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Life cycle carbon accounting and waste valorisation in litchi supply chains for climate-resilient food systems

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The growing environmental concerns necessitate sustainability assessment in agricultural food systems. The present study quantified carbon emissions in litchi supply chains using a circular tiered hybrid-life cycle assessment (CrTH-LCA) framework, accompanied by carbon emission forecasting, using statistical (ARIMA and Prophet) and deep learning (LSTM and GRU) models, along with an economic feasibility assessment of waste valorisation. This study estimated a total carbon footprint of 7305.17 $kgCO_2$-e ha^{-1}, with household waste (40.44%) and cultivation (31.96%) identified as the major contributors. Carbon absorption and waste valorisation contributed to mitigation strategies, offering an economic potential of \$2607.02 per hectare, with waste valorisation alone accounting for 63.06% of the total carbon emissions offset. The Monte Carlo simulation confirmed fertilizer and household wastages as the key uncertainty drivers. Forecasting using deep learning (LSTM) models achieved a high predictive accuracy (MAE = 34.92; RMSE = 35.62), projecting an upward trend in future emissions and emphasizing the need for adaptive mitigation strategies. Based on the six-year forecast trend, a community-based biogas model at the farmer-level demonstrated strong financial feasibility, achieving a high return on investment of 164.01% with a payback period of 28 months. Overall, the study offers a replicable and data-driven framework, linking life cycle assessment, circular waste management, and forecasting for a climate resilient decision-making. Aligning with SDGs 2, 12, and 13, the findings emphasize policy shifts *via* strengthening carbon crediting and targeted financial incentives, such as leveraging government subsidies and carbon finance, to enhance farmers' income, promote waste-to-energy valorisation, and accelerate India's transition to a low-carbon, circular agri-food system.

Sustainability spotlight

This study advances sustainable food systems by developing a circular tiered hybrid life cycle assessment (CrTH-LCA) framework to evaluate and reduce carbon emissions in the litchi supply chain. By integrating circular economy strategies, such as waste valorisation into biofuel and compost, alongside the carbon sequestration potential of orchards, this approach identifies mitigation pathways that could reduce emissions by over 60%. The study also applies AI-driven forecasting models (LSTM and GRU) to predict emissions under changing production and climate conditions. The findings provide actionable insights for reducing the environmental impacts by enhancing the resource efficiency and creating carbon credit opportunities, thereby directly contributing to SDG 12 (responsible consumption and production) and SDG 13 (climate action).

1. Introduction

Litchi (*Litchi chinensis* Sonn.) is a high-value fruit in India's horticultural sector, with Bihar accounting for approximately 45% of its national production.[1] The geographical indication (GI)-tagged Shahi litchi of Muzaffarpur district offers significant export and economic values with supply to major cities through a perishable supply chain that spans from farmers to consumers, making way through wholesalers and retailers. Despite its economic importance, the litchi supply chain faces sustainability challenges like shorter shelf life, high perishability, and reliance on non-refrigerated vehicles that exacerbates post-harvest losses.[2] The losses are further aggravated due to inadequate handling, microbial spoilage, and environmental stress, leading to carbon emissions (CEs).[1,2] The carbon footprint of agricultural supply chain (ASC) accounts for over 24% of the global green-house gas (GHG) emissions[3] and nearly 30% of global energy consumption.[4] Thus, evaluation of carbon footprint (CF) is necessary toward designing low-emission, climate-resilient food systems.

Life cycle assessment (LCA), particularly the process-based approach, is a widely accepted systematic method for

