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An Integrated Framework for Zero-Waste Processing and Carbon Footprint Estimation in 'Phulae' Pineapple Systems

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Abstract

This study proposes an integrated framework for sustainable tropical agriculture by combining biochemical waste valorization with spatial carbon footprint estimation in 'Phulae' pineapple production. Peel and eye residues from fresh-cut processing were enzymatically converted into rare sugar, achieving average conversion efficiencies of 35.28% for peel and 37.51% for eyes, with a benefit–cost ratio of 1.56 and an estimated unit cost of USD 0.17 per gram. A complementary zero-waste pathway produced functional gummy products using vinegar fermented from pineapple eye waste, with the preferred formulation scoring a mean of 4.32 out of 5 on a sensory scale with 158 untrained panelists. For spatial carbon modeling, the Bare Land Referenced Algorithm (BRAH) and Otsu thresholding were applied to multi-temporal Sentinel-2 and THEOS imagery to estimate plantation age, which strongly correlated with field-measured emissions (r = 0.996). This enabled scalable mapping of plot-level greenhouse gas emissions, yielding an average footprint of 0.2304 kg CO_2 eq. per kilogram of fresh pineapple at the plantation gate. Together, these innovations form a replicable model that aligns tropical fruit supply chains with circular economy goals and carbon-related trade standards. The framework supports waste traceability, resource efficiency, and climate accountability using accessible, data-driven tools suitable for smallholder contexts. By demonstrating practical value addition and spatially explicit carbon monitoring, this study shows how integrated circular and geospatial strategies can advance sustainability and market competitiveness for the 'Phulae' pineapple industry and similar perennial crop systems.

Keywords: 'Phulae' pineapple; rare sugar; carbon footprint; BRAH algorithm; zero-waste agriculture

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1. Introduction

Sustainable agriculture is increasingly recognized as a cornerstone for addressing the intertwined challenges of global food security and climate change [1,2]. Agriculture contributes a significant share of greenhouse gas (GHG) emissions while simultaneously depending on ecosystems that are highly sensitive to environmental degradation [3]. To meet these challenges, current strategies emphasize climate-smart practices, resource-efficient production, and integrated frameworks that combine waste minimization with carbon accountability across the agricultural value chain.

One critical issue is that many tropical horticultural systems generate large volumes of underutilized biomass and lack robust mechanisms for traceable emission estimation at the farm level. This is particularly evident in the production of 'Phulae' pineapple, a geographically protected and economically significant fruit from northern Thailand. Despite its premium status, the fresh-cut processing of 'Phulae' pineapple results in considerable peel, crown, and eye residues, which are typically discarded or used inefficiently [4]. Additionally, the absence of accessible field-level emission tracking tools creates uncertainty for carbon labeling and compliance with emerging climate-related trade measures.

In response, this study proposes an integrated dual-component framework that combines biochemical waste valorization with remote-sensing-based carbon footprint modeling. By demonstrating how fruit processing residues can be converted into high-value products and how plantation age mapping can serve as a proxy for spatially explicit GHG estimation, this framework aligns with Thailand's Bio-Circular-Green (BCG) economy model and contributes to the global transition toward zero-waste, low-emission agriculture.

1.1. Sustainable Agriculture in the Context of Climate Accountability

The transition toward sustainable food systems is now central to addressing escalating environmental challenges and climate change. The agriculture sector accounts for approximately one-quarter of global anthropogenic greenhouse gas (GHG) emissions [1], making it a key contributor to global warming. At the same time, agriculture is particularly vulnerable to climate impacts, including yield reductions and increased variability in production. This dual role, as both a source and a victim of climate change, underscores the imperative for climate-resilient and low-emission agricultural systems [2].

To address these challenges, emphasis is increasingly placed on climate accountability, particularly through the development of farm-level carbon accounting frameworks. Accurate monitoring and quantification of emissions from inputs such as fertilizers, irrigation, and machinery are fundamental to improving management practices [5]. Tools such as life cycle assessment (LCA), farm-based carbon calculators, and standardized emission factor models are now widely used to estimate agricultural footprints and inform mitigation strategies [6]. The emergence of environmental labeling schemes and sustainability certifications further reflects global market trends that increasingly favor transparent supply chains. As agrifood exports face carbon-related regulations and voluntary sustainability standards, reliable tools for emission traceability and monitoring have become essential [3].

1.2. The Significance of 'Phulae' Pineapple in Thailand's Bio-Circular-Green Economy

'Phulae' pineapple (Ananas comosus var. 'Phulae'), a unique cultivar endemic to Chiang Rai province in northern Thailand, plays a significant role in the regional economy. In 2021, cultivation covered over 28,288 rai and produced more than 59,380 tons of fruit. Its distinctive sweetness and firm texture have supported its recognition as a high-value product with geographical uniqueness. The majority of 'Phulae' pineapples are processed as fresh-cut fruit, a practice that generates a substantial proportion, often reported at 30–45 percent, of inedible residues, such as peels, crowns, and cores [4,7].

Within Thailand's Bio-Circular-Green (BCG) economic strategy, the 'Phulae' pineapple sector is well positioned to contribute to sustainability transitions. The BCG model promotes resource efficiency and circularity through the valorization of agricultural residues. Pineapple waste, which is particularly rich in fermentable sugars and bioactive compounds, has been demonstrated to hold substantial potential for bioconversion into value-added products, such as rare sugar, organic acids, and biofuels [4,8]. Recent studies have confirmed that pineapple peel and other tropical fruit residues are effective substrates for enzymatic conversion to rare sugars, with yields comparable to sugar-rich feedstocks, such as fructose syrups [9,10]. Developing such pathways not only reduces the environmental burden from waste disposal but also provides opportunities for income diversification among smallholder producers. This positions 'Phulae' pineapple production as a practical model for zero-waste, high-value agriculture aligned with Thailand's national sustainability priorities.

1.3. Research Gaps in Waste Valorization and Spatial Carbon Footprint Estimation

Despite increasing interest in low-carbon agriculture and waste valorization, two interrelated challenges remain insufficiently addressed. First, there is a disconnect between advancements in biochemical waste conversion and the spatial modeling of carbon emissions. While recent studies have demonstrated the feasibility of converting pineapple residues into value-added products through enzymatic and microbial processes [4,8,9], most investigations remain limited to laboratory scale and do not explicitly quantify how these valorization pathways affect farm- or landscape-level GHG balances. Life cycle assessments (LCAs) of waste conversion often exclude spatial heterogeneity and rely on static assumptions for field emissions [3]. This methodological gap limits the ability to link circular resource use to verifiable climate outcomes.

Second, a key limitation in carbon footprint estimation lies in the availability of geospatial agronomic data, particularly plantation age. Age-related variations strongly influence biomass accumulation, soil respiration, and the intensity of fertilizer or fuel applications, yet these variables are frequently missing from standard carbon accounting frameworks [5]. Traditional footprint models typically apply uniform coefficients that overlook within-region differences in planting dates and field management. Remote sensing technologies provide a practical solution by enabling time-series analyses of vegetation cover and phenology. Recent developments in the Bare Land Referenced Algorithm (BRAH) have shown promise for identifying field establishment dates using hyper-temporal satellite imagery [11–13]. This approach supports scalable, cost-effective, and reproducible plantation age mapping, offering a critical input for more precise carbon modeling across heterogeneous agricultural landscapes.

To date, however, waste valorization and spatial carbon modeling have largely evolved in parallel rather than in an integrated manner. Combining these domains could close an important gap by connecting biochemical circularity with spatially explicit environmental performance. This integration creates a holistic framework that links on-site residue conversion with landscape-scale climate accountability, an approach not yet widely implemented for tropical horticultural systems.

1.4. Aim of the Study in Developing an Integrated Sustainability Framework

This study proposes and tests a dual-purpose sustainability framework for 'Phulae' pineapple production, illustrated in Figure 1. The first component develops an industrially relevant pathway for biochemical waste valorization, focusing on the conversion of fresh-cut processing residues into commercially viable rare sugars and functional vinegar products. By demonstrating feasible extraction yields, economic viability, and consumer acceptance, this element provides evidence for upgrading low-value residues into high-value biochemicals under real supply chain conditions.

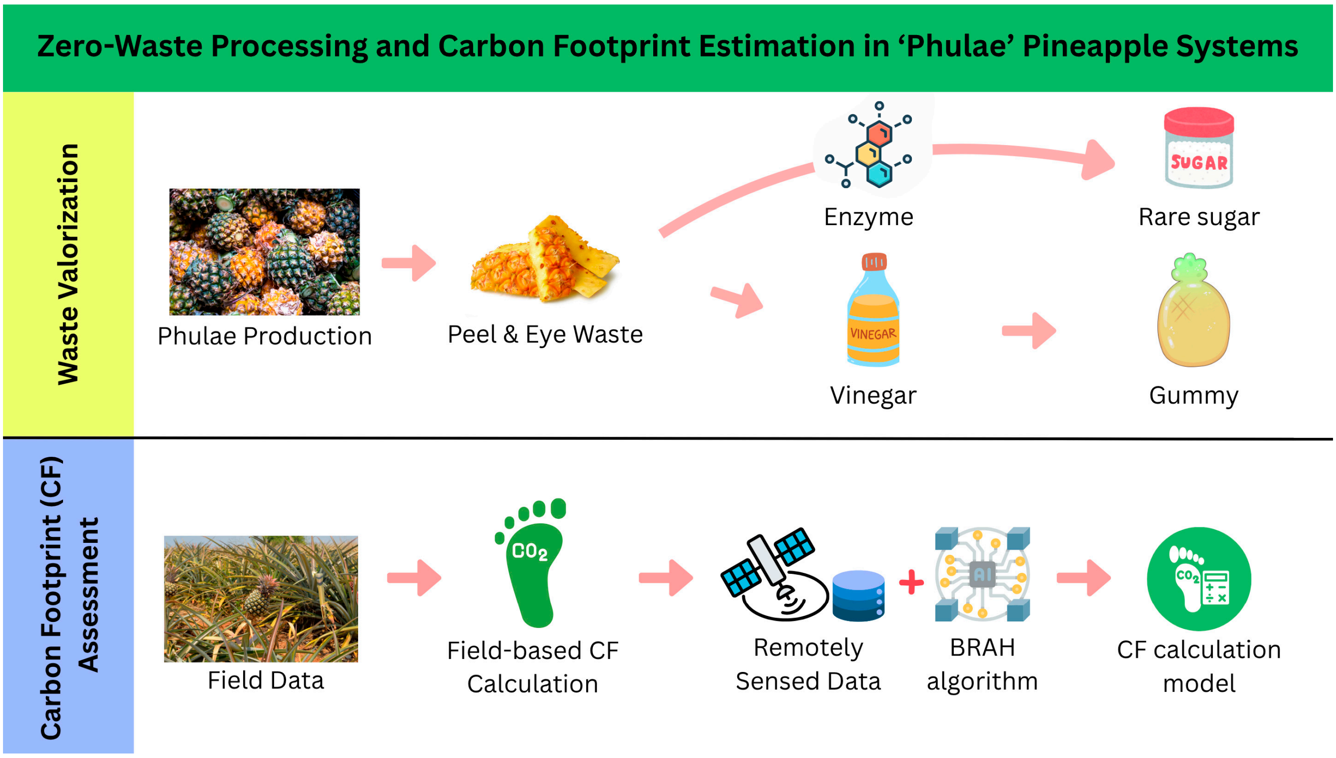

Figure 1. Overview of the dual-component sustainability framework for 'Phulae' pineapple production.

