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Exploring the implementation feasibility of the sol-char sanitation system using machine learning and life cycle assessment

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ABSTRACT

Globally, 1.5 billion people still lacked access to safe sanitation facilities in 2022, which exacerbated health risks and environmental degradation. To address this, we created the Sol-Char sanitation system, a potential solution for expanding secure sanitation alternatives. This study aimed to develop a machine learning model that could evaluate the viability of implementing the Sol-Char system in 76 countries with high rates of open defecation in 2022. Using the Random Forest model, we identified suitable locations considering factors such as solar energy availability and economic feasibility. The model successfully identified 42 countries (55 %), mainly in Sub-Saharan Africa and South Asia, as appropriate candidates for implementing the system. In addition, a framework was developed to guide solar technology suitability prediction using our machine learning model. Furthermore, we conducted an ex-ante life cycle assessment (LCA) study to evaluate the environmental impacts across different implementation scenarios. The baseline scenario (Scenario 1) produced the least emissions, with 299 kg CO_2-eq. In contrast, the scenario (Scenario 2) involving international transportation had the highest emissions at 395 kg CO_2-eq (32 % higher), while the localized scenario (Scenario 3) landed in between with 337 kg CO_2-eq emissions. The LCA and contribution analysis highlighted that optimizing materials and design was essential to reduce emissions across these scenarios. Local manufacturing, particularly in high-transportation scenarios like Scenario 2, could reduce emissions from logistics but required careful consideration of local resources and energy structures, as demonstrated in Scenario 3.

1. Introduction

According to the United Nations Children's Fund (UNICEF) findings in 2022, approximately one-fourth of individuals across thirteen different countries still practiced open defecation (UNICEF, 2023; WHO & UNICEF, 2023). Alarmingly, around 1.5 billion people globally lacked access to basic sanitation facilities. This issue is particularly concerning in rural areas of Sub-Saharan Africa, Central and Southern Asia, and Oceania, where open defecation and inadequate sanitation can lead to the spread of diseases and various health problems (Freeman et al., 2017; Mara et al., 2010; Prüss-Ustün et al., 2019). Each year, hundreds of thousands of child deaths occur due to diseases such as cholera, dysentery, and typhoid, directly linked to the lack of proper sanitation (Hannah Ritchie and Max Roser, 2021; Prüss-Ustün et al., 2019). Additionally, recurrent diarrhea cases can result in malnutrition and stunted growth among children. Inadequate sanitation could pose health hazards and negative environmental impacts, as untreated human waste can pollute water bodies, disrupt aquatic ecosystems, degrade soil quality, and contribute to greenhouse gas emissions (Mukherjee et al., 2019). Beyond health and environmental consequences, inadequate sanitation has socioeconomic implications, including increased healthcare costs, reduced productivity due to illness, and educational impacts due to frequent absenteeism (Belizario et al., 2015; Morgan et al., 2017). The lack of proper and private restroom facilities particularly impacts women, as it could expose an individual to potential safety risks and may impede attendance at schools or workplaces during menstruation

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(Beardsley et al., 2021; Morgan et al., 2017; Speich et al., 2016).

Given these challenges, there is an urgent need for viable sanitation technologies. These technologies should conserve water, harness renewable energy, function autonomously, require minimal maintenance, and so on. Therefore, we have developed the Sol-Char ("Solar-Biochar") sanitation system as a feasible solution (Fisher et al., 2021). The system features an integrated design with multiple key components. A foundational frame supports other elements. A sensor-driven, radar--like solar collector maximizes sunlight tracking and collection, as shown in Fig. 1. The collected sunlight is transmitted to the reactor via the connected optical fibers. Fecal material is transformed through pyrolysis into useful biochar in the reactor (Fisher et al., 2021; Yaashikaa et al., 2020). Dual reactors allow alternate use for continuous processing. An integrated urine disinfection system utilizes solar-derived heat, while an odor control system manages smells during usage. In addition, the disinfected urine can be used for irrigation after solar pasteurization (Mihelcic et al., 2011; Pivelli et al., 2008). The Sol-Char system presents a sanitation solution that effectively disinfects human waste and repurposes it into valuable resources (Fisher et al., 2021; University of Colorado Boulder, 2021). It can be a step forward after large-scale implementation to potentially benefit the billions lacking safe sanitation and promote public health, environmental preservation, and energy efficiency.

However, the system's applicability varies across regions due to solar energy availability and socioeconomic conditions. In this study, we employed machine learning techniques to predict the suitability of installing the Sol-Char sanitation system in certain areas based on data published by the United Nations and other sources (Global Solar Atlas, 2023; Solargis, 2023; WHO & UNICEF, 2023; World Meteorological Organization Standard Normals | World Meteorological Organization, 2023). In addition, we applied ex-ante life cycle assessment (ex-ante LCA) to evaluate the environmental impact (carbon emissions) across different implementation scenarios to better analyze the deployment strategy. Therefore, this approach ensured that our recommendations for the Sol-Char system were based on thorough and data-driven analyses and could lead to a suitable solution for decision-makers to implement the Sol-Char system.

2. Methods

2.1. Data Collection and Processing

As per sanitation data released by the WHO and UNICEF in July 2023 (UNICEF, 2023; WHO & UNICEF, 2023), we screened, organized, and visualized the information relevant to our study. This document presents open defecation rates and lack of basic water access for various countries and regions worldwide from 2015 to 2022 (see *Supplementary Material 1 (SM1)* for details). Notably, numerous countries enhanced their sanitation standards between 2015 and 2022, leading to a decline in the overall open defecation rates worldwide. For example, the total open defecation rate in India decreased from 30 % in 2015 to 11 % in 2022 (WHO & UNICEF, 2023). However, given the population size, its sanitation system still faced significant challenges. Additionally, there was a noticeable difference between urban and rural areas in open defecation rates. For instance, in India in 2022, the national average open defecation rate was 11 %, with less than 1 % in urban areas but around 17 % in rural areas (WHO & UNICEF, 2023). In other countries, such as Afghanistan, Mongolia, and Yemen, rural rates significantly exceeded urban rates, sometimes several times higher (WHO & UNICEF, 2023). Therefore, in this study, we utilized the average values for both urban and rural areas.