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quantifying the environmental impacts of a product throughout its life cycle, from raw material sourcing to its final disposal. In process-based LCA, individual processes involved in the product system (*e.g.*, cultivation, packaging, and transport) are modelled using detailed, site-specific input–output data. The LCA bottom-up method offers high resolution and accuracy, making it especially useful for analysing litchi supply chains.[5] The limitations of current environmental modelling approaches, from LCA to emission prediction, reveal a critical gap: the inability to integrate macro-scale economic models with high-resolution, micro-level operational and climatic data. Traditional LCAs partially address the truncation errors of process-based models,[6] but remain too coarse to capture the demands of the circular economy (CrE) systems.[7] Furthermore, conventional hybrid models struggle to effectively integrate detailed, site-specific process data such as specific irrigation energy or fertilizer application rates with macro-level upstream data.[8] In agricultural supply chains, critical flows like emissions from fruit respiration and the proper allocation of environmental credits/burdens from diverting post-harvest losses (*e.g.*, to composting or biogas) are often overlooked, leading to incomplete assessments. Similarly, emission studies rely heavily on macro-scale economic models,[9,10] failing to capture micro-level agricultural variations due to insufficient integration of climatic factors like temperature and rainfall.[11,12] Few studies employ advanced deep learning models (LSTM and GRU) for micro-scale agricultural carbon emission (ACE) prediction that explicitly incorporate climatic and area-specific variables.[13] This highlights the need for a refined framework bridging traditional macro-scale approaches with localised, climate-sensitive ACE forecasting.

Despite a substantial body of research on ASCs and its associated CEs, several critical gaps persist that constrain the advancement of robust predictive and decision-support frameworks:

- The interlinkage between post-harvest losses and lifecycle CEs remains inadequately addressed, despite such losses constituting a significant share of total emissions.
- The carbon offset potential of waste valorisation pathways (composting, biogas generation, and nutrient recycling) has not been systematically integrated into lifecycle assessments.
- The role of carbon credit mechanisms and related financial instruments in fostering sustainable adoption among stakeholders is largely unexplored.
- Existing forecasting studies predominantly employ univariate approaches, overlooking essential multivariate drivers (*e.g.*, cultivated area, climatic variability, and input intensity) that critically influence both productivity and emissions.

The present study addresses these critical gaps with a novel circular tiered hybrid life cycle assessment (CrTH-LCA) framework combined with a univariate/multivariate forecasting approach for carbon emission estimation. The proposed framework overcomes the existing gaps through a dynamically tiered hybrid structure. The framework ensures the system boundary completeness while explicitly integrating circularity metrics and high-resolution technical data into the process-LCA foreground. The CrTH-LCA framework has linked physical and environmental flows with technical performance, enabling precise, quantitative evaluation of circular supply chain strategies along with waste recyclability and disposal achieving a level of granularity and coverage not attained by existing hybrid models. Complementing this, the multivariate forecasting framework of statistical (ARIMA, Prophet) and deep learning (LSTM, GRU) models enables accurate, context-specific predictions by capturing nonlinear patterns, temporal dependencies, and interactions among multiple influencing factors. The present study combined approach bridges macro-scale forecasting with localized, climate-sensitive ACE predictions. In supply chains, spoiled or damaged produce are often subjected to composting, biogas generation, or animal feed production further adding toll to the overall CF.

The primary objectives of the study are:

- Quantify stage-wise CEs using CrTH-LCA and assess the carbon offset potential from CrE strategies, including composting and biogas generation.
- Explore the feasibility of carbon credit mechanism towards incentivizing sustainable practices in the horticulture supply chain.
- Forecast CEs using time series-based statistical and deep learning models incorporating both production and climatic variables (*e.g.*, area, temperature, and rainfall) as input variables to improve the prediction accuracy.

The integrative approach advances the methodological rigor of carbon assessment in horticultural systems and provides scalable insights for sustainable supply chain design. The study also supports policy alignment with global sustainability goals, particularly SDG 12 (responsible consumption and production) and SDG 13 (climate action). Following the introduction, which establishes the context of carbon emissions, life cycle assessment, and forecasting. Section 2 provides a detailed literature review covering carbon emissions, life cycle assessment approaches, circular economy perspectives, and forecasting models. Section 3 outlines the comprehensive methodology adopted for estimating and forecasting carbon emissions across the supply chain. Section 4 presents and critically discusses the empirical results, including the identification of carbon emission hotspots and forecasting outcomes. Finally, Section 5 summarizes the key conclusions and highlights the theoretical contributions as well as policy implications of the study.

2. State of the art

The increasing global demand for food, coupled with the urgency of mitigating climate change, has spurred extensive research into the environmental impacts on agrifood systems.[14] Within this domain, fresh produce supply chains are of particular interest due to their essential role in nutrition, complexity, and often globalized nature.[12,15] The literature review synthesizes current insights into CEs in fresh produce supply chains, focusing on LCA, emission hotspots, influencing factors, mitigation strategies, and predictive modelling.