The second component advances a spatial carbon modeling approach based on multi-temporal remote sensing. Specifically, it applies the BRAH algorithm to detect bare land states, estimate plantation age, and link this temporal variable with farm-level greenhouse gas emissions. This improves the resolution and accuracy of carbon footprint estimation in perennial crop systems, addressing data gaps in field emission reporting.

By combining biochemical process innovation with geospatial intelligence, the integrated framework aims to deliver measurable progress toward zero-waste implementation and verifiable spatial carbon accounting. The approach emphasizes low-cost, scalable technologies, making it practical for smallholder production contexts. The resulting methodology directly supports Thailand's Bio-Circular-Green (BCG) economy objectives and offers a replicable model for other perennial or semi-perennial fruit systems. Ultimately, this research provides a concrete example of how combined circular economic strategies and precision monitoring tools can contribute to the transformation of agri-food systems under global climate-smart and low-emission goals.

2. Materials and Methods

2.1. Study Area and Research Framework

This study was conducted in Chiang Rai province, northern Thailand, which is a major production area of 'Phulae' pineapple recognized under the national Geographical Indication (GI) scheme. The province's favorable tropical climate, distinct terrain, and consolidated production zones provide an appropriate context for implementing sustainable agricultural frameworks within the tropical fruit supply chain. The dominant processing approach for 'Phulae' pineapple is the fresh-cut ready-to-eat product line, which generates substantial volumes of by-products, such as peel, crown, and eye fractions.

To ensure consistency and traceability throughout the valorization pathways, pineapple residues were systematically prepared following standard industrial fresh-cut processing. The process included washing with clean water and chlorinated water, manual peeling, crown and eye removal, a secondary water wash, and coarse chopping or grinding. Residues were then dried using a tray dryer to reduce moisture content prior to biochemical conversion. AOAC Official Methods [14] and established industrial practices for pineapple waste valorization [4].

The research framework integrates three methodological components to demonstrate a replicable zero-waste and low-carbon production model. First, processing residues were transformed into value-added products, including rare sugars and functional vinegar-based gummies. Second, the spatial carbon footprint was quantified for the full cultivation and processing chain, combining field data with satellite-derived spatial modeling. Third, plantation age detection was performed using the Bare Land Referenced Algorithm (BRAH) combined with Otsu thresholding, applied to multi-temporal satellite imagery to enable scalable age estimation while minimizing reliance on UAV-based surveys.

Key independent variables include the plantation age categories, spectral reflectance values from satellite bands, and field management practices under Good Agricultural Practice (GAP). The primary response variables comprise the carbon footprint per functional unit and the validated plantation age. Specific input ranges and technical details for carbon footprint modeling and age estimation are described in subsequent sections.

This integrated framework supports Thailand's Bio-Circular-Green (BCG) economic model and aligns with international environmental mechanisms, such as the Carbon Border Adjustment Mechanism (CBAM). The spatial distribution of the selected study plots, covering diverse cultivation practices and field conditions, is presented in Figure 2.

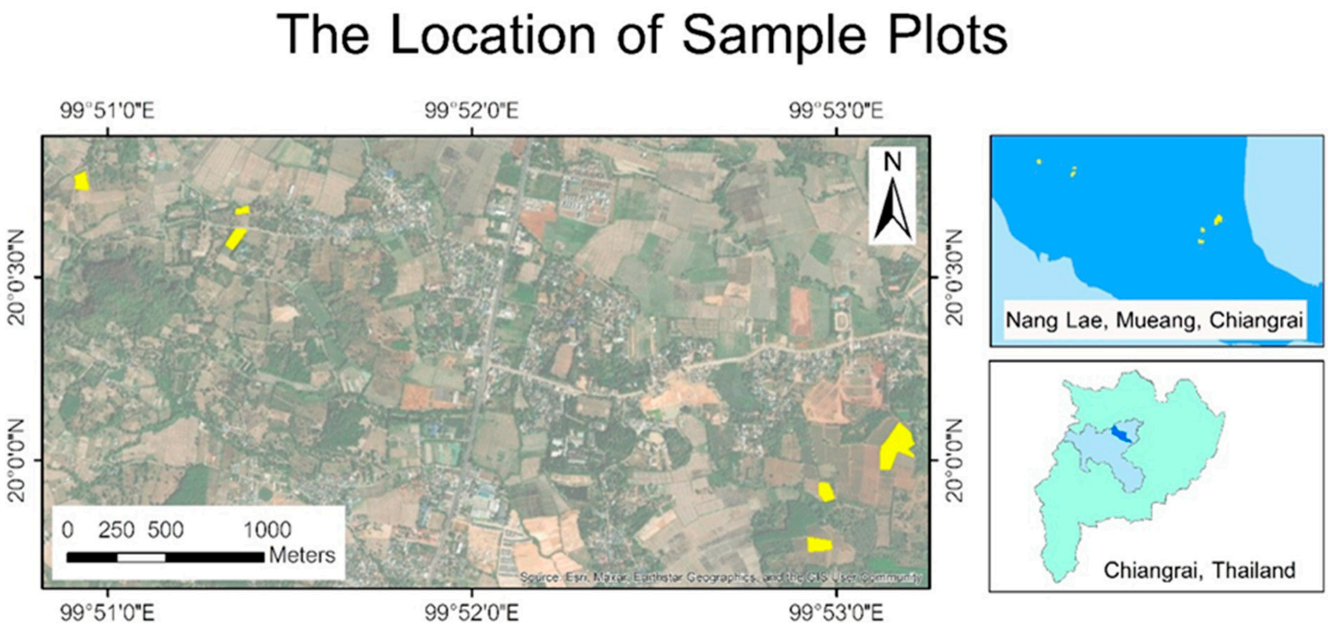

Figure 2. Example location of sample 'Phulae' pineapple plantations in Chiang Rai province. The selected plots were used for carbon footprint analysis.

2.2. Waste Valorization Process

In alignment with the zero-waste objective of this study, pineapple processing residues were valorized through two complementary pathways, each demonstrating distinct approaches to agricultural by-product utilization.

The first pathway explored the feasibility of producing rare sugars from peel and eye fractions through enzymatic transformation. This conceptual stage involved preliminary conversion trials to assess the technical viability of obtaining rare sugar, a low-calorie sugar of emerging commercial interest in food and pharmaceutical applications. Due to ongoing intellectual property protection, the specific enzymatic conditions and process parameters are not disclosed herein; however, key indicators, such as overall conversion yield, were used to validate the potential of this pathway as part of the integrated framework [4,14].

The second pathway focused on a practical and scalable valorization route: the production of functional vinegar-based gummies using pineapple eye waste. The selected residues were washed thoroughly prior to juice extraction, which was then used for vinegar fermentation through a controlled two-step process. This vinegar was subsequently developed into gummy prototypes enriched with bioactive components, including inulin and collagen. The gummy formulation process involved systematic variations in vinegar content to establish treatment comparisons and baseline controls for sensory evaluation and acceptability analysis.

This dual-pathway approach illustrates how the 'Phulae' pineapple supply chain can transition from conventional waste disposal to high-value product development under the Bio-Circular-Green (BCG) economic model. Detailed protocols, treatment conditions, and control measures for the gummy production and evaluation are provided in the following sections.

2.2.1. Rare Sugar Feasibility

In this study, the feasibility of producing rare sugar from fresh-cut 'Phulae' pineapple residues was assessed as part of an integrated zero-waste valorization framework. Residues comprising peel and eye fractions were collected from the main fresh-cut processing line and subjected to standardized pretreatment, including washing with chlorinated water, air drying, and mechanical grinding to reduce the particle size for subsequent extraction steps.

Preliminary sugar extraction was carried out by soaking the powdered biomass in distilled water under controlled conditions to release fermentable sugars. The resulting extract was analyzed using high-performance liquid chromatography (HPLC) following standard sugar profiling methods, as specified by AOAC [14] and comparable to Mu et al. (2012) [15]. The HPLC system was operated under typical settings for sugar detection, using a refractive index detector and an appropriate column, maintained at an industry-standard temperature range, with HPLC-grade water as the mobile phase. Certified glucose, fructose, and sucrose standards were used to confirm the presence of target sugars by retention time comparison.

Fructose served as the main substrate for enzymatic transformation into rare sugar. The conversion process was conducted under laboratory conditions using proprietary enzyme preparation. To protect intellectual property, detailed enzyme concentrations, reaction volumes, and specific chromatographic parameters are not disclosed here. However, the average conversion efficiency was determined to be within an expected practical range of about 30–40%, aligning with previous efficiencies [9,10,15].

Following conversion, the rare sugar solution was processed into powder form using a bench-scale two-fluid nozzle spray dryer operated at a typical inlet temperature range (approximately 140–160 °C) with a feed rate within standard laboratory capacity. The dried residues were milled and sieved to a uniform fine powder for product quality evaluation. The resulting product quality was assessed in reference to ICUMSA specifications for very-high-polarization sugar [16]. A preliminary benefit–cost analysis, which considered raw material input, energy use, and enzyme cost, indicated the economic viability of integrating rare sugar production into the 'Phulae' pineapple supply chain. Additional process details and specific equipment settings remain confidential to safeguard the proprietary process design (Table 1).

Table 1. Protocol 1. Conceptual Procedure for Rare Sugar Production from Pineapple Peel and Eyes.