We mapped regions with open defecation rates exceeding 1 %, as shown in Fig 2(a). The processed results highlighted that much of the global population had to resort to open defecation due to the absence of secure sanitation systems. From the map, most countries were in Saharan Africa, South Asia, Southeast Asia, and South America regions. Specifically, Eritrea, Chad, and South Sudan in Africa were the most affected, with 67 %, 63 %, and 60 % of the populations resorting to open defecation, respectively. Moreover, these regions often face water shortages, as exemplified by South Sudan in Fig. 2(b), where around 60 % of the population lacked regular domestic water access. This water scarcity rendered conventional flush toilets impractical, coinciding with the lack of basic sanitation systems.

We collected solar resource data, including annual sunlight hours, average Direct Normal Irradiance (DNI), and maximum/minimum DNI values, from UN, World Bank, and Global Solar Atlas and other open data sources (Data.world, 2019; Global Solar Atlas, 2023; World Bank Group; ESMAP; Solargis, 2023; World Meteorological Organization Standard Normals | World Meteorological Organization, 2023). After

Fig. 1. Sol-Char sanitation system (a) Overview (b) Solar concentration system (c) Optical fiber bundles (d) Pyrolysis reaction tank (e) Solar collector for urine disinfection and (f) the biochar converted from human feces by solar pyrolysis.

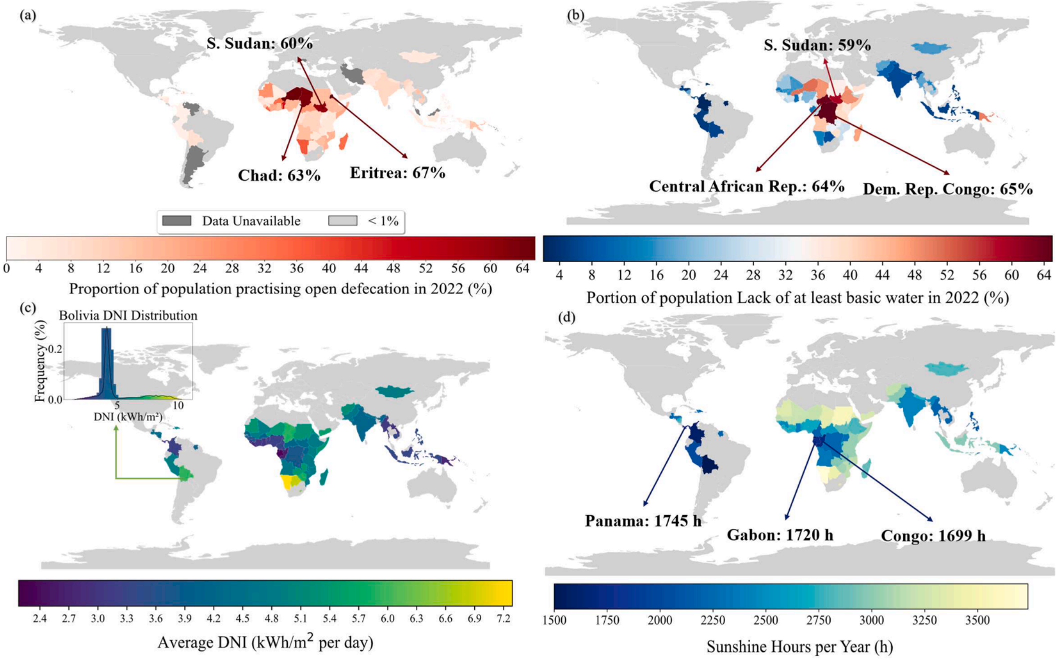


Fig. 2. (a) The Proportion of the population practicing open defecation in 2022 (%). (b) The proportion of the population (%) lacked at least basic water, including limited access (more than 30 mins), unimproved water facilities, and use of surface water. (c) The Average daily DNI of the highlighted countries. (d) The number of Sunshine hours per year in the highlighted countries.

screening the DNI data and annual sunshine hours for these countries, we visualized them on a map (Fig. 2(c)). However, a high DNI does not always indicate system feasibility, as DNI distribution may be uneven within a country or region. For instance, Bolivia's DNI ranged from 2.15 to 9.71 kWh/m^2 (average 5.93 kWh/m^2). Still, the inset in Fig. 2(c) shows that the actual DNI fell between 4.2 - 4.6 kWh/m^2 with a probability of at least 25 %, and was less than 4.2 kWh/m^2 50 % of the time, suggesting uneven solar resource distribution. Although its overall solar resources were abundant, the southwestern part of the country was far more than other region (Cheng et al., 2022; Lopez et al., 2021). Therefore, maximum and minimum DNI values should be considered alongside the average.

Furthermore, many countries can achieve up to 2500 sunshine hours per year, with some parts of Sub-Saharan Africa exceeding 3000 hours, as illustrated in Fig. 2(d). However, some countries with high average DNI might have shorter sunshine hours annually. For instance, while Panama had an average DNI exceeding 3 kWh/m^2, its sunshine hours only amounted to 1744 hours per year. This could indicate periods of overcast or rainy weather/season (Becker, 1987; Ruane et al., 2013), which could impact the daily operation of the system.

GDP per capita data was extracted from the World Bank (THE WORLD BANK, 2022) as described in *SM2*. All processed data served as parameters for machine learning, organized into two supplementary material files: *SM3* for 2022 and *SM4* for 2015. The machine learning codes and a *README* document explaining the methods are also available in *SM5* and *SM6*, respectively.

2.2. Energy Requirement

We determined the Sol-Char system required approximately 2 MJ of energy to convert 1 kg of wet (untreated) human feces into biochar. This included the energy required to evaporate water, heat the feces to the reaction temperature, and drive the endothermic pyrolysis reaction. The thermal efficiency was found to be approximately 37 %, necessitating the provision of roughly 5.4 MJ of energy to transform 1 kg of wet feces into biochar. Our design utilized 8 fibers, each of which could supply 85.5 W under ideal conditions, which was equivalent to 1 kWh/m^2 of DNI. Assuming a local DNI of 0.8 kWh/m^2, 8 hours of sunlight per day, and the processing of 1 kg of feces at a time, then, with 0.8 kWh/m^2 of DNI, it implied:

$$8\ (\text{fibers})\ \times 85.5\ \left(\frac{\text{watts}}{\text{fiber}}\right) \times \frac{0.8\ (\text{kwh/m}^2)}{1\ (\text{kwh/m}^2)} = 547\ \text{W}$$

of energy can be delivered to the first-stage reactor of the Sol-Char system. Consequently, with 8 hours of sunlight, 15.7 MJ of energy could be transported to the reactor. Thus, even with a light intensity of 0.8 kWh/m^2 and 8 hours of sunlight per day, there was an excess of about 10 MJ of energy.