2.1. Carbon emissions in fresh produce supply chains

CFs of fresh fruits vary considerably due to differences in nutrient requirements, farming practices, fertilizer use, climatic

Table 1 Summary of the key studies analysing CFs across various agri-food and supply chains

Study	Key findings	Gaps/limitations	References
Systematic review and meta-analysis of 369 LCA studies of 168 varieties of fresh produce; at regional distribution centre (RDC)	Grains, fruit, and vegetables had the lowest impact	LCA excluded most end-of-life activities (food storage, disposal)	Clune *et al.*[17] and Martin-Gorriz *et al.*[18]
Systematic review using PA-LCA of fruits, predominantly cradle-to-farm-gate	Production stage is the primary hotspot	Whole-of-life CF under-represented; carbon sequestration largely ignored	Subedi *et al.*[14]
Analysis of production technology of frozen vegetable-based products; field-to-gate basis	Freezing fruits and vegetables is energy-intensive; refrigeration is the main source of CO_2-e emissions in frozen products	Limited systemic transitioning to low-emission food production using CO_2-e metrics	Liu *et al.*[19] and Wróbel-Jędrzejewska and Polak[20]
Cradle-to-farm-gate emission factors of fresh fruit and vegetables	Quantified the substantial embedded emissions arising from avoidable food losses due to cosmetic standards	Emissions from beyond farm supply chain stages omitted	Porter *et al.*[21] and Porter *et al.*[22]
Multilinear regression and stochastic frontier analysis of imported fruits and vegetables were applied on cradle-to-consumer/disposal	Transportation and sales/distribution are the two key factors of CO_2-e. Transportation increases CO_2 emissions by 10 tonnes per tonne of imported F&V	Food waste and packaging excluded from redefined LCA due to data gaps and complexity	Ferguson Aikins and ramanathan[23]
Integrated framework of ecologically based life cycle assessment and linear programming (DEA) for ecological performance assessment of 54 agricultural and food industries sectors	Grain farming, dairy food, and animal production-related sectors had the greatest shares in environmental impact	LCA limited by inconsistent impact indicators and high uncertainty; cradle-to-grave boundaries needed to include use and EoL phases	Park *et al.*[24]

Table 2 Key studies applying circular life cycle assessment (circular LCA) in agri-food systems

Study	Key findings	Gaps/limitations	References
Critical comparison of LCA case studies highly heterogeneous, cradle-to-gate with system expansion of olive oil	Major hotspots: agricultural phase (fertilization/pesticides). Transport and energy in husk processing	Lack of data on circular processes	Arzoumanidis *et al.*[7]
Process-based LCA (farm-to-shelf) of fresh pineapple	Farming stage constitutes 60% of CF; and N_2O emissions occur from fertilizer application	The study did not include any evaluation of waste valorisation	Ingwersen[27]
Consequential LCA (C-LCA) of wine supply chain	Packaging and transportation were identified as major hotspots	The end-of-life phase is often omitted, excluding assessment of recyclability	Arzoumanidis *et al.*[7]
Bibliometric analysis combined with network and content analyses. Classified papers by TBL pillar and supply chain phase of agrifood supply chain	The environmental pillar received greater attention compared to the economic and social pillars	Few studies address the post-consumption phase of agri-food supply chains and lack circular economy	Agnusdei and Coluccia[28]
Hybrid LCA (integrated process-based LCA with input-output analysis (IOA)) of pasta	Focused on inventory refinement for impacts due to fertilizers and pesticides	Hybrid approach avoids closed-loop incompleteness; IO-LCA works best with traditional LCA to prevent missing data or errors	Arzoumanidis *et al.*[7]

conditions, and system boundaries.[12,16] Although fruits and vegetables generally exert a lower environmental impact than dairy, meat, and fish products,[7] their footprints vary substantially across production systems (conventional *vs.* organic), geographic origins, and transport distances. Table 1 synthesizes the key studies assessing the CFs of agri-food, emphasizing variations across production methods, regions, and supply chain stages.