Step 1: Collection and Pretreatment
1. Collect peel and eye waste generated from 'Phulae' pineapple fresh-cut processing. 2. Wash residues thoroughly with chlorinated water and remove unwanted material. 3. Dry the residues at moderate temperatures until an appropriate moisture level is reached. 4. Coarsely grind or mill the dried material to reduce particle size for extraction.
Step 2: Sugar Extraction
1. Soak the powdered biomass in distilled water under standard laboratory conditions. 2. Filter the extract using conventional separation techniques (e.g., vacuum filtration and centrifugation). 3. Perform qualitative sugar profiling by HPLC based on AOAC standard methods to confirm the presence of target sugars.
Step 3: Enzymatic Conversion to Rare sugar
1. Conduct the enzymatic conversion of fructose to rare sugar using a proprietary enzyme preparation under optimized conditions. 2. Specific details regarding enzyme strains, reaction conditions, and co-factors are not disclosed due to pending intellectual property protection. 3. Typical conversion efficiencies achieved in laboratory trials indicate a feasible yield for pilot-scale valorization.
Step 4: Powder Production
1. Apply standard thermal treatment to terminate enzymatic activity. 2. Process the solution to obtain powdered rare sugar using a laboratory-scale drying technique. 3. Assess product quality with reference to ICUMSA standards for sugar purity.
Step 5: Economic Feasibility Assessment
1. Evaluate the overall benefit–cost ratio by incorporating raw material, processing inputs, and energy costs. 2. Statistical and sensitivity analyses are reserved for proprietary reporting.

2.2.2. Gummy Product from Pineapple Vinegar

To complement the rare sugar valorization pathway, a functional gummy product was developed using pineapple eye residues converted into pineapple vinegar. Pineapple juice was first extracted from the cleaned eye fractions and adjusted to an initial sugar concentration of approximately 18 °Brix. The alcoholic fermentation was initiated with *Saccharomyces cerevisiae* TISTR 5019 (TISTR, Pathum Thani, Thailand) at an inoculum level of 5% v/v for 5–7 days to produce ethanol. The fermented broth was then subjected to acetic acid fermentation using *Acetobacter pasteurianus* TISTR 102 (TISTR, Pathum Thani, Thailand) at an inoculum level of 10% v/v, maintained at pH 4–5 and 30 °C for 10–14 days until the desired acetic acid concentration was reached (not less than 4%, following the Notification of the Ministry of Public Health (No. 204) B.E. 2543 (2000) Re: Vinegar).

The resulting vinegar was monitored for acidity (4–5% w/v) and pH to ensure compliance with food safety standards [14,17–19]. Three prototype gummy formulations were developed, each incorporating varying proportions of pineapple vinegar (10–20% v/v), gelatin (5–7% w/w), sugar, and water. The mixtures were heated to 70–80 °C to ensure complete dissolution and homogeneity before being poured into silicone molds and cooled under refrigeration at 4 °C until fully gelled. Final products were vacuum-packed to maintain texture and prevent microbial spoilage.

A consumer sensory evaluation was conducted using a 5-point hedonic scale. The attributes evaluated included color, texture, taste, and overall liking, which were selected based on standard sensory practice for gelatin-based confections [20]. The panel consisted of 158 untrained consumers aged 18–50 years recruited from the local community. No formal training was provided, but a short briefing was conducted to explain the scale and attribute definitions to ensure consistency. Reproducibility was addressed by randomizing the sample presentation order and by conducting duplicate testing with a subsample of the panelists.

Optimization of the gummy recipe was based on the mean overall liking score, with a threshold acceptance criterion of a mean score $\geq$ 4.0 indicating good consumer acceptance for further product development. This approach illustrates the practical potential for converting pineapple processing residues into functional value-added products, thus reinforcing the zero-waste concept within the 'Phulae' pineapple supply chain. Table 2 outlines the procedure used to develop a functional gummy product from pineapple eye residues.

Table 2. Protocol 2. Gummy Product Development from Pineapple Vinegar.

Step 1: Raw Material Preparation 1. Collect pineapple eye waste from the fresh-cut processing line. 2. Wash thoroughly with chlorinated water and extract juice by mechanical pressing. 3. Adjust the extracted juice to an initial sugar concentration of approximately 18 °Brix using a refractometer.
Step 2: Fermentation to Produce Vinegar 1. Inoculate the juice with *Saccharomyces cerevisiae* TISTR 5019 (TISTR, Pathum Thani, Thailand) at an inoculum level of 5% v/v and ferment at pH 4–5 and 28–30 °C for 5–7 days to convert sugars into ethanol. 2. After alcoholic fermentation, inoculate the broth with *Acetobacter pasteurianus* TISTR 102 (TISTR, Pathum Thani, Thailand) at 10% v/v and maintain at pH 4–5 and 30 °C for 10–14 days to oxidize ethanol into acetic acid. 3. Monitor acidity (target 4–5% w/v) and pH to ensure vinegar quality suitable for food applications.
Step 3: Formulation of Gummy Mixtures 1. Prepare three gummy prototypes with varying vinegar content (10–20% v/v) combined with gelatin (5–7% w/w), sugar, and distilled water. 2. Heat the mixture to 70–80 °C while stirring continuously to fully dissolve all ingredients and ensure uniform blending.
Step 4: Molding and Setting 1. Pour the hot gummy mixture into silicone molds of uniform size. 2. Cool at 4 °C under refrigeration for 2–4 h to allow complete gelling.
Step 5: Packaging and Storage 1. Carefully remove fully set gummies from the molds. 2. Vacuum-pack the gummies in food-grade packaging to maintain texture and hygiene during storage.
Step 6: Sensory Evaluation 1. Conduct a 5-point hedonic test with 158 untrained consumer panelists aged 18–50 years. 2. Evaluate color, texture, taste, and overall liking. Attributes were selected based on standard practice for confectionery sensory analysis. 3. Brief panelists on scoring criteria before testing to ensure consistency. Randomize sample presentation to minimize bias. 4. Determine the preferred formulation using the mean overall liking score, with a target acceptance criterion of $\geq$4.0 to guide further product development.

2.3. Carbon Footprint Evaluation

A carbon footprint evaluation was conducted to estimate greenhouse gas (GHG) emissions associated with 'Phulae' pineapple cultivation in Chiang Rai province. The analysis followed an emission-factor-based methodology, as outlined by the Intergovernmental Panel on Climate Change (IPCC), and used activity data combined with standardized emission coefficients to calculate carbon dioxide equivalent (CO_2 eq.) values.

The system boundary encompassed all processes from land preparation to harvest. The functional unit (FU) was defined as 1 kg of fresh 'Phulae' pineapple at the plantation gate. Primary data were collected from a 7 rai (1 rai = 1600 m^2) pineapple field operating under a 5-year crop cycle. Data were gathered through structured interviews with farm operators and direct field observation. Recorded inputs included diesel fuel, synthetic and organic fertilizers, irrigation water, and agrochemical applications. Where necessary, shared inputs were allocated proportionally to the functional unit.

Emissions were calculated using Equation (1):

$$\text{Carbon Emission (kgCO}_2\text{ eq.)} = \text{Activity Data} \times \text{Emission Factor} \tag{1}$$

All calculations were performed using a custom spreadsheet model constructed in Microsoft Excel for Microsoft 365 (Version 2506 Build 16.0.18925.20076), which systematically integrated field input data with the corresponding emission factors to derive total CO_2 equivalent emissions per FU. This practical approach aligns with standard agricultural carbon accounting practice under the IPCC framework [21].

Emission factors (EFs) were sourced from the Thailand Greenhouse Gas Management Organization (TGO) [22] and validated literature. Emission sources were categorized into four major activities: (1) land preparation, (2) fertilization, (3) weed and pest control, and (4) harvesting operations.

2.4. Plantation Age Estimation and Carbon Modeling

Temporal information on perennial crop systems is essential for understanding carbon dynamics over cultivation cycles. In this study, the plantation age was used as a central variable for estimating carbon emissions associated with 'Phulae' pineapple cultivation. Due to the uniformity of agricultural practices within each cycle, the plantation age was hypothesized to be strongly associated with biomass accumulation and emission-relevant inputs. A combination of statistical analysis and remote sensing classification was employed to develop a spatially scalable model for carbon footprint estimation.

2.4.1. Correlation Analysis Between Plantation Age and Carbon Emissions

To assess the utility of plantation age as a proxy for carbon emission estimation, a correlation analysis was performed using data from pineapple fields with recorded planting dates and corresponding emission inventories. Emission values were calculated using activity-based field data collected across multiple plots within Chiang Rai province. Agronomic practices were verified to be consistent across sites to minimize variability in cultivation intensity. Pearson correlation analysis was applied to examine the statistical association between plantation age and cumulative GHG emissions. Additionally, several agronomic and remote-sensing-derived parameters, such as vegetation indices and spectral reflectance values, were tested for their correlation with emissions. Plantation age was selected for further modeling based on the methodological relevance and consistency of observed relationships during exploration analysis.

2.4.2. Satellite Data Acquisition and Preprocessing

To support spatial estimation of plantation age, multi-sensor satellite imagery was sourced from the Thai Earth Observation Satellite (THEOS) and the European Space Agency's Sentinel-2 platform. THEOS imagery provided higher spatial detail for local perennial crop monitoring, while Sentinel-2 ensured frequent revisit intervals and standardized spectral bands for vegetation index computation. Imagery acquisition involved both on-demand THEOS orders and archival retrieval of Sentinel-2 Level-2A products through the Copernicus Open-Access Hub. Scenes were selected for minimal cloud cover, with a preference for dry season captures to reduce atmospheric interference. Validated plantation boundary shapefiles were used to clip all imagery for area consistency.

Preprocessing included atmospheric correction of Sentinel-2 scenes using the Sen2Cor processor, orthorectification of THEOS imagery, and radiometric adjustments as needed. THEOS data were resampled to 10 m using bilinear interpolation to harmonize with Sentinel-2 resolution. Visual inspection of common tie points and control features was used to verify co-registration accuracy between sensors, ensuring consistency for pixel-level analysis. Cloud and shadow masking was conducted using QA bands, and NDVI and NDRE indices were calculated for each scene. These indices were then contrast-enhanced through histogram equalization to strengthen classification performance. The processed imagery stack formed the input for plantation age classification using the Bare Land Referenced Algorithm (BRAH), as described in Section 2.4.3.

2.4.3. Plantation Age Classification for Landscape-Scale Carbon Footprint Estimation

To enable spatially explicit estimation of plantation age for large-scale carbon modeling, a workflow integrating the Bare Land Referenced Algorithm from Hyper-Temporal Data (BRAH) [11–13] and Otsu's automatic thresholding method were applied to satellite imagery. The objective was to detect the last known bare land state of each pixel and infer the plantation age based on subsequent vegetation growth. Initially, NDVI was calculated from atmospherically corrected and cloud-masked satellite images, including those from THEOS and Sentinel-2. Histogram equalization was applied to enhance image contrast. The Otsu method was then used to derive an adaptive threshold for classifying bare land from each NDVI image. Each classified image retained the acquisition date only at pixels identified as bare land, while non-bare land areas were set to zero. These temporally tagged binary layers served as input for the BRAH algorithm.