The following equation was at the basis of the calculations:

$$E_{total} = N \times E \times DNI \times H \tag{1}$$

Where E_{total} was the total daily energy required for pyrolysis; N was the number of fibers (adjustable according to local conditions); E was energy that each fiber can transport, *DNI* for Direct normal irradiance, and H was sunshine hours per day.

2.3. Cost Calculation

We determined the cost of the whole system by gathering cost information on the components, materials, and auxiliaries. Hard-to-estimate costs were determined using average values. For instance, the estimated cost of small-scale solar concentrator systems using fiber optics ranged from \$200–500/m^2, with an average of \$350/m^2. We gathered the cost data for different types of the Sol-Char system, designed to serve varying numbers of people and communities, from a household of 4 and 10 people to a community-shared model of up to 50 people. This allowed for different application scenarios and enabled comparing the cost per individual to the country's per capita GDP. The annualized cost was calculated by taking the total capital cost and adjusting it for time using a discount rate over the expected lifespan, as shown in Eq. 2:

$$Annulized\ Cost = \frac{Total\ Capital\ Cost\ \times Discount\ Rate}{1 - (1 + Discount\ Rate)^{-Life\ \ Years}} \tag{2}$$

In this study, the *Discount Rate* was assumed to be 6 % (a commonly used value), and the system's *Life Years* were set at 20 years.

The cost per person per year could be calculated using Eq. 3:

$$Cost\ per\ Person\ per\ Year = \frac{Annulized\ Cost}{Number\ of\ users} \tag{3}$$

2.4. Machine Learning Approach – Random Forest

We treated the suitability of a region for installing a Sol-Char system as a binary classification problem and used the Random Forest model for it. Random Forest is an ensemble algorithm that combines multiple decision trees and makes final predictions based on majority voting (Lovatti et al., 2019). Fig. 3 shows the flowchart of the machine learning process in this study.

We selected seven features for prediction: *Non-basic least water* (%), *rate of open defecation* (%), DNI_{min} (kWh/m^2 per day), DNI_{max} (kWh/m^2 per day), *Average DNI* (kWh/m^2 per day), *Sunshinehours* (h), *and per capita GDP* (current US$). The data was collected and processed in Section 2.1. All missing values were replaced with the median value of each column. After preprocessing, the data were standardized using StandardScaler to achieve a mean of 0 and a standard deviation of 1. For parameter tuning, we employed grid search (GridSearchCV) to identify the optimal parameters. Grid search is an exhaustive search method that finds the best model parameters by traversing through a given combination of parameters (Lovatti et al., 2019; Probst et al., 2019). In terms of model evaluation, we performed cross-validation on the model to assess its performance on the training set. Subsequently, we evaluated the generalizability of the model using its performance on an independent test set (the data for the year 2015 for 90 countries with open defecation rate > 1 %). For model validation, we applied K-Fold cross-validation for model tuning, which evaluated the accuracy of a model by averaging the performance metrics over K iterations of the training-validation cycle, using a different dataset partition each time to

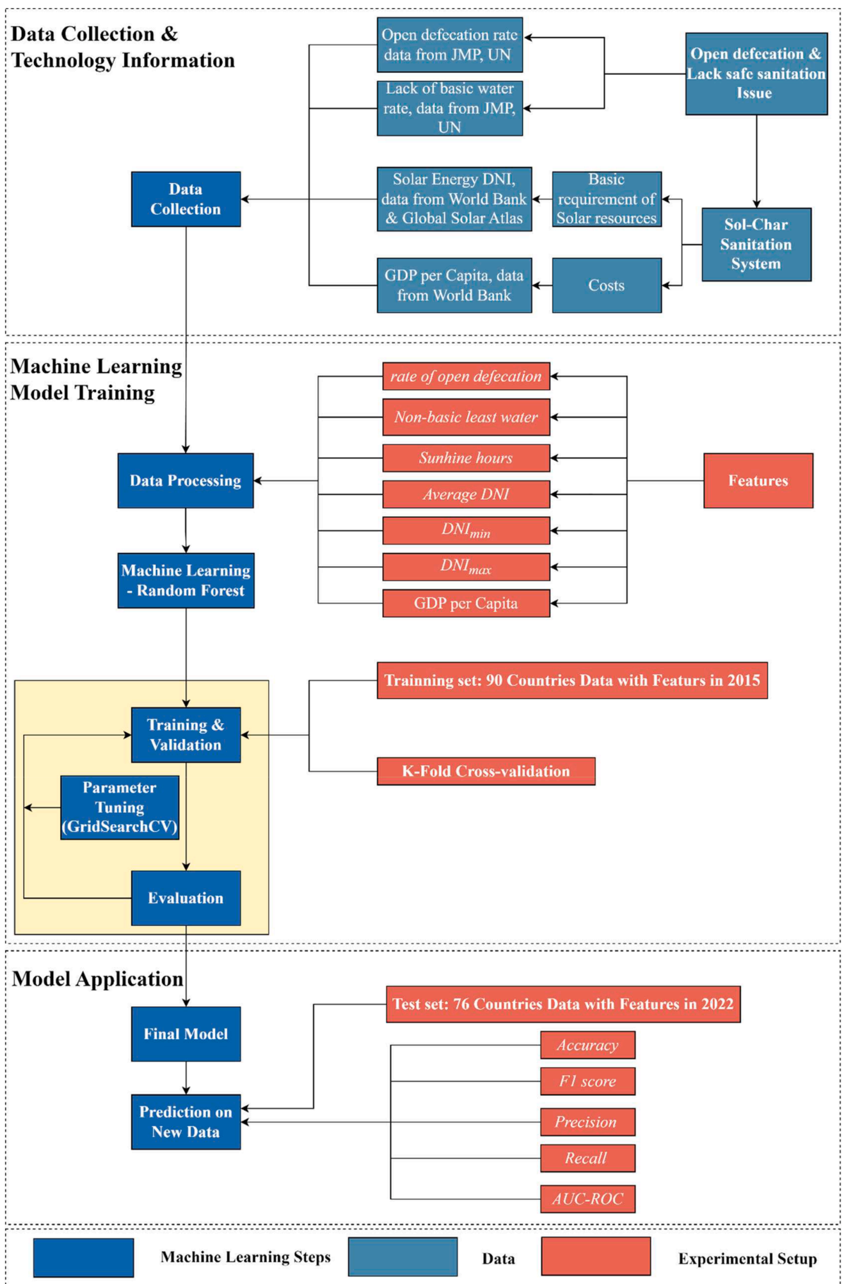


Fig. 3. Machine learning workflow for this study, from data collection to model training, to model application.

ensure that the evaluation is comprehensive and unbiased (Hossin and Sulaiman, 2015).