2.2. Circular life cycle assessment

LCA has emerged as a fundamental methodology for evaluating environmental impacts on fruit production, with its application increasing significantly since 2005.[15] The integration of LCA with sensitivity analysis enhances analytical robustness by offering comprehensive insights into system-wide emissions and enabling more transparent sustainability evaluations.[14,15,25] Furthermore, embedding the circular economy (CrE) perspective within LCA frameworks strengthens sustainability outcomes by promoting the valorisation of post-harvest waste in fruit supply chains.[26] Table 2 presents the key studies that have applied circular life cycle assessment (circular LCA) in agri-food systems, highlighting methodological advancements and sustainability implications.

2.3. Carbon emission prediction models

For proactive climate planning, predictive models are essential to anticipate future emissions. Impact factor models such as IPAT, Kaya, and STIRPAT help identify major emission drivers

Table 3 Summary of recent studies employing predictive modelling approaches

Study	Key findings	Gaps	References
Utilizes machine learning (ML) and deep learning (DL) techniques in forecasting models in agri-fresh supply chains	ML and DL improve demand forecasting, reducing supply-demand mismatches and high inventory or transport costs	ML and DL enhance demand prediction, reducing supply-demand mismatches and inventory or transport costs	Kumar and Agrawal[29]
Deep learning approach: LSTM neural network optimized using tree-structured Parzen estimator Bayesian optimization in agricultural carbon emissions	TPEBO-LSTM achieved high performance; LSTM effectively handles multiple time-variable inputs with superior accuracy and stability over traditional ML models	Need to analyze micro-scale data to refine forecasts	Xie *et al.*[13]
Comparative univariate time series modeling using SARIMA, LSTM, and GRU in global sulfur hexafluoride emissions	LSTM showed the best performance; and GRU was preferred for faster, and more efficient computation	All unexpected or sudden external factors constitute an important limitation for forecast models	Tuğba Önder[30]
Comparative univariate time series modelling using SARIMA, LSTM, and GRU global methane emission	SARIMA performed best; with GRU offering faster results using fewer parameters	Models use only historical data (univariate modelling)	Önder[31]
Comparative analysis of ARIMA and Prophet forecasting model. Performance assessed in strawberry-cultivating greenhouse	The ARIMA model outperformed the Prophet model across all data collection intervals	Integration of other variables (*e.g.*, temperature, humidity, ventilation) into the prediction models is lacking	Shin *et al.*[32]

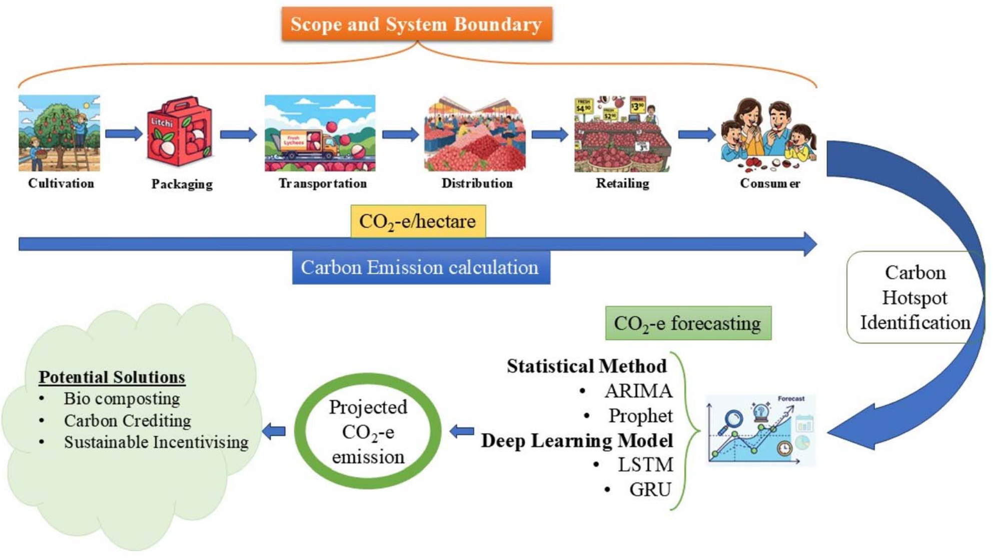

Fig. 1 Flowchart illustrating the research methodology for quantifying carbon emissions in litchi supply chains.