The BRAH logic was adapted to process large temporal datasets by chronologically assessing each bare land layer and updating a base raster with the latest bare land date for each pixel. If a pixel's value in a new image was bare land and had a later acquisition date than the current record, the pixel's value in the base raster was updated accordingly. This cumulative operation across all scenes generated a bare-land-referenced layer encoding the most recent bare land appearance for each pixel in the study area. The core processing logic was implemented using a custom Python script (in Python 3.11), and key pseudocode steps are provided in Table 3 to support reproducibility.

To estimate plantation age, the acquisition date of the reference plantation map was compared to the bare land date stored in the BRAH layer. Positive differences represented the number of days since the last bare land state and were used as proxies for the plantation age. Pixels with invalid or negative differences, indicating no valid bare land occurrence prior to the reference date, were excluded from analysis. This workflow enables consistent, automated age estimation across extensive cultivation areas with high spatial resolution, supporting regional carbon footprint modeling at scale.

Table 3. Protocol 3. BRAH-Based Algorithm for Plantation Age Classification.

Part 1: NDVI Calculation and Preprocessing

1. Acquire THEOS and Sentinel-2 images.
2. Apply atmospheric correction.
3. Resample THEOS imagery to 10 m resolution to match Sentinel-2 data.
4. Clip all images to the plantation boundary using shapefiles.
5. Calculate NDVI from each image.
6. Apply histogram equalization to improve image contrast and prepare for thresholding.

Part 2: Bare Land Classification Using Otsu's Method1.

1. Compute the histogram of each NDVI image after equalization.
2. Normalize the histogram and compute cumulative sums and means.
3. Determine the optimal NDVI threshold using Otsu's method (maximize between-class variance).
4. Classify pixels as bare land if NDVI $\leq$ threshold, otherwise as vegetated.
5. Tag bare land pixels with the acquisition date; set all others to zero.
6. Repeat for all NDVI images, generating a stack of temporally tagged binary layers.

Part 3: Temporal Compositing via BRAH Algorithm1.

1. Initialize a base raster to store the most recent bare land date per pixel.
2. Loop through all binary layers chronologically:
    a. If a pixel is bare land and has a more recent date than the base raster, update the base raster.
    b. Retain only the most recent bare land date for each pixel.
3. Output the Bare Land Referenced Layer (BRAH Layer), storing the last known bare land state for every pixel.

Part 4: Plantation Age Calculation1.

1. Overlay the BRAH layer with the date of the plantation reference map.
2. Subtract the BRAH date from the reference map date to compute plantation age (in days).
3. Mask invalid or negative values (indicating no prior bare land evidence).
4. Use the resulting plantation age map to estimate carbon emissions at pixel or plot levels.

3. Results

3.1. Waste Valorization Outcomes from 'Phulae' Pineapple Processing

3.1.1. Rare Sugar Production from Peel and Eye Residues

'Phulae' pineapple processing generates significant volumes of peel and eye residues, typically accounting for around 50–60% of the total biomass from fresh-cut operations. These residues were valorized as feedstock for rare sugar production through an enzymatic bioconversion route (Figure 3). Pretreatment involved hot-air drying at a moderate temperature range (approximately 60–70 °C) until the moisture content was sufficiently reduced (around 10%). The dried material was then ground and sieved through a fine mesh (approximately 250 µm) to produce a uniform substrate powder. Soluble sugars were extracted using a simple aqueous soaking method, followed by sequential centrifugation and vacuum filtration to clarify the extract. HPLC analysis confirmed that fructose was the dominant sugar component, which was, therefore, selected as the primary substrate for enzymatic conversion. The enzymatic process was carried out under controlled laboratory conditions using a specific epimerase enzyme, achieving typical conversion efficiencies in the range of 30–40%, yielding rare sugar at concentrations around 2.5–2.6 g/L. Both peel- and eye-derived fractions showed comparable outcomes under identical conditions, indicating no significant practical difference for production applications (Table 4). The resulting extract was then spray-dried at an inlet temperature of approximately 150 °C, with a feed rate around 500 mL/h, to produce a pale brown, highly soluble crystalline powder without bleaching or additives (Figure 4). The product quality was consistent with specifications for very-high-polarization sugar, with color and pH levels meeting standard industry ranges.

(**a**)

(**b**)

Figure 3. Preparation of pineapple peel and eyes for rare sugar production: (**a**) dried samples after hot-air drying and (**b**) fine powder obtained after grinding and sieving.

Table 4. Rare sugar yield range and indicative economic assessment for pilot-scale pineapple processing waste valorization.

Substrate	Rare Sugar Yield (g/L)	Conversion Efficiency (%)	Production Cost (USD/Batch)	Yield (g/Batch)	Product Value (USD/Batch)	Benefit–Cost Ratio
Pineapple peel	2.61	35.28	11.85	70	18.57	1.56
Pineapple eyes	2.55	37.51	11.85	70	18.57	1.56

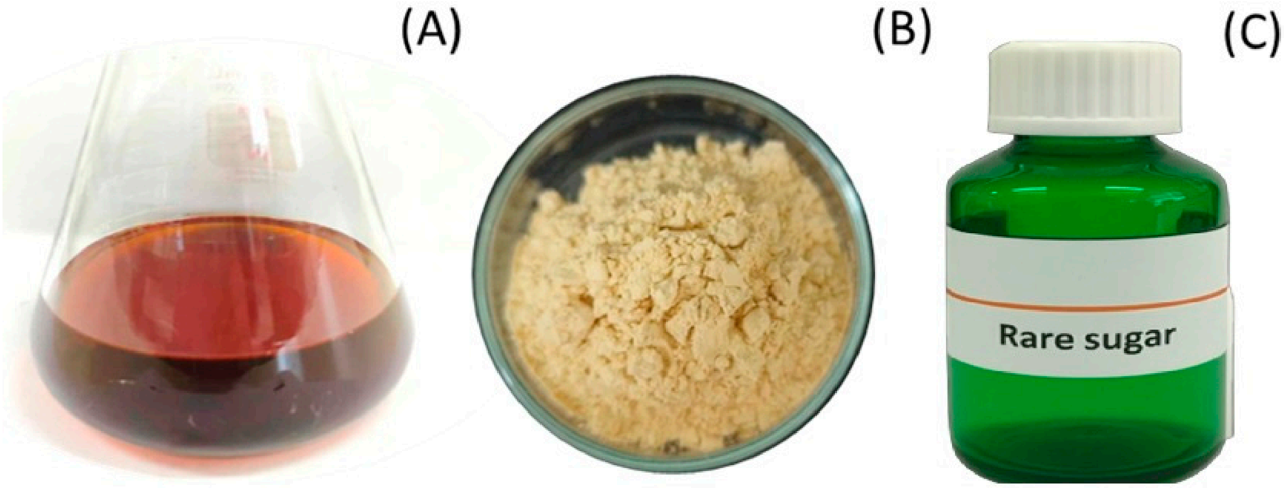

Figure 4. Rare sugar powder obtained from spray drying of enzymatically converted extract from 'Phulae' pineapple waste: (**A**) syrup form, (**B**) powder form, and (**C**) prototype packaging.

A preliminary economic assessment was performed for a pilot-scale batch using about 1 kg of dried pineapple eye powder as input, producing an estimated 60–80 g of rare sugar powder. The unit production cost and benefit–cost ratio fell within an economically promising range for future scale-up (approximate unit cost 0.17 USD per gram, benefit–cost ratio above 1.5). A basic sensitivity analysis indicated that minor reductions in conversion efficiency could slightly lower profitability, highlighting the importance of process control. Please note that the specific detailed process parameters and exact performance data are withheld to protect proprietary intellectual property pending patent application.

3.1.2. Gummy Product Development from Pineapple Vinegar

In addition to rare sugar production, a complementary waste valorization pathway was implemented through the development of functional gummy products derived from fermented pineapple eye residues. These residues, which remain after trimming for fresh-cut packaging, retain sufficient fermentable sugars and were processed through a two-stage fermentation technique. The first stage involved alcoholic fermentation using *Saccharomyces cerevisiae* TISTR 5019 (TISTR, Pathum Thani, Thailand) with an inoculum concentration of approximately 0.015% w/v to convert sugars to ethanol, followed by acetic acid fermentation using *Acetobacter pasteurianus* TISTR 102 (TISTR, Pathum Thani, Thailand) at 10% v/v of the fermented medium. The initial pineapple core juice was adjusted to 18 °Brix, and pH was monitored daily, ranging from 4.05 to 4.12 during alcoholic fermentation (5 days, final ethanol content 8.30%) and from 4.05 to 4.20 during acetic acid fermentation (6 days, final acetic acid content 5.53%).

The resulting pineapple vinegar demonstrated consistent acidity, stable pH, and acceptable aroma profiles for food-grade formulation. Three gummy prototypes were prepared using the produced vinegar, fresh pineapple juice, sugar, gelatin, citric acid, pineapple flavor, and pectin (where applicable). The blending ratios were as follows: Formulation 1 (40% pineapple juice, 15% vinegar, 28.5% sugar, 12% gelatin, 2% pineapple flavor, 2% pectin, 0.5% citric acid), Formulation 2 (40% pineapple juice, 16% vinegar, 28.5% sugar, 12% gelatin, 2% pineapple flavor, 1% pectin, 0.5% citric acid), and Formulation 3 (40% pineapple juice, 17% vinegar, 28.5% sugar, 12% gelatin, 2% pineapple flavor, 0% pectin, 0.5% citric acid) (Table 5).

Table 5. Blending ratios (% w/w) for pineapple vinegar gummy formulations.

Ingredient	Formulation 1 or F1 (%)	Formulation 2 or F2 (%)	Formulation 3 or F3 (%)
Pineapple Juice	40	40	40
Pineapple Vinegar	15	16	17
Sugar	28.5	28.5	28.5
Gelatin	12	12	12
Pineapple Flavor	2	2	2
Pectin	2	1	0
Citric Acid	0.5	0.5	0.5

All formulations followed the same procedure: ingredients were combined and gently heated until fully dissolved, then poured into silicone molds and cooled under refrigeration until fully gelled. Finished gummies were vacuum-packed to maintain texture and hygiene for storage and testing (Figure 5).