The trained model (the Final model) was applied to predict new data (the data for the year 2022 for 76 countries whose open defecation rate > 1 %). The new data was preprocessed similarly and fed into the trained model. Since this task is a binary classification task with unbalanced labels, the following five evaluation metrics were used to fully assess the performance. *Accuracy* measures the overall correctness of the model but may be misleading for unbalanced categories. *Precision* assesses the model's ability to identify only true positives (successfully predicting a region is suitable for constructing the Sol-Char sanitation system). *Recall* assesses the model's ability to capture all positives, which is critical in high-risk situations. The *F1 score* reconciles precision and recall and is useful in unbalanced datasets. *AUC-ROC* (Area Under the Receiver Operating Characteristic Curve) quantifies the model's ability to discriminate between categories at different thresholds, with higher values indicating better performance, especially in binary classification (Hossin and Sulaiman, 2015; Naidu et al., 2023).

2.5. *Ex-ante Life Cycle Assessment*

After identifying regions suitable for deploying the system, our next goal was to evaluate the environmental performance of the system within these regions, focusing on the impact of various deployment strategies. To do this, we conducted an ex-ante life cycle assessment (ex-ante LCA, "ex-ante" refers to "before the event") study. Ex-ante LCA can evaluate the potential environmental impacts before full-scale implementation. This measure allows for informed decisions during the design and development phases to minimize negative environmental impacts (Cucurachi et al., 2018). Therefore, an ex-ante LCA often explores various scenarios where new technology with high uncertainties might operate in the future (Cucurachi et al., 2018).

We examined the impact of the major components and operational phase regarding greenhouse gas emissions. Since the system was developed in Colorado, USA, we used the community-shared model applied there as the baseline scenario. Key sub-systems included the CSP (Concentrated Solar Power) System, Urine Disinfection System, Reaction System, and Odor Treatment System, as mentioned in the Introduction section. A simplified flowchart of the system is shown in Fig. 4, and a complete version can be found in *SM7*.

The system boundary of the Sol-Char system followed a cradle-to-grave approach. The functional unit was defined as the provision of a sanitation service for a 32-person community in one year using the Sol-Char sanitation system. The life cycle inventory (LCI) data came from our developed prototype and field tests (Fisher et al., 2021; University of Colorado Boulder, 2021), and the complete LCI is in *SM8*. We used the Activity Browser software (Steubing et al., 2020) with the ecoinvent 3.91 database as the background for modeling (Wernet et al., 2016). We used the "US" background data for construction materials and global average data ("GLO") when the "US" data was unavailable. Transportation impacts were considered for international transport only, excluding local transport. *IPCC 2021 no LT, climate change no LT, global warming potential (GWP100)* was utilized for the environmental impact calculation (Masson-Delmotte et al., 2021).

As mentioned above, we chose the community-shared model in the USA (Scenario 1) for comparison within the different implementing strategies. Scenario 2 involved a build-then-transport approach, while Scenario 3 was based on a local construction strategy. In Scenario 2, all components were prepared in Denver, Colorado, USA, and then transported to N'Djamena, Chad (a representative of Africa areas in this study), via rail (Denver to Port of Los Angeles, ~1400 km), sea (Los Angeles to Douala Port, Cameroon, ~14,500 km) and road transport (Douala Port to N'Djamena, Chad, ~1600 km). For the simulation of Scenario 3, representing South Asia, most parts were sourced locally in India. Therefore, the background inventory information regarding materials in India ("IN") was applied. For components that were not available in the ecoinvent database for India, the nearby countries or Rest of the World ("RoW") data was used. In this study, a cut-off rule of 0.5 % was applied to the Activity Browser. Maintenance was considered in the operational phase, especially for components in the CSP system. Moreover, we conducted a sensitivity analysis on the component with the highest environmental impact, aiming to identify materials with lower impact by substituting parts based on the baseline scenario.

3. Results and Discussion

3.1. *Energy Requirement*

For the community-shared model, assuming each user produced 200 g of feces per day, then 6.4 kg of feces were processed daily based on the

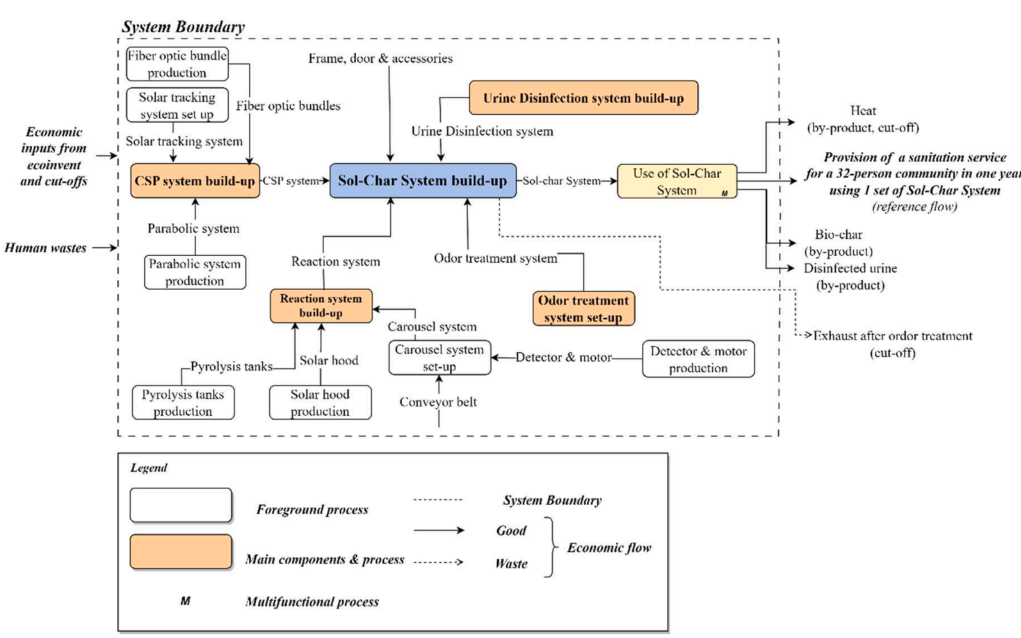


Fig. 4. Simplified LCA flowchart for the Sol-Char sanitation system.