but are often constrained by data subjectivity and limited analytical scope. In contrast, time series models like ARIMA and advanced deep learning techniques such as SVM, LSTM, and GRU are increasingly utilized for their ability to capture complex nonlinear patterns in historical emission data.[10] Table 3 summarizes the recent studies employing these predictive modelling approaches, highlighting their methodologies, data requirements, and forecasting accuracy in emission analysis.

3. Methodology

The present research employs a circular tiered hybrid life cycle assessment (CrTH-LCA) framework to evaluate CEs across the supply chain. The methodological integrates life cycle inventory modelling, circular economy interventions with carbon credit adjustment mechanism, and time-series forecasting, to enable a comprehensive and forward-looking carbon mapping approach. Fig. 1 illustrates the overall research framework and methodological flow adopted in this study.

3.1. Supply chain mapping and system boundary definition

The present study analyses the flow of litchi through the designated supply chain from farm to consumer, integrating various operations required for the movement. The study included certain assumptions, which are listed as follows:

(i) The land area used for estimation was one hectare with one hundred trees.

(ii) Total yield of litchi per hectare was taken as 7754 kg.[33]

(iii) Muzaffarpur was taken as source location for farm.

(iv) Delhi was taken as destination location with a total travel time of 35 h.

(v) Non-refrigerated truck was considered for transportation.[1]

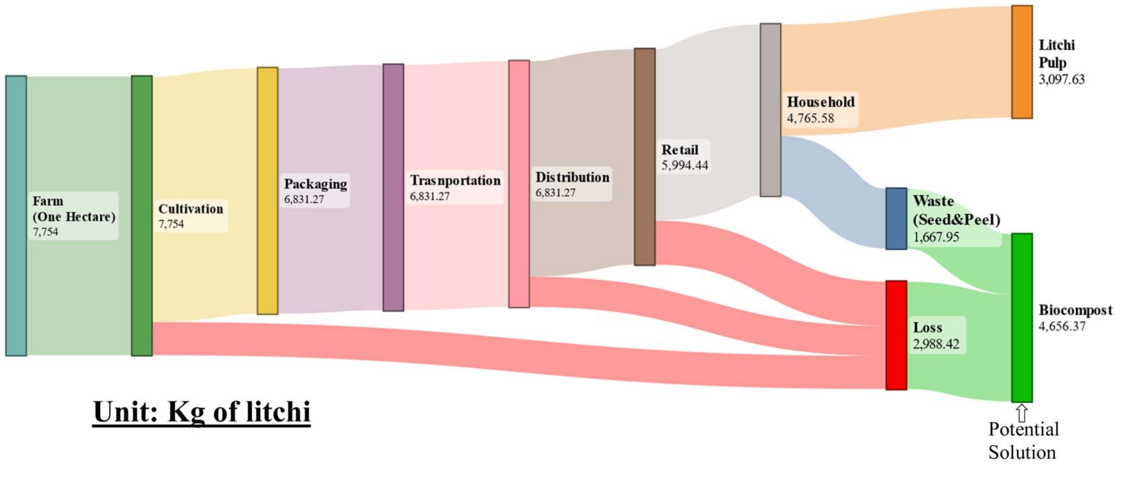

Fig. 2 Production of litchi and its flow through the supply chain.

(vi) No loss is considered during the packaging and transportation stages, as losses are accounted during the cultivation and distribution stage only.

The data used in this study were based on secondary data sources. The data were systematically sourced mainly from peer-reviewed scientific publications indexed within the Scopus or Web of Science database, official government reports, and statistical releases from national and international agencies.