A sensory evaluation was conducted using a 5-point hedonic scale, with 158 untrained consumer panelists (74.1% female, 25.9% male; age range predominantly 18–25 years) evaluating 4 key attributes: color, aroma, texture, and overall liking. The selection of these attributes was based on their critical role in consumer acceptance of gummy products. Among the three prototypes, Formulation 3 (F3) achieved the highest mean scores for all tested attributes, reflecting the optimal balance between sweetness, acidity, and texture (Table 6). The main optimization criterion was the mean score of overall liking, which exceeded 4.0 for F3. This confirms that high-moisture pineapple residues can be successfully valorized into shelf-stable, consumer-accepted products within a zero-waste processing framework.

Figure 5. Gummy products formulated from pineapple vinegar using three different recipes: (**Left**): F1, (**Center**): F2, and (**Right**): F3. The third formulation (F3) received the highest consumer preference scores.

Table 6. Sensory evaluation scores of gummy formulations using a 5-point hedonic scale (n = 158).

Attribute	Formulation 1	Formulation 2	Formulation 3
Color	3.97 ± 0.78 c	4.32 ± 0.72 b	4.58 ± 0.63 a
Aroma	4.15 ± 0.85 b	4.21 ± 0.77 b	4.42 ± 0.75 a
Texture	3.79 ± 0.97 b	4.08 ± 0.86 a	4.24 ± 0.81 a
Overall Liking	3.86 ± 0.87 b	4.15 ± 0.81 a	4.32 ± 0.73 a

Values are mean scores ± standard deviation. Scores with different superscripts within a row differ significantly ($p < 0.05$). Scale: 5 = like extremely; 1 = dislike extremely.

3.2. Carbon Footprint Estimation and Spatial Plantation Age Modeling

3.2.1. Activity-Based Carbon Emissions from Cultivation Practices

Emission sources were categorized into three major activities: (1) land preparation, (2) fertilization and weed control, and (3) harvesting operations (Figure 6). As is typical for perennial systems, certain inputs and field operations are not repeated annually but are conducted once per cropping cycle to establish suitable soil and agronomic conditions. Practices such as initial land preparation, primary tillage, and soil amendment application are undertaken prior to planting and their benefits extend throughout the cycle. Therefore, material inputs were normalized to an annual basis by dividing total inputs over a five-year crop cycle.

The results showed that the post-harvest phase, specifically the management of leaf and crown residues, contributed the largest share of emissions, accounting for an average of 0.1330 kg CO_2 eq. per kilogram of fresh product (approximately 58% of total emissions). Fertilization activities contributed about 26% of emissions, while fuel use and pesticide applications accounted for the remaining share (Figure 7). The total carbon footprint at the plantation gate was estimated at approximately 0.2304 kg CO_2 eq. per kilogram of fresh 'Phulae' pineapple. Variation in this estimate primarily reflects differences in fertilizer application rates and field residue management, as documented in comparable systems [1,5].

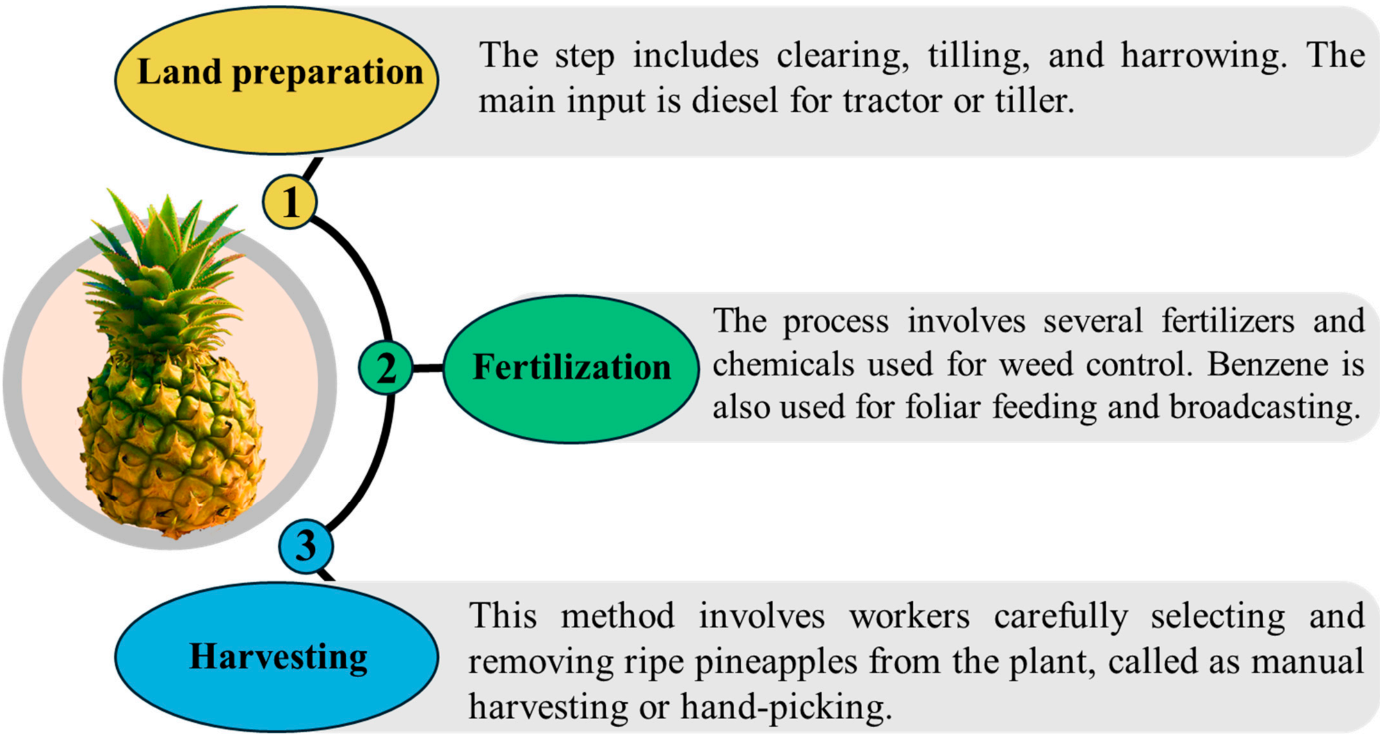

Figure 6. Activities and emission sources in pineapple cultivation.

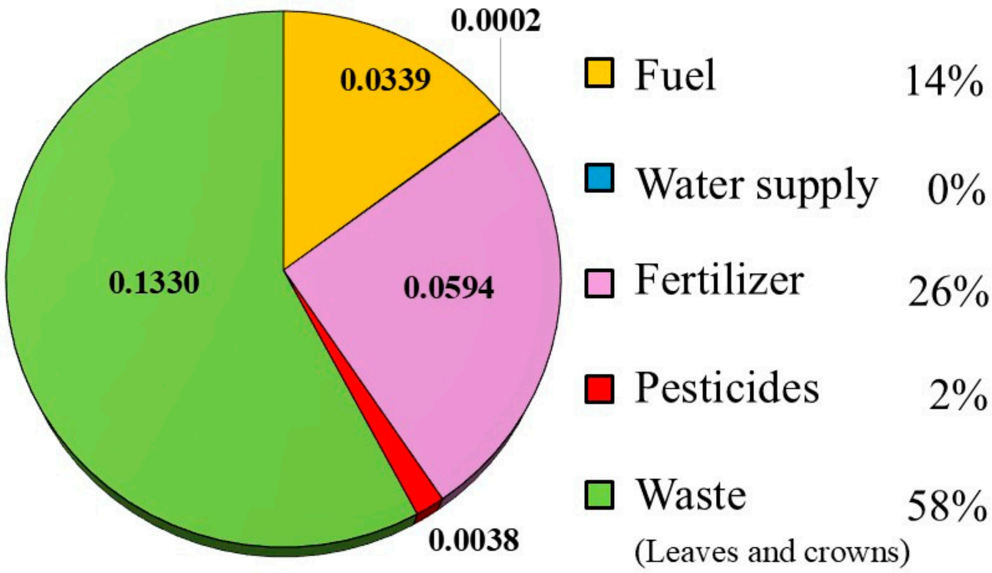

Figure 7. Contribution of greenhouse gas emissions (numbers in the pie chart refer to the emission per 1 kg of fresh 'Phulae' pineapple).

This result is consistent with published benchmarks for tropical perennial fruit systems with high-input management and significant biomass waste. A mass balance diagram illustrating the distribution of inputs and emission flows throughout the crop cycle is provided in Figure 8.

The total carbon footprint figure reported in this study was derived from a single pilot-scale demonstration plot covering seven rai of 'Phulae' pineapple, calculated according to the standard carbon footprint of product (CFP) guidelines of the Thailand Greenhouse Gas Management Organization (TGO) [22]. As no inter-annual or multi-site replication was available, a statistical standard deviation for the plot-level activity data could not be determined. The principal source of uncertainty stems from the use of secondary emission factors, which inherently carry documented variability in the CFP methodology. To strengthen the robustness of future estimates, additional annual data collection will be conducted at multiple farms to capture inter-plot variation and reduce uncertainty.