32-person system, corresponding to an energy requirement of 34.6 MJ. If there were 8 hours of sunlight per day, it required 1.8 kWh/m^2 of DNI.

According to Eq. 1 and our test data, $E_{total} = 34.6$ MJ, if $N = 8$ (8 fibers), and $E = 85.5$ W. This led to the relationship:

$$DNI \times H = 14$$

If H ranged from 6 to 8, i.e., 6 to 8 hours of sunlight per day, then DNI values ranged from 1.8 to 2.3. This implied that a DNI of at least 1.8–2.3 kWh/m^2 was required to meet the daily processing energy requirements. As shown in Fig. 2(c), most countries met this standard (1.8–2.3 kWh/m^2), and some, such as Sudan, Zambia, and Namibia, can even exceed 5 kWh/m^2. Furthermore, 6–8 hours of sunlight corresponded to an annual sunshine duration of 2190–2920 hours. Therefore, the outcomes of this part also led to thresholds applied in the machine learning features that $DNI_{min} > 1.8$ and $Sunshinehours > 2200$.

3.2. Cost Calculation

In addition to the energy requirements, the cost of the Sol-Char system could pose certain challenges. As shown in Table 1, we reported that the total capital costs for a 4-person household model were about $1600, while the community-shared mode for 50 users costs over $16,000. Note that the solar concentration part including optical fiber bundles accounted for over 80 % of the capital costs. For a household mode of 4 individuals in the first year, the financial burden per individual would amount to more than $400. Therefore, not all regions in the world could afford the installation and use of such a system due to the economic situation. Moreover, the discount rate we applied is one of the frequently utilized values across infrastructure, real estate, and utilities and is often recommended by government bodies and expert organizations (Carrasco-Garcés et al., 2021; Price and Willis, 2024). Therefore, our financial analysis adhered to these established norms for accuracy and relevance. However, this number is not fixed and should be adjusted based on specific project contexts. In some cases, a low discount rate or even a zero-discount rate is preferred, especially for projects with a long-term societal impact like climate change projects (Weitzman, 2013; Arrow et al., 2013).

In terms of economic feasibility, the Sol-Char system offered several potential advantages. For instance, it could result in material savings (as no sewage was needed), water and energy savings (no water required, no extra power required), improved sanitation, and potential revenue from the sale of byproducts. For example, the byproduct of the system, biochar, had commercial potential as a fertilizer or fuel, which could generate income of $0.05 to $0.09/user/day for local users (Kung et al., 2013; Maroušek et al., 2023; McCarl et al., 2012). However, these benefits should be weighed against the costs, and strategies to make the system more affordable should be explored. This could involve simplifying the design, scaling up production, using cheaper and locally sourced materials (for instance cheaper solar and electric components from India or China), and implementing payment plans or loans that spread the capital cost over a longer period. These measures would help lower the initial costs and distribute the financial burden more evenly. As an outcome of this section, a threshold of $400 would be used as a threshold for *GDP per Capita* feature in machine learning.

Table 1
Cost information of different types of sol-char systems.

Cost Item	Household Model		Community-share Model	
	4-Person System	10-Person System	32-Person System	50-Person System
Sol-Char system (reactor included)	$1257	$3129	$10,500	$15,582
Reactor	Aluminum $230 or Stainless Steel $545	Aluminum ~ $400 - $450 or Stainless Steel ~$900 - $1000	Aluminum ~ $500 - $700 or Stainless Steel ~$1100 - $1600	Aluminum $700 or Stainless Steel $1635
Toilet Base Structure	$380	$380	$600	$850
Superstructure	≤$50	≤$50	≤$50	≤$50
Total Capital Costs	$1637	$3509	$11,100	$16,432
Total Capital Cost per Person	$409	$351	$347	$329
Annualized Cost	$142	$303	$930	$1412
Annualized Cost per Person	$35.50	$30.30	$29.20	$28.10

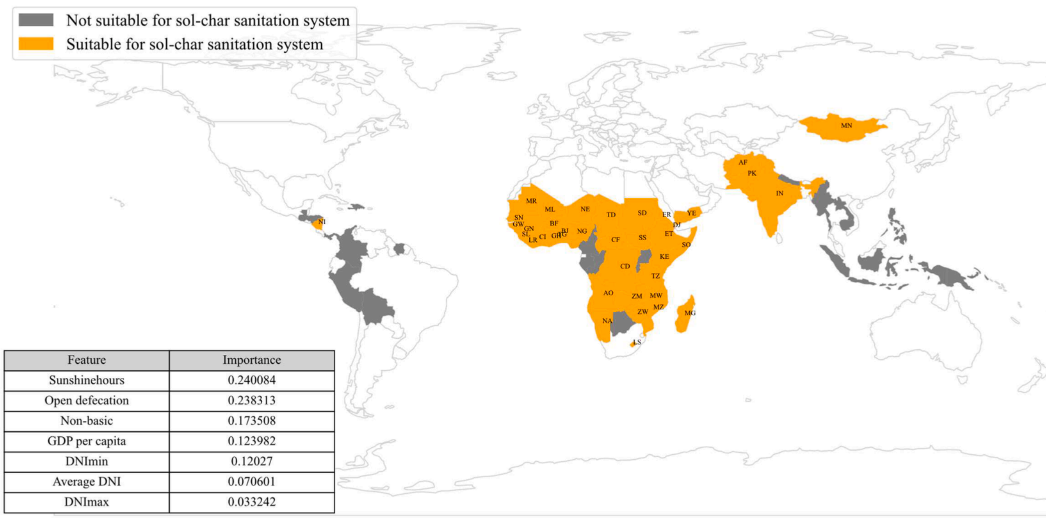
3.3. Machine Learning

From the above energy and cost analysis, we identified key parameters to assess whether a region is suitable for the Sol-Char sanitation system, but the exact importance of each was not clear. Therefore, we treated these parameter conditions as variables, predicting the suitability of installing the system in different regions using the Random Forest method from machine learning as described in the Methods section. The thresholds used in this analysis came from the computational results mentioned earlier. The Random Forest model calculated the target variable to determine if a country was suitable for implementing the Sol-Char system.