Based on these assumptions, a comprehensive assessment on the sustainability of the litchi supply chain from Muzaffarpur to Azadpur mandi in Delhi (~1000 km) was done by analysing CEs and energy use across six interconnected stages: input application, cultivation and harvesting, post-harvest handling, transportation, distribution, and end-of-life management (composting organic waste and reusing packaging), as shown in Fig. 2. This study adopts the internationally recognized framework established by the Society of Environmental Toxicology and Chemistry (SETAC), IPCC tier 3 model, and the ISO, particularly the principles and framework outlined in ISO 14040 (Environmental Management-LCA-Principles and Frameworks), which builds upon the SETAC framework.[34] Using a CrTH-oriented, process-based LCA framework, the research identifies emission hotspots and explores opportunities for resource recovery and waste valorisation.

The system boundary adopts a cradle-to-circular reintegration perspective with a circularity of outputs back into the system, integrating both material and energy flows. Energy inputs such as diesel, electricity, and fuel are traced throughout the chain, providing a comprehensive estimate of direct and indirect CO_2 emissions. To ensure consistent evaluation of CEs and energy consumption, the functional unit is defined kilogram of litchi or litchi produced per hectare delivered from the farm to the market. The weight-based approach facilitates comparisons across various stages and systems, aligning with market standards and circular economy objectives.

3.2. Carbon emission accounting approach

3.2.1. Calculation method of carbon emissions. Standard approaches to quantify CEs include direct measurement, material balance, and coefficient-based calculations. The direct measurement method involves capturing actual CO_2 concentration, while the material balance method applies mass balance principles to estimate emissions. The study employs the emission coefficient method, which is widely applied in process-based life cycle carbon accounting. In this approach, total CEs, measured in $kgCO_2$-e kg^{-1}, are calculated by multiplying the activity data of each process (A_i), such as litres of diesel used, with its corresponding emission factor (ε_i), which indicates the amount of CO_2 released per unit of that activity (*e.g.*, per m^3 and per kg). Generalised CEs are calculated using eqn (1), and the emission factors for individual activity are listed in Table 4. Process-based life cycle CE inventory analysis is chosen for the current study.[35]

$$\mathrm{CE} = \sum_{i=1}^{n} (A_i \varepsilon_i) \tag{1}$$

3.2.2. Litchi supply chain life cycle assessment framework. Building upon the identified CE sources and selected methods, the model quantifies emissions across all stages using supply chain-specific parameters gathered through comprehensive data collection.

3.2.2.1. Cultivation. The carbon emissions during the litchi cultivation stage (CE_c) were calculated using eqn (2), which integrates emissions from on-farm activities. Emissions from fertilizers (urea, DAP, MOP, FYM) and pesticides were estimated using standard emission factors, as given in Table 1. Irrigation-related emissions were calculated based on 80% surface and 20% sprinkler irrigation use accounting for differences in energy and emission intensities, as shown in Table 5. Additionally, post-harvest respiration emissions for a period of 6 h during cultivation stage were considered. The CO_2 mitigation *via* photosynthesis throughout the year was also considered in the final emission balance.

$$\mathrm{CE_c}\left(\mathrm{kgCO_2\text{-}e\ kg^{-1}}\right) = \left(\overbrace{\sum_i \left(\varepsilon_{\mathrm{f},i}\lambda_{\mathrm{f},i}\right)}^{\text{Fertiliser}}\right) + \overbrace{\left(\varepsilon_\mathrm{p}\lambda_\mathrm{p}\right)}^{\text{Pesticide}} + \overbrace{\left\{\lambda_\mathrm{w}\left(\left(\partial_{i,\mathrm{su}}\varepsilon_{i,\mathrm{su}}\right) + \left(\partial_{i,\mathrm{sp}}\varepsilon_{i,\mathrm{sp}}\right)\right)\right\}}^{\text{Irrigation}} + \overbrace{\left(\lambda_{\mathrm{rP}}\tau_{\mathrm{rP}}\right)}^{\text{Respiration}} - \overbrace{\left(\theta_{\mathrm{ab}}\right)}^{\text{Absorption}} \tag{2}$$

3.2.2.2. Packaging. The carbon emissions during the packaging stage (CE_{Pk}) of the supply chain were calculated using eqn