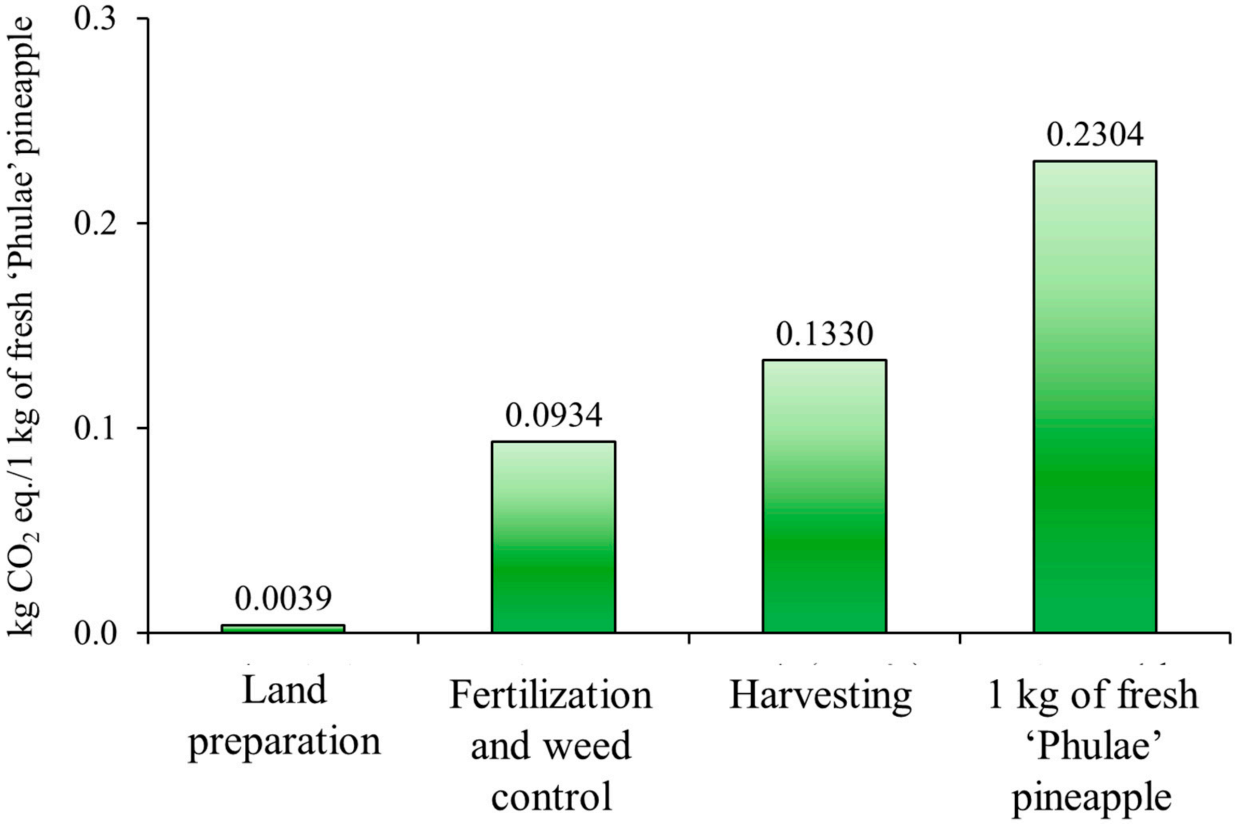

Figure 8. Mass balance of carbon emissions associated with 'Phulae' pineapple cultivation.

3.2.2. Carbon Footprint Estimation Using BRAH-Based Plantation Age Mapping

The plantation age layer, generated using the BRAH algorithm in combination with Otsu's NDVI-based thresholding, served as the primary spatial input for landscape-scale carbon emission modeling. To ensure classification reliability, a bare land referenced map was constructed by detecting the last bare land state for each pixel across multi-temporal satellite imagery (Figures 9–11). To confirm the accuracy of the bare land classification step that underpins the BRAH workflow, a random sample comprising ten percent of all bare land layers was selected for validation. Fifty random points per layer were visually checked against high-resolution base imagery by domain experts to verify whether each pixel was correctly classified as bare land or vegetation. This procedure yielded an average classification accuracy of 82.90 percent with a standard deviation of 7.12 percent. The validation result demonstrates that the derived bare land masks are sufficiently reliable for generating the plantation age input required for subsequent spatial carbon footprint modeling (Figure 9).

The derived plantation age profile was cross-validated with ground-based planting records collected from 104 pineapple plots distributed throughout the study region (Figure 10). The age estimates demonstrated an average deviation of 4.03 months with a standard deviation of 14.90 months when compared to farmer-reported planting dates. This empirical range shows that the model's practical temporal deviation mostly clusters within approximately fifteen months, which aligns with the expected uncertainty when relying on historical satellite data and local record limitations.

To assess the potential impact of this temporal deviation on carbon footprint estimates, a sensitivity check was performed. The results confirmed that minor variations in age classification did not substantially affect cumulative carbon output per unit area. This outcome reflects the fact that the primary contributors to emissions, including biomass residues and input use, accumulate gradually over multi-year cultivation cycles, which minimizes the effect of short-term age estimation uncertainty.

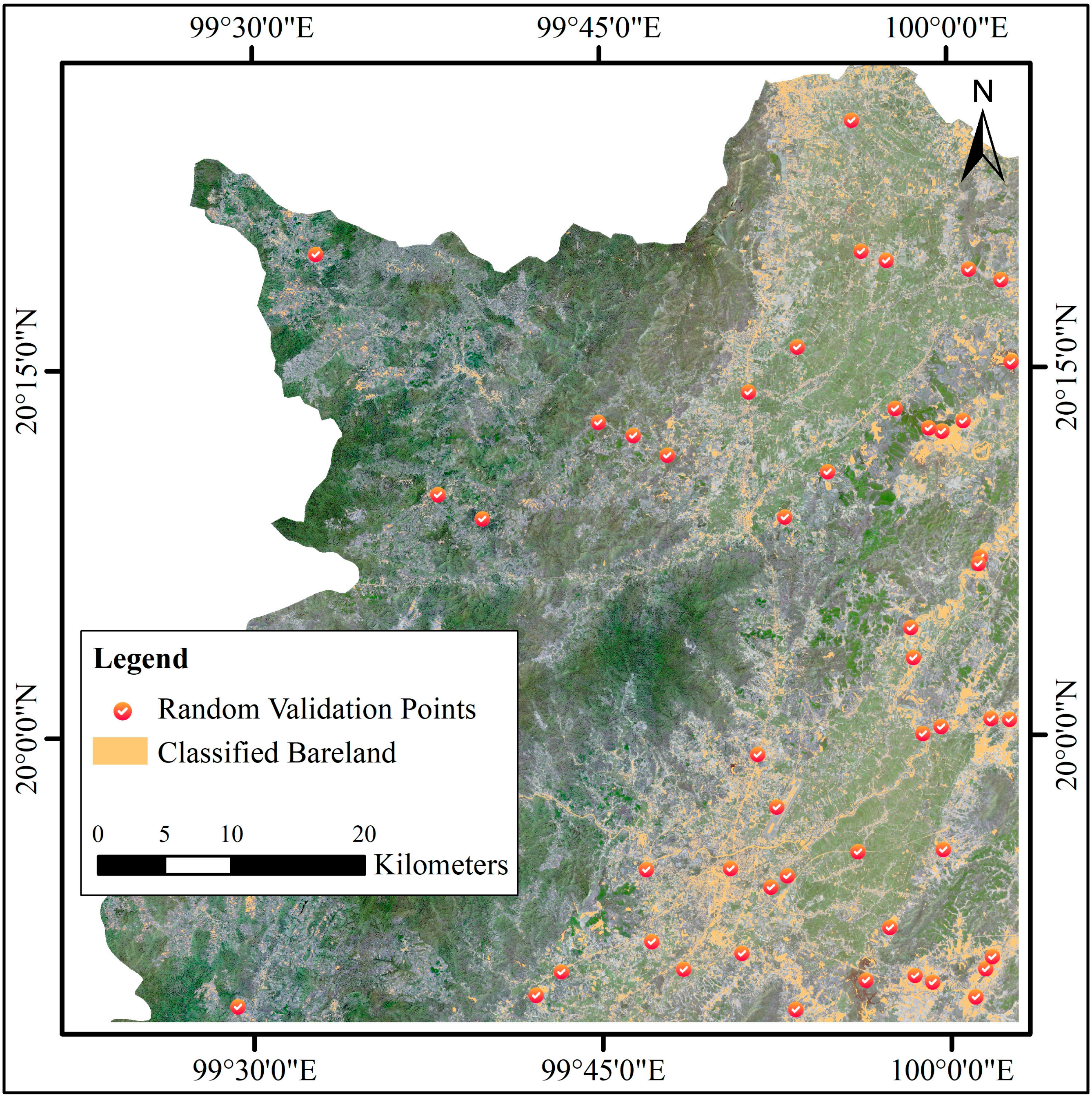

Figure 9. Representative classified bare land layer with random validation points overlaid for visual accuracy assessment.

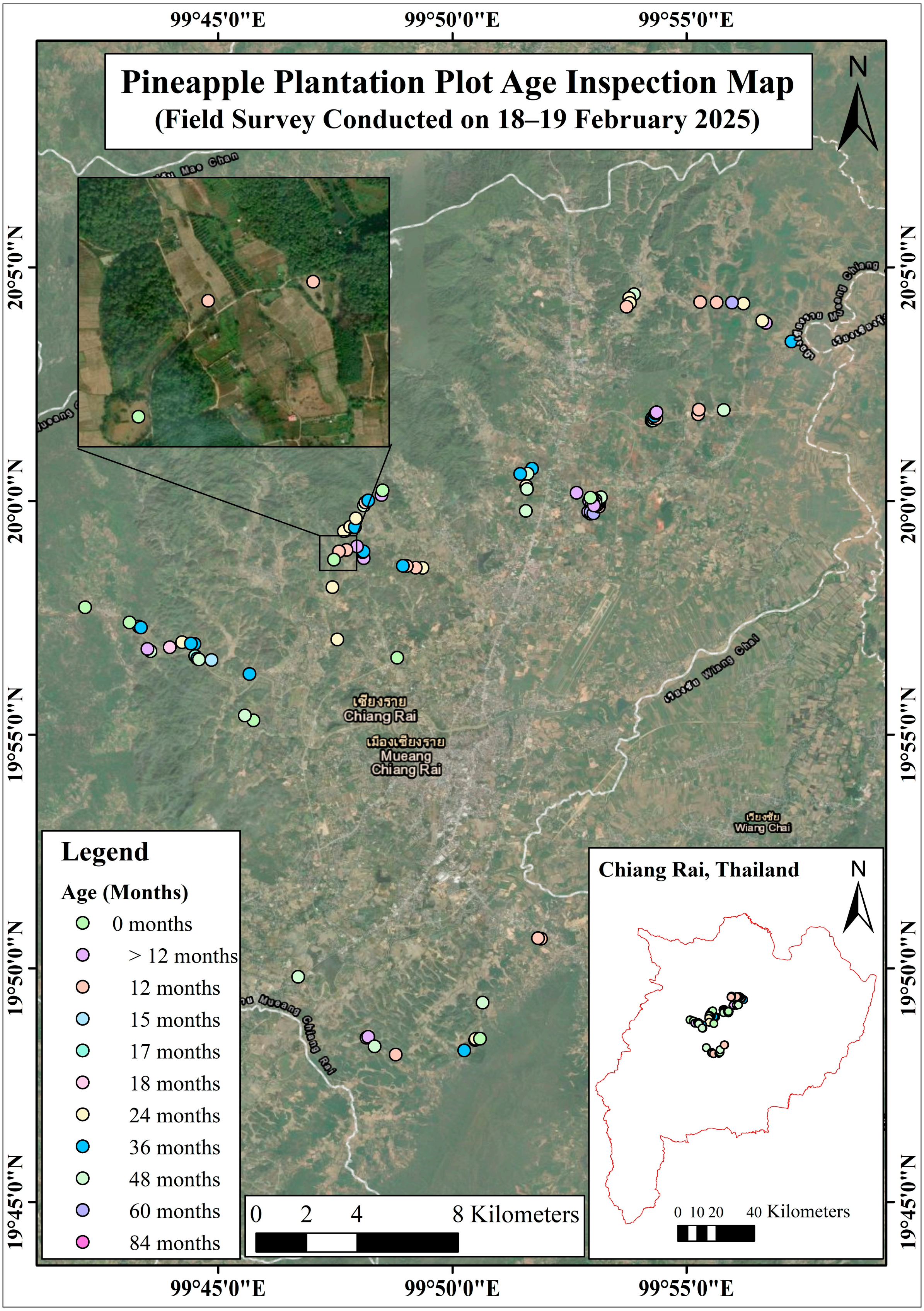

Figure 10. Georeferenced pineapple plantation plots with field-surveyed planting dates used to validate the BRAH-derived plantation age estimates.