As demonstrated in Fig. 5, the results from the Random Forest machine learning model indicated that over half of the 76 countries studied (42 countries, 55 %) were suitable for implementing the Sol-Char system. The complete list of the machine learning prediction results is available in *SM9*. Most of these countries were in the Saharan Africa region and a few were in South Asia. In contrast, most of South America and most of Southeast Asia were found unsuitable. As assessed by the model, the importance rankings for each feature can be seen in the inset table of Fig. 5. In the first column, the rankings in descending order of importance were as follows: *Sunshine hours, Average DNI, Open defecation, Non-basic least water,* DNI_{min}, *GDP per capita*, and DNI_{max}. The importance values for these features were listed in the second column. The overall performance of our model was good, with a *K-Fold cross-validation accuracy*: 0.90 (+/- 0.18), *accuracy* of 0.83, *F1 score* of 0.84, *precision* of 0.80, *recall* of 0.89, and *AUC-ROC* of 0.83.

Concerning the Random Forest model, it was generally impossible to directly extract precise formula or function as it was an ensemble model composed of many decision trees, each splitting based on a set of randomly selected features. Consequently, predictions were made through a voting or averaging process across these decision trees, unlike linear regression models which provided a precise mathematical formula (Jamal et al., 2021; Lovatti et al., 2019; Probst et al., 2019). As such, manually deriving a formula to determine whether an area was suitable for construction was challenging. However, we can analyze the feature importance by looking at the feature weights calculated by the model. These weights showed how much each feature contributes to the model's predictions. Higher importance values indicated a stronger influence of the feature on prediction (Jalal et al., 2022; Lovatti et al., 2019). The following analysis and discussion were based on these feature importance values in the inset table in Fig. 5.

One benefit of our model was its ability to rank the significance of various features, which could aid decision-makers in prioritizing factors for solar-powered systems. According to the predictions, the feature importance value for *Sunshinehours* was 0.240, making it the most crucial feature in determining the suitability of the system. This suggested that regions with longer hours of sunshine per day were better suited for the Sol-Char system. As mentioned in the Method part, while some countries had high DNI values, their annual sunlight hours were shorter due to specific climate conditions like prolonged rainy seasons,



Feature	Importance
Sunshinehours	0.240084
Open defecation	0.238313
Non-basic	0.173508
GDP per capita	0.123982
DNImin	0.12027
Average DNI	0.070601
DNImax	0.033242

Fig. 5. Suitability for implementing a Sol-char sanitation system using machine learning Random Forest, with feature importance table attached.

which resulted in frequent cloudy and rainy weather (Becker, 1987; Ruane et al., 2013). As the system relied on solar energy for heating and disinfection, this lack of consistent sunlight would reduce its performance and efficiency, potentially disrupting daily operations.

The *rate of open defecation* (0.238) was another important factor affecting the suitability results which was almost equal to *Sunshinehours*. This implied that regions with higher open defecation rates were well-suited for this system, aligning with the system's primary aim to decrease open defecation. The model, therefore, prioritized areas with higher open defecation rates, aiming to bring clean, sanitary, and safe toilet facilities to those in need.

Water is essential for life and hygiene, and the model results suggested that areas lacking a basic water supply could significantly benefit from the Sol-Char system to enhance sanitation and reduce pollution.

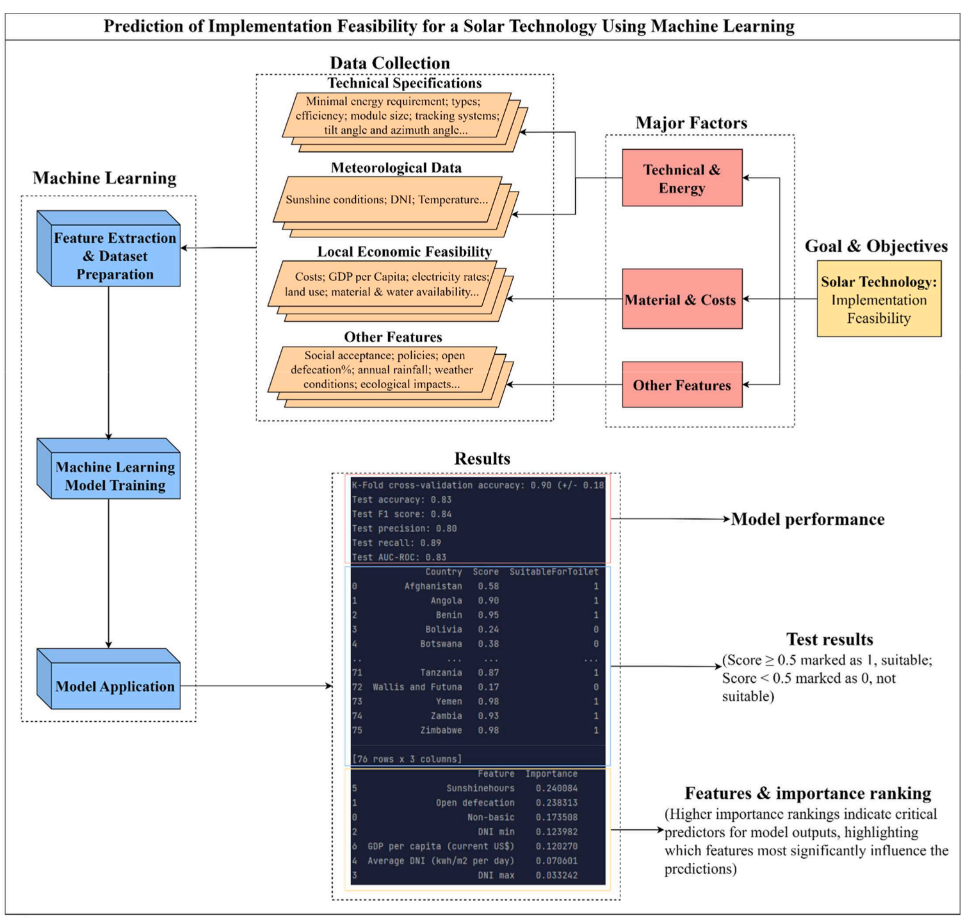


Fig. 6. A Framework was developed in this study to model and identify suitable deploying locations in the world using the machine learning model for solar technology.

Consequently, the *Non-basic least water* had an importance value of 0.174. Moreover, the *per capita GDP* should not be underestimated, as its importance value was 0.124. The system was not cheap and required ongoing operation and maintenance, which may be a challenge for some countries with a lower per capita GDP.