Table 4 Emission factors used for the CF assessment across different stages

Component	Emission factor	Reference
Urea ($\varepsilon_{f,U}$)	2.02 $kgCO_2$-e per kg urea	Kumar *et al.*[36]
Diammonium phosphate (DAP) ($\varepsilon_{f,D}$)	1.84 $kgCO_2$-e per kg DAP	
Muriate of potash (MAP) ($\varepsilon_{f,M}$)	0.25 $kgCO_2$-e per kg MAP	
Farmyard manure (FYM) ($\varepsilon_{f,FY}$)	0.89 $kgCO_2$-e per kg FYM	Mori[37]
Surface water irrigation ($\varepsilon_{i,su}$)	0.0585 $kgCO_2$-e per m^3 water	Qin *et al.*[38]
Sprinkler water irrigation ($\varepsilon_{i,sp}$)	0.1884 $kgCO_2$-e per m^3 water	
Pesticide (ε_p)	5.1 $kgCO_2$-e per kg pesticide	Cech *et al.*[39]
Wooden crate (WC) ($\varepsilon_{Pk,wo}$)	0.47 $kgCO_2$-e kg^{-1}	Del Borghi *et al.*[40]
Plastic crate (PC) ($\varepsilon_{Pk,pl}$)	2.65 $kgCO_2$-e kg^{-1}	
Corrugated cardboard box (CCB) ($\varepsilon_{Pk,ccb}$)	1.19 $kgCO_2$-e kg^{-1}	
Diesel (ε_d)	2.7 $kgCO_2$-e L^{-1}	Jakhrani *et al.*[41]

Table 5 Components of on-farm carbon emission sources

Component	Value	Reference
Urea input rate ($\lambda_{f,U}$)	0.0128 kg urea per kg	Yadav and Shalendra[42]
DAP input rate ($\lambda_{f,D}$)	0.0193 kg DAP per kg	
MOP input rate ($\lambda_{f,M}$)	0.0064 kg MOP per kg	
FYM input rate ($\lambda_{f,FY}$)	0.2579 kg FYM per kg	
Pesticide input rate (λ_p)	0.0096 kg pest per kg	
Water consumption rate (λ_w)	0.2594 m^3 kg^{-1}	Pandey[43]
Proportion of surface irrigation ($\partial_{i,su}$)	80%	
Proportion of sprinkler irrigation ($\partial_{i,sp}$)	20%	
Respiratory CO_2 rate (λ_{rP})	0.0002 $kgCO_2$ kg^{-1} h^{-1}	Kumar *et al.*[1]
Respiration time (τ_{rP})	6 h	
Absorption rate (θ_{ab})	0.13 $kgCO_2$ kg^{-1}	Liu *et al.*[19]

(3), which incorporates emissions from three commonly used packaging types: wooden, plastic crate, and CCB. Emissions were estimated based on each packaging usage share, service life, and fruit-holding capacity, with wooden and plastic crates evaluated over multiple cycles and CCB treated as single use. In addition, emissions from fruit respiration during the holding period between loading and departure were included. The packaging characteristics and parameter values used in the calculation are summarized in Table 6.

$$\mathrm{CE_{Pk}}\left(\mathrm{kgCO_2\text{-}e\ kg^{-1}}\right) = \overbrace{\sum_i \left(\frac{\partial_{\mathrm{Pk},i}}{\mu_{\mathrm{Pk},i}\nu_{\mathrm{Pk},i}} \times \varepsilon_{\mathrm{Pk},i}\right)}^{\text{Packaging}} + \overbrace{(\lambda_{\mathrm{Pk}}\tau_{\mathrm{Pk}})}^{\text{Respiration}} \quad (3)$$

3.2.2.3. Transportation. Carbon emissions from transportation (CE_T) were estimated using eqn (4) by considering fuel-based emissions and fruit respiration during transit. Fuel emissions were assessed based on the travel distance, vehicle fuel consumption, and non-refrigerated truck holding capacity, combined with the diesel emission factor, as shown in Table 7, along with respiration emissions during the transit period.

$$\mathrm{CE_T}\left(\mathrm{kgCO_2\text{-}e\ kg^{-1}}\right) = \overbrace{\left(\frac{\chi_T\phi_T}{\nu_{T,tr}} \times \varepsilon_d\right)}^{\text{Fuel}} + \overbrace{(\lambda_T\tau_T)}^{\text{Respiration}} \quad (4)$$