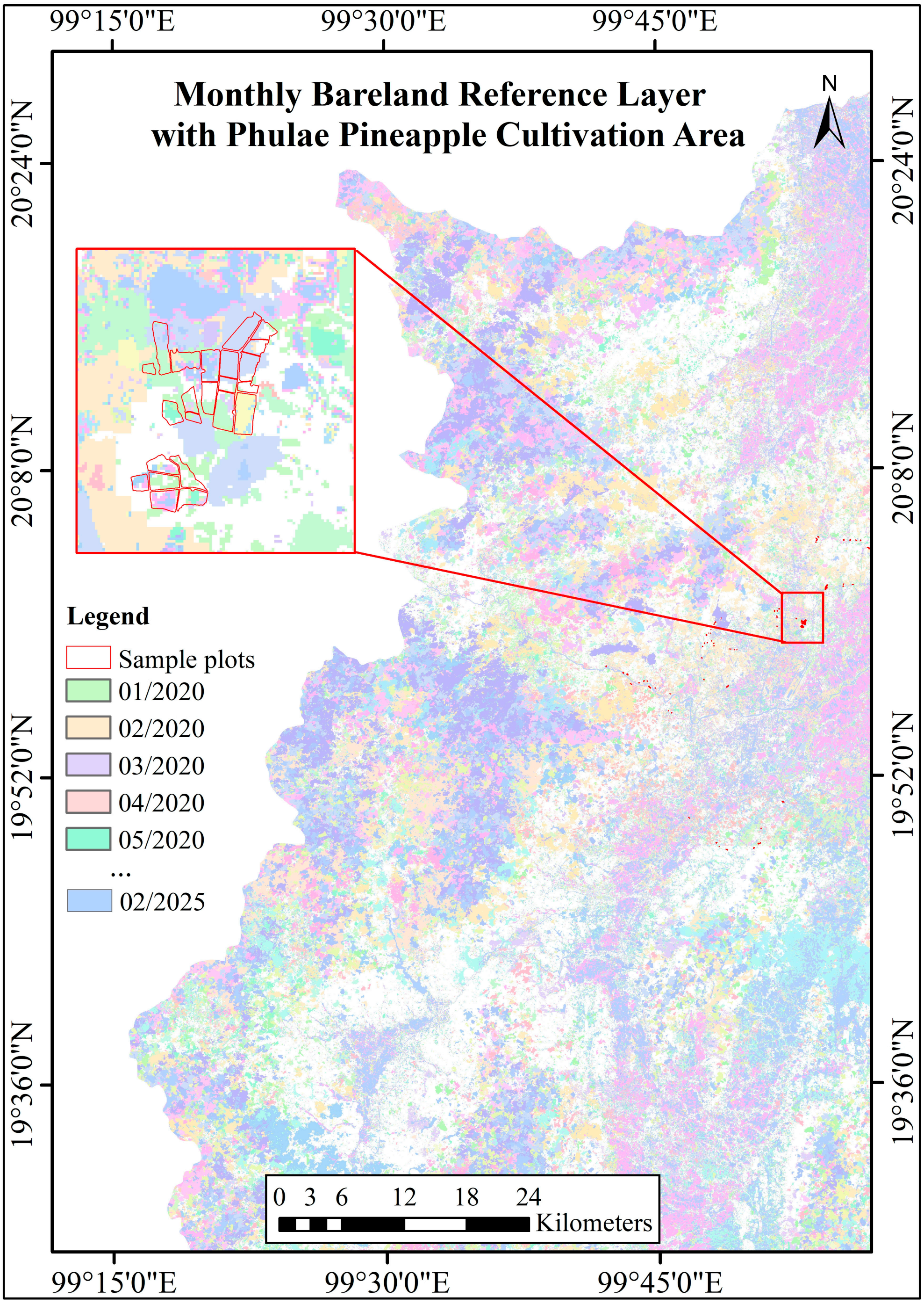

Figure 11. Bare land referenced layer showing plantation age distribution across the study area with an inset highlighting sample plots.

Statistical analysis confirmed that plantation age had a very strong positive correlation with cumulative greenhouse gas emissions ($r = 0.996$, $p < 0.01$), which strongly supports its role as a key predictor for carbon footprint estimation. By comparison, NDVI alone showed a moderate correlation with emissions ($r = 0.678$, $p < 0.01$). This result underscores the advantage of using plantation age derived from the BRAH framework rather than relying solely on direct spectral indices for estimating regional emissions (Table 7). This strong statistical association affirms that plantation age, as derived from the BRAH procedure, is a practical and reliable input for cost-effective and scalable carbon accounting in perennial fruit systems.

Table 7. Pearson correlation coefficients among plantation age, spectral bands, vegetation indices, and cumulative carbon emissions.

Variable	Age	Blue	Green	Red	Red_Edge	NIR	NDVI	NDRE	Carbon Emission
Age	1	−0.188	−0.092	−0.378	0.104	0.263	0.657	0.351	0.996
NDVI	0.657	−0.524	−0.354	−0.631	0.273	0.471	1	0.364	0.678
Carbon emission	0.996	−0.208	−0.125	−0.398	0.105	0.267	0.678	0.361	1
(Other coefficients omitted for brevity)									

Note: Blue, Green, Red = visible spectral bands; Red_edge = red edge band; NIR = near-infrared band; NDVI = Normalized Difference Vegetation Index; NDRE = Normalized Difference Red Edge Index.

The final age–emission relationship enabled the generation of a spatially explicit carbon footprint map that illustrates the distribution of emission intensity across the 'Phulae' pineapple cultivation zones (Figure 12).

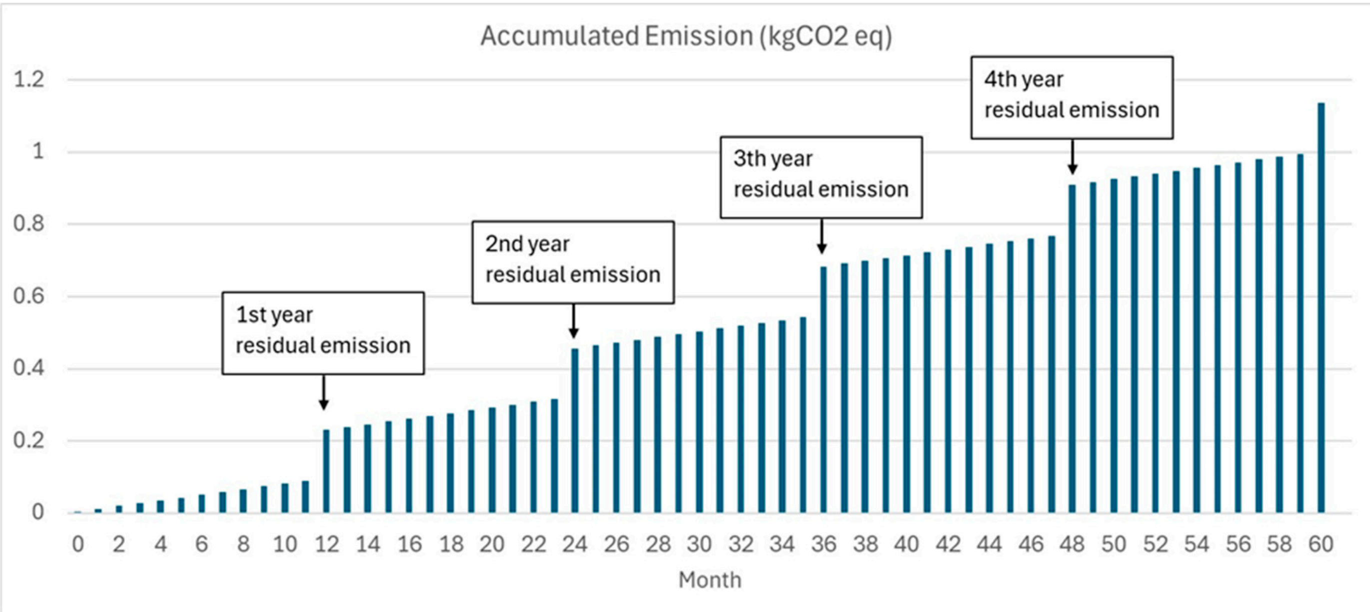

Figure 12. Cumulative carbon emissions considered monthly. A clear positive relationship was observed between plot age and cumulative emissions.

4. Discussion

4.1. Commercial Potential of Rare Sugar Extraction and Its Role in Zero-Waste Agriculture

The successful extraction of rare sugar from pineapple peel and eye residues demonstrated a promising high-value utilization strategy within a zero-waste agricultural framework. The conversion yields obtained in this study were within the typical range for enzymatic epimerization of fructose using a specific enzyme, which generally achieves approximately 30–40% conversion under controlled laboratory conditions [9,10]. The slightly higher performance observed for eye residues may be attributed to their naturally higher proportion of residual free sugars compared to peel fractions, which tend to contain more lignocellulosic matrix that can limit sugar release during pretreatment and extraction [4]. While detailed compositional and process data remain confidential to protect proprietary know-how, HPLC profiling confirmed that the eye tissues provide a rich fructose substrate for enzymatic conversion.

A preliminary economic feasibility assessment at the laboratory scale indicated a positive benefit–cost ratio, with production costs comparable to other small-scale rare sugar processes reported in the literature. These outcomes are influenced by enzyme efficiency, substrate sugar content, and key operational factors, such as controlled particle size and cofactor management, which are known to enhance enzyme activity [10,15]. Prior research has also shown that process improvements, such as enzyme immobilization and cofactor optimization, can further enhance yield and stability [23,24].