The DNI measures the amount of solar energy available on the ground surface, and regions with a higher average DNI are more suitable for the Sol-Char system. Although the minimum solar irradiance (DNI_{min}) was ranked fifth in importance, its weight value of 0.120 was similar to that of the *per capita GDP*, indicating a similar influence. It represented the minimum solar energy needed for the system's basic operation. The importance of the *Average DNI* was 0.071. The average value could reflect the stability of the system receiving solar energy. Though the DNI_{max} value was low at 0.033, it still held practical importance. Higher DNI_{max} meant the system could harness more solar energy simultaneously, which was significant for the system expansion (not studied in this research).

Moreover, the machine learning model we developed was not limited to just the Sol-Char system case. A framework was developed to model solar technology, identifying suitable deployment locations worldwide using our machine learning model, as demonstrated in Fig. 6. This model could serve as a versatile tool for various solar-powered projects, especially in regions where solar energy is plentiful, and conventional energy sources are scarce or unreliable. Primarily, when evaluating technology, users can consider several factors, such as technical and energy requirements, materials, costs, and more. Data collection could align with these considerations, involving technical specifications such as energy efficiency, module size, and tracking systems (see Data Collection in Fig. 6). Moreover, local meteorological data including sunshine levels, direct normal irradiance (DNI), and temperature could be gathered along with economic viability indicators like CAPEX, OPEX, GDP per capita, electricity rates, land usage, and the availability of materials, etc. Other relevant considerations may include social acceptance, policies, hygiene, and weather patterns.

These elements can be instrumental in making decisions about solar initiatives, such as for solar water heaters (Cui et al., 2023), solar cookers (Khatri et al., 2022), solar-powered irrigation (Ashraf and Jamil, 2022), solar-based steam generation (Gao et al., 2022), and so on. For example, regions with limited clean water could benefit from solar-driven water purification systems. In such cases, those features (and dataset) can be considered in the machine learning model to guide decisions such as sunlight exposure, water source and quality, water demand, purification capacity, existing infrastructure, climate conditions, etc. Similarly, for solar-powered irrigation, the model can consider factors or features such as agricultural land, yearly rainfall, types of targeted crops, and water requirements (Battersby, 2023; Havrysh et al., 2022; Trommsdorff et al., 2022). Therefore, adjusting the inputs and criteria allows it to support various research objectives. With clear criteria, relevant data can be collected and processed into a dataset for machine learning analysis using our model and codes. This enables the model to highlight optimal locations for deploying the technology, providing insights for decision-making based on feature importance and model indicators.

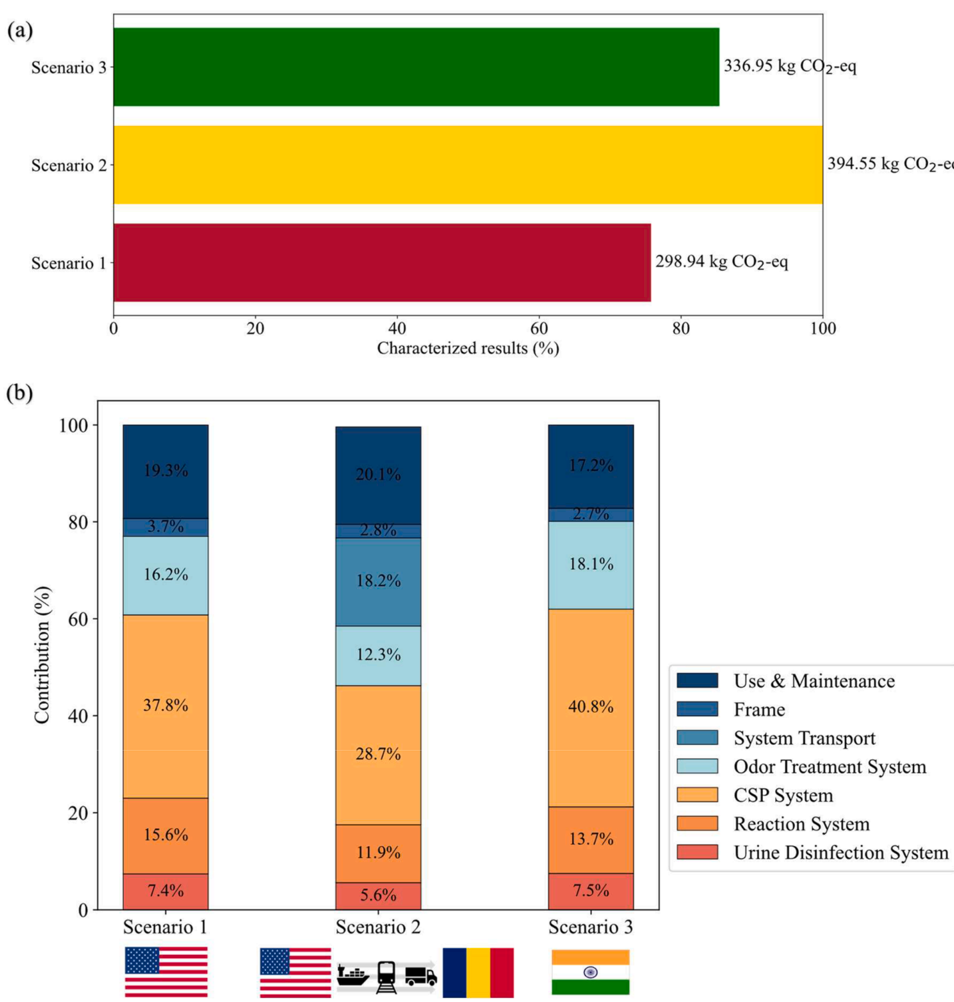


Fig. 7. (a) Characterized LCA results regarding climate change (carbon emissions) for the four scenarios and (b) contribution analysis of the main components.

3.4. Life Cycle Assessment

The LCA conducted in this study aimed to evaluate the environmental impact of the Sol-Char system while providing suggestions on various deployment strategies. As seen in Fig. 7(a), CO_2 emissions differed across the three scenarios due to variations in implementation strategies. Fig. 7(b) illustrates the contribution analysis which breaks down the emissions by system components and usage phases. In all three systems, the frame and urine disinfection systems consistently contributed less than 10 % of total emissions, while the reaction and odor treatment systems each contributed about 15 %. The use and operation phase accounted for approximately 20 % of total emissions, primarily due to system maintenance. However, the CSP system had a significant share of emissions in all the systems, highlighting an area for improvement.

