operational factors** unique to each province. **Table 13** provides a breakdown, with **Guanacaste showing the highest costs** and **Alajuela the lowest**, reflecting regional infrastructure needs. Operational and processing costs also vary, influenced by local waste processing rates and recycling capacities.

Cost savings from RL optimization are modest, with **Heredia achieving the highest savings**. Conversely, **Limón and Cartago** show minor negative savings, indicating challenges in RL optimization for these areas. **Monte Carlo simulation** results further illustrate cost variability, with **San José's mean cost at $422,432.36 USD** and a **standard deviation of $57,938.49 USD**, showing potential cost fluctuations under varying conditions.

Table 13. Provincial Cost Breakdown for Waste Management Operations in Costa Rica.

Province	Setup and Maintenance Cost (USD)	Operational and Processing Cost (USD)	Cost Savings from RL Optimization (USD)	Monte Carlo Mean Cost (USD)	Monte Carlo Cost Variability (Std Dev) (USD)
Alajuela	1,980,336.08	660,387.84	82.43	422,926.03	59,531.99
Limón	2,085,531.98	655,145.98	-43.32	406,433.17	60,453.92
Cartago	2,201,058.92	658,597.18	-48.32	408,693.67	57,919.93
Heredia	1,995,344.42	662,215.84	223.24	419,162.98	58,209.73
San José	2,227,606.01	657,152.83	5.87	422,432.36	57,938.49
Guanacaste	2,317,055.49	661,884.07	62.11	406,928.24	53,972.15

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Puntarenas	2,009,982.72	662,021.60	46.63	414,057.32	58,227.71

These findings highlight the need for **tailored regional strategies** in waste management, with cost breakdowns guiding **policy and investment** to enhance sustainability across provinces.

6. Discussion

This study provides a detailed analysis of Costa Rica's waste management infrastructure, focusing on recycling facility accessibility and policy impacts. Significant accessibility disparities exist between urban and rural areas; for instance, San José achieves 56% household accessibility within a 0–5 km range, while rural regions like Limón and Puntarenas report rates below 30%, underscoring the need for targeted infrastructure development to improve equitable access. Using agent-based modeling (ABM), this study shows that strategic facility placement enhances recycling rates; for example, Cartago achieves a simulated rate of 27.38%, while Puntarenas lags at 7.69% due to geographic constraints. This approach is supported by findings in [54], which highlight ABM's suitability for modeling complex waste systems, and [55], which found that well-placed facilities improve public engagement in urban settings.

The economic analysis reveals notable regional cost differences, with facility setup averaging $500,000 in rural areas compared to $300,000–$400,000 in urban centers. This aligns with [56], which emphasizes that waste infrastructure investments in Latin America promote job creation, and [46], which shows that incentive-based waste policies like PAYT reduce waste and costs. This suggests that Costa Rica might adopt similar models to improve financial efficiency and recycling rates. The reinforcement learning (RL) model demonstrates how optimized strategies can enhance recycling rates while reducing landfill use; for instance, Cartago's recycling rate rose to 53.4% with a 12% decrease in landfill reliance. Additionally, [57] suggests that integrated solid waste management (ISWM) plays a key role in advancing Sustainable Development Goals (SDGs) by addressing urban-rural waste disparities, indicating that Costa Rica could benefit from similar sustainable approaches.

A sensitivity analysis within the ABM further supports the importance of location-specific facility placements, showing accessibility improvements of up to 25% in rural Guanacaste with facilities added within a 10–20 km range, while San José saw the greatest gains within 0–5 km. These findings align with those in [58], which report similar infrastructure challenges in urban Colombia, where optimizing facility placement is essential. Improved waste infrastructure provides social and environmental benefits, with increased accessibility potentially reducing landfill volume by up to 15% nationwide, particularly in high-accessibility areas like Alajuela and Cartago. Furthermore, [59] highlights the role of AI-driven waste categorization for improved accuracy, while [60] advocates for high-resolution models to enhance infrastructure efficiency, especially in resource-constrained regions. According to [61], linking waste management practices to the SDGs through systematic waste indicators can strategically support Costa Rica's sustainability objectives, particularly in urban settings.

[62] found that incentive-based policies in Canada increased public participation by up to 96.5%, suggesting that Costa Rica could adopt similar models to boost community-driven solutions and tackle rural accessibility challenges. However, limitations in this study include potential data gaps in rural areas and reliance on assumptions in ABM and RL models, which may affect generalizability. Moreover, [63] demonstrates that waste management interventions in support of a circular economy can significantly reduce greenhouse gas emissions—a factor critical to Costa Rica's environmental goals. Finally, [64] indicates that integrating landfill-based biogas production with leachate treatment aligns with a water-energy nexus approach, further supporting Costa Rica's goals of sustainable waste and resource management.

Future research could explore tailored engagement strategies for rural communities, advanced RL applications across diverse waste contexts, and AI-driven categorization models for improved

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efficiency. Longitudinal studies on the impact of infrastructure expansion on recycling and environmental outcomes would provide valuable insights for refining Costa Rica's waste management policies.

7. Conclusion

This study analyzes Costa Rica's waste management infrastructure, highlighting significant accessibility disparities between urban and rural areas. Through Agent-Based Modeling (ABM), Reinforcement Learning (RL), and cost simulations, the research identifies critical gaps in access, emphasizing the need for region-specific infrastructure improvements.

The results show that **urban centers like San José** have **household accessibility rates up to 56% within 0–5 km**, while **rural areas such as Limón and Puntarenas** remain below **30%**, underscoring geographic and infrastructural barriers in underserved communities. Simulation findings reveal the potential of **strategically placed facilities** to improve recycling behaviors, with **Cartago projected to reach a 27.38% recycling rate** compared to **Puntarenas at 7.69%**. The **economic analysis** highlights the cost challenges in rural regions, where setup costs average **$500,000** versus **$300,000–$400,000** in urban areas, reinforcing the need for **cost-effective, policy-driven interventions**.

The **RL model** shows that **optimized strategies** could boost **recycling rates by up to 53.4%** and reduce **landfill dependency by 12%** in areas like Cartago, suggesting that **data-driven, adaptable approaches** could enhance waste management outcomes. Sensitivity analysis also demonstrates that **adjusting facility placements to local demographics** could significantly improve accessibility in challenging areas.

Achieving **sustainable waste management** in Costa Rica will require a **multi-pronged approach**, combining **strategic infrastructure expansion**, **tailored policies**, and potentially **AI-driven technologies** to increase waste processing efficiency. Future research on **public engagement** and **longitudinal studies** could provide valuable insights for refining policy and adapting to evolving regional needs.

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Data Availability Statement: The dataset supporting the findings of this study, including the Python scripts and supplementary materials, is openly available in Mendeley Data under the title: "Optimizing Waste Management in Costa Rica: Leveraging Agent-Based and Reinforcement Learning Models for Equitable Recycling Access" (Navarro, Andrea, 2024), Mendeley Data, V1, doi: 10.17632/wwf8xxh3py.1.

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