The final spray-dried rare sugar product met food-grade quality criteria consistent with very-high-polarization sugar standards, without requiring chemical bleaching or modification, supporting its potential for direct use in food and nutraceutical applications. Notably, rare sugar is recognized as Generally Recognized as Safe (GRAS) by the U.S. FDA and continues to gain global market interest as a rare, low-calorie sugar substitute with low glycemic impact [9,10].

From a sustainability perspective, rare sugar production offers a clear improvement over conventional low-value waste disposal methods, such as composting or incineration. The integrated valorization of both peel and eye residues maximizes biomass utilization by recovering fermentable sugars under mild pretreatment and enzymatic conditions. While these laboratory-scale results are encouraging, scaling up to industrial production will require further advancements in enzyme cost efficiency, consistent feedstock quality, and integration with existing fresh-cut processing lines. This valorization approach can be adapted for other tropical fruit residues with similar sugar profiles, such as banana, mango, and jackfruit, contributing to a practical circular economy within tropical agri-food supply chains.

4.2. Consumer Acceptance and Functional Potential of Pineapple Vinegar-Based Gummy Products

This study demonstrated the feasibility of transforming pineapple eye residues, an underutilized by-product, into a consumer-acceptable gummy product through fermentation and functional formulation. The two-stage fermentation process using *Saccharomyces cerevisiae* TISTR 5019 (TISTR, Pathum Thani, Thailand) and *Acetobacter pasteurianus* TISTR 102 (TISTR, Pathum Thani, Thailand) yielded pineapple vinegar with stable acidity and aroma profiles suitable for food applications, consistent with previous studies on tropical fruit vinegar production [17–19]. Several works have highlighted the nutritional value and sensory potential of fermented fruit vinegars when applied in novel food products [20].

Among the three gummy prototypes evaluated, Formulation 3 (F3) consistently received the highest sensory scores for color, aroma, texture, and overall liking. The relatively higher preference for F3 may be partly attributed to its balanced vinegar-to-sugar ratio and slightly softer texture due to differences in gelatin and pectin content. However, it should be noted that sensory preference is inherently subjective and may vary among individuals. To minimize the impact of this variability and ensure that the scores reflect general consumer acceptance, a large untrained consumer panel of 158 participants was employed.

Overall, this work provides a practical model for valorizing high-moisture fruit residues into shelf-stable, value-added products with verified consumer acceptance. The approach directly supports sustainable food innovation and zero-waste processing strategies within agro-industrial systems [25]. Approximately 25 percent of the total pineapple biomass is composed of eye residues, demonstrating the significant resource recovery potential that can be achieved through this pathway.

4.3. Strengths and Limitations of BRAH and Otsu-Based Remote Age Estimation

The integration of a bare land referencing logic with Otsu thresholding in this study provided an effective and scalable method for estimating plantation age using multi-temporal satellite imagery. This approach made it possible to detect bare land states and infer planting dates across extensive areas without relying on direct in situ records. By automatically determining NDVI thresholds for each scene, Otsu's method reduced subjectivity and improved consistency in bare land classification across time-series data.

One of the principal strengths of this method lies in its accessibility and cost-effectiveness. It depends entirely on freely available satellite imagery from platforms such as Sentinel-2 and THEOS, making it feasible for use in other regions or crop systems [12,26]. While the specific BRAH workflow developed here has not previously been applied to pineapple, the general principle of multi-temporal bare land detection has been demonstrated in perennial crop monitoring, including oil palm and tea plantations, where detecting canopy establishment from prior bare soil states supports plantation management and carbon accounting. Validation of the bare land classification confirmed its practical reliability. Visual inspection of randomly sampled points across the classified bare land layers demonstrated an average accuracy of 82.90 percent with a standard deviation of 7.12 percent. This empirical check supports the use of the automated Otsu thresholding and BRAH workflow as a robust remote sensing tool, particularly where field data are limited.

The workflow requires no ground-truth training samples, which is particularly advantageous in data-scarce contexts. Its capacity to process large volumes of multi-temporal scenes and generate temporally explicit outputs enables its application at regional or national scales for dynamic monitoring. However, the method is not without limitations. The central assumption of the BRAH algorithm, which assumes that the most recent bare land detection marks the true planting date, may not always hold in systems with multiple tillage events, delayed canopy development, or overlapping crop cycles. In such situations, plantation age may be over- or under-estimated. Furthermore, while Otsu's method enhances automation, its performance can decline in areas affected by frequent vegetation anomalies, cloud cover, or sub-canopy variations that distort NDVI signals.

Spatial resolution is also a constraint. Although Sentinel-2 provides 10 m resolution, this may be inadequate for detecting plot boundaries in highly fragmented or smallholder-dominated landscapes. Higher-resolution imagery could improve delineation accuracy but usually entails higher costs and limited revisit frequency. Validation in this study relied on field-reported planting dates, which were recorded in annual increments. This coarse temporal detail limited the possibility for formal accuracy metrics beyond the deviation and standard deviation reported. Nevertheless, the BRAH-derived estimates fell within an acceptable error range and offered improved temporal precision relative to conventional plantation records.

Overall, the method presented here is reliable for its intended scope. It offers a practical mechanism for estimating plantation age at scale when combined with structured preprocessing and post-classification checks. This capacity underlines its potential integration into carbon monitoring frameworks, sustainable land management, and agricultural traceability tools for perennial crops.

4.4. Broader Applicability of Plantation Age Modeling in Carbon-Labeled Agriculture

The findings of this study indicate that remotely sensed plantation age can serve as a reliable proxy for modeling carbon emissions in perennial crop systems. This approach addresses a key gap in carbon-labeled agriculture, where field-level emissions are often difficult to estimate due to limited access to accurate planting records or inconsistencies in farmer-reported data. By enabling spatially continuous age estimation, the method provides a more transparent and scalable foundation for emission accounting.

The broader applicability of this approach lies in its potential extension to other perennial crops that follow a similar land preparation and canopy development pattern. Previous remote sensing research has successfully demonstrated plantation age estimation and bare soil referencing for oil palm and rubber plantations, confirming that these crop systems are suitable for multi-temporal analysis and canopy monitoring [13,27,28]. Provided that an identifiable bare land stage exists and sufficient temporal satellite data are available, the BRAH and Otsu-based method [11] can be adapted to crops such as banana, mango, oil palm, and rubber in other tropical regions.

This modeling strategy aligns with current trends in sustainability certification and climate-related trade regulations. As policies such as the Carbon Border Adjustment Mechanism (CBAM) and voluntary carbon market protocols gain wider application, there is an increasing need for standardized, verifiable, and spatially explicit methodologies. Remote-sensing-based plantation age estimation supports these requirements by offering a replicable and cost-effective means of linking field conditions to carbon footprint models without requiring site-specific ground sensor calibration.

In this context, plantation age modeling is more than a technical exercise. It represents a strategic component in the design of traceable, low-emission agricultural supply chains. Its compatibility with open-access data platforms and standard geospatial tools further strengthens its value for governments, certification agencies, and exporters seeking to meet international environmental reporting standards.

4.5. Contribution of the Integrated Workflow as a Scalable Framework for Sustainable Agriculture

This study introduced a practical and transferable framework that integrates biochemical waste valorization with remote-sensing-based carbon footprint estimation. By combining the production of high-value rare sugars from fruit processing residues with plantation age modeling derived from satellite data, the proposed workflow addresses both waste minimization and emission transparency within a unified operational structure.

The innovation of this framework lies in its capacity to connect biochemical conversion technologies with geospatial analytics to support sustainable decision-making at scale. This approach responds to two common limitations in agricultural systems: the inefficiency of biomass utilization and the lack of accessible, cost-effective tools for field-level carbon monitoring in smallholder contexts, as noted in carbon footprint guideline reports, such as the IPCC (2006) and Thailand's TGO CFP Manual [21,22]. By using only freely available satellite imagery and minimal ground-truthing, the remote sensing component provides a replicable solution for resource-constrained regions.

Moreover, the modular structure of the workflow allows it to be adapted across different perennial crop systems and diverse geographical contexts. The remote sensing component can be deployed wherever perennial cultivation features identifiable planting stages, while the biochemical valorization module can be tailored to the compositional profile of local residues. This adaptability enhances its relevance for both commercial implementation and policy support. The integrated workflow aligns with national Bio-Circular-Green (BCG) economy strategies and international mechanisms, such as carbon border adjustment measures. The plantation age layer developed here demonstrated practical accuracy within an approximately ±15-month deviation from farmer-reported planting dates, while the rare sugar and gummy product modules showed economic feasibility and positive consumer acceptance, respectively, providing empirical support for the framework's operational capability.

By producing spatially explicit, verifiable data, the workflow strengthens traceability, supports carbon labeling initiatives, and informs climate-smart agricultural planning. As such, it contributes not only to improved environmental performance at the farm level but also to institutional readiness and market competitiveness in a carbon-constrained global economy.

5. Conclusions

This study presented an integrated sustainability framework for 'Phulae' pineapple cultivation and processing that combines biochemical waste valorization with satellite-based carbon footprint estimation. By converting peel and eye residues into high-value rare sugar and vinegar-based functional gummy products, the system provides a viable zero-waste pathway within fruit supply chains. The rare sugar extraction demonstrated favorable conversion yields and a benefit–cost ratio above unity, confirming its technical and economic feasibility at pilot scale. Likewise, the gummy product formulation showed strong consumer acceptance, supporting the practical use of fermented residues for functional food innovation. On the environmental side, the study validated the BRAH algorithm combined with Otsu's NDVI thresholding as an accurate and scalable method for estimating plantation age using multi-temporal satellite imagery. The plantation age layer proved reliable within a $\pm$15-month deviation from ground reports and served as a robust predictor for activity-based carbon footprint modeling. Together, these components form a transferable model that addresses two key sustainability challenges: inefficient biomass utilization and the lack of accessible, verifiable data for field-level carbon accounting.

This framework aligns with the principles of the Bio-Circular-Green economy and supports transparent carbon labeling, traceable supply chains, and readiness for climate-related trade policies, such as the Carbon Border Adjustment Mechanism (CBAM). Beyond 'Phulae' pineapple, the integrated approach is well suited for application in other perennial crops, including oil palm, rubber, and tropical fruits, with similar land preparation patterns. It offers a practical template for scaling up zero-waste production and geospatial carbon monitoring in diverse regions worldwide, especially where low-cost, open-access tools are needed.

Future research should focus on industrial-scale pilot trials for rare sugar recovery, more extensive multi-site validation of remote age estimation across other crops, and the integration of this framework into formal certification schemes for carbon-labeled agricultural products.

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