In Scenario 1, the system produced and used in the U.S. generated 299 kg eq-CO_2 emission. The CSP system was responsible for 37.7 % (113 kg eq-CO_2) of total emissions, with the parabolic system production making up nearly half of it due to the extensive use of aluminum. The solar tracking system and stand contributed 11 % and 7.5 %, respectively. This suggested the need for more efficient materials and processes to minimize the environmental impact. The contribution results also hint at potential challenges in scaling up, especially for larger community-scale systems requiring more solar tracking systems.

Scenario 2 differed from Scenario 1 due to the long-distance transportation, which accounted for 18.2 % (71.8 kg eq-CO_2) of emissions. Furthermore, replacing components during maintenance was also affected by long-distance transportation (6 %). Overall, the total emissions (395 kg eq-CO_2) were 32 % higher than Scenario 1. This implied the importance of logistics optimization, particularly for heavy components. This scenario also emphasized the value of local sourcing in reducing transportation emissions. Despite the impact of transportation, the CSP system remained the main contributor to emissions. Modular designs that simplify maintenance and reduce the need for specialized parts could be beneficial in this scenario. In the future, setting up a local production facility in Africa could help reduce transportation emissions and adapt designs to better use local materials and manufacturing capabilities. This localization strategy was partly demonstrated in Scenario 3.

Scenario 3 (India) shared similarities with Scenario 1 in design and scale but utilized more localized production in India. The emissions were 337 kg CO_2 equivalent (13 % higher than Scenario 1), placing it between Scenarios 1 and 2. This difference was mainly due to the local materials and energy sources in India, which relied heavily on fossil fuels (background data). Although the usage phase of the system did not require electricity, the extraction and processing of materials did rely on the Indian energy infrastructure. The CSP system alone accounted for 41 % of emissions (137 kg eq-CO_2). Additionally, emissions from auxiliary components like odor management were more noticeable in this model (18 %, or 61 kg eq-CO_2). These findings indicated that resource efficiency and carbon emissions in localized contexts required careful consideration due to the reliance on fossil fuels. Reducing emissions in this scenario would involve using low-carbon alternative materials, refining production processes, and incorporating renewable energy. Therefore, when introducing the Sol-Char system to emerging markets for localization, all aspects should be carefully evaluated, with customizations and improvements tailored to local resources and conditions.

From the analysis of the three scenarios, the CSP system had the highest environmental impact. This was mainly due to the use of aluminum in the parabolic dish and its concentrator substrate components, which resulted in high carbon emissions. In the sensitivity analysis, replacing aluminum with steel and recalculating the emissions led to a 23 % reduction in carbon emissions (or 68 kg eq-CO_2 less). Therefore, it would be advisable to consider replacing aluminum in the system to minimize its environmental impact. However, as seen in Table 1, aluminum was cheaper and lighter than stainless steel, despite its higher environmental impact. Decision-makers should weigh these factors carefully to balance the environmental impact and material cost and ensure that any trade-offs are well-justified.

Furthermore, we briefly compared our results with a case in the literature. The study investigated the environmental impacts of many on-site source-separated wastewater treatment solutions (de Simone Souza et al., 2023). The study showed that large amounts of carbon emissions were found in many scenarios during the usage phase, which included emissions from treatment and electricity consumption. During the construction phase, emissions ranged from approximately 10 to 50 kg CO_2 equivalent per person per year. Therefore, for a group of 32 people for comparison, this translated to about 320 to 1600 kg CO_2 equivalent annually. The emissions in the referenced study were partially due to the extensive use of materials such as PVC, masonry, gravel, sand, reinforced concrete, polyethylene, and so on (de Simone Souza et al., 2023). Our results of the Sol-Char system, which ranged from 300 to 400 kg CO_2 equivalent, were slightly lower, showing the environmental advantages of the system. However, our LCA study focused exclusively on carbon emissions and did not assess other environmental impacts such as water-related, land use, potential pollutants, or additional impact categories. Therefore, a more comprehensive assessment is needed. Moving forward, conducting comprehensive LCA studies across more countries and scenarios (even future scenarios) would help create a dataset that could be integrated into machine learning. Using the LCA results dataset in machine learning models would enhance predictions and assessments of the viability of sanitation systems in different scenarios and designs. In addition, this study did not consider the positive environmental impact and economic benefits of applying biochar and disinfected human urine. This will be a part of the future work.

4. Conclusion

In this study, the objective was to determine suitable locations for the implementation of the Sol-Char sanitation system and evaluate its environmental impact in those regions. We started by reviewing countries with high rates of open defecation, based on United Nations data. We then collected solar energy information for these countries, which was essential for the Sol-Char system's efficient operation due to its reliance on sunlight. We also included GDP per capita to assess the economic feasibility of implementing the system and used it as a feature in our machine learning model. We employed the Random Forest model from machine learning to evaluate 76 countries based on the extracted features. The model was accurate in its predictions, identifying 42 countries (55 %) as suitable for the Sol-Char system, mostly located in Sub-Saharan Africa and South Asia. Moreover, the machine learning model can be applied more broadly to serve as a preliminary feasibility tool for solar-related projects beyond just solar toilets.

We applied ex-ante life cycle assessment to evaluate the carbon emissions of the Sol-Char system across various implementation scenarios based on regional differences. Emissions from core components such as CSP systems required focused improvements regarding material efficiency and process optimization. Moreover, managing carbon emissions in transport phases was crucial for remote implementation models. Local energy mix and material availability were worth considering in the localization scenario. These insights could inform targeted optimization strategies for the Sol-Char system's global deployment. However, a more detailed LCA should be performed in the future to assess other impact categories and better understand the system's environmental performance. Additionally, LCA results for various scenarios could be incorporated as a feature in future machine-learning model iterations. Therefore, further research is needed to develop more viable solutions for developing regions and people who need safe sanitation.

CRediT authorship contribution statement

Justin Z. Lian: Writing – original draft, Methodology, Conceptualization. **Nan Sai:** Writing – review & editing. **Luiza C. Campos:** . **Richard P. Fisher:** Writing – review & editing. **Karl G. Linden:** Writing – review & editing, Supervision, Methodology, Conceptualization. **Stefano Cucurachi:** Writing – review & editing, Supervision, Methodology, Conceptualization.

Declaration of competing interest

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

Data availability

The datasets generated and analyzed during the current study are available in the Supplement Materials at: https://surfdrive.surf.nl/files/index.php/s/m0I05oi7cndAsQi.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.resconrec.2024.107784.

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