3.2.2.4. Distribution. Carbon emissions at the distribution stage (CE_D) were estimated using eqn (5), which considers the respiratory activity of fruits during a holding period of 24 h (λ_D) at a respiration rate of 0.0002 $kgCO_2$ kg^{-1} h^{-1} (τ_D).

$$\mathrm{CE_D} = \overbrace{(\lambda_D\tau_D)}^{\text{Respiration}} \quad (5)$$

3.2.3. Integration of circular economy principles. Carbon emissions from fruit loss at various stages of supply chain and household waste were evaluated for methane generation under anaerobic conditions, as detailed in eqn (6). The evaluation includes emissions from losses, during harvest (cracking = 3.8%, and mechanical damage = 8.1%); packaged transport and distribution (WC = 12.4%, PC = 12.76%, CCB = 4.2%), and retail (20.5%), and household waste (35%). Table 8 enlists the losses and wastes, particularly their dry matter content along with methane emissions.

$$\mathrm{CE_{Cr}}\left(\mathrm{kgCO_2\text{-}e\ ha^{-1}}\right) = \left[\overbrace{\{\eta_{Cr}\alpha_{Cr}\psi_{Cr}\}}^{\text{Loss}} + \overbrace{\{\eta_{Cr}\beta_{Cr}\psi_{Cr}\}}^{\text{Waste}}\right] \quad (6)$$

3.3. Carbon valuation and credit potential assessment

Carbon crediting incentivizes emission reductions and encourages the adoption of more sustainable practices. The study estimates the CE cost ($C_{CE,c}$) by applying an illustrative carbon price of $100 USD per tCO_2-e to LCA-derived CE per hectare using eqn (7).[52]

The carbon emission value serves to highlight potential financial liabilities associated with existing emissions and

Table 6 Components of packaging carbon emission sources

Component	Value	Reference
Wooden crate percentage ($\partial_{Pk,wo}$)	92%	MoFPI[44]
Plastic crate percentage ($\partial_{Pk,pl}$)	6%	
CCB percentage ($\partial_{Pk,pl}$)	2%	Ketkale *et al.*[45]
Wooden crate reusability ($\mu_{Pk,wo}$)	20 times	Del Borghi *et al.*[40]
Plastic crate reusability ($\mu_{Pk,pl}$)	66 times	
CCB reusability ($\mu_{Pk,ccb}$)	1 time	
Wooden crate capacity ($\nu_{Pk,wo}$)	18 kg	Purbey *et al.*[46]
Plastic crate capacity ($\nu_{Pk,pl}$)	15 kg	Ribal *et al.*[47]
CCB capacity ($\nu_{Pk,ccb}$)	15 kg	
Respiratory CO_2 production rate (λ_{Pk})	0.0002 $kgCO_2$ kg^{-1} h^{-1}	Kumar *et al.*[1]
Respiration time (τ_{Pk})	4 h	

Table 7 Components of transportation carbon emission sources

Component	Value (unit)	Reference
Distance travelled (χ_T)	1000 km	Kumar *et al.*[1]
Fuel mileage (ϕ_T)	0.39 L km^{-1}	
Truck holding capacity ($\nu_{T,tr}$)	10 000 kg	MoFPI[44]
Respiratory CO_2 production rate (λ_T) (24 h)	0.0003 $kgCO_2\ kg^{-1}\ h^{-1}$	Kumar *et al.*[1]
Respiratory CO_2 production rate (λ_T) (11 h)	0.0002 $kgCO_2\ kg^{-1}\ h^{-1}$	
Respiration time (τ_T)	35 h	

Table 8 Components of loss and waste carbon emission sources

Component	Value (unit)	Reference
Methane production (η_{Cr})	0.11 kg per kg dry weight	Dach *et al.*[48]
Whole fruit loss (cultivation, transportation, wholesale, and retail) (γ_{Cr})	2988.83 kg ha^{-1}	Kumar *et al.*[1]
Household waste (seed and peel) (δ_{Cr})	1667.80 kg ha^{-1}	Bangar *et al.*[49]
Whole fruit dry weight (α_{Cr})	537.98 kg	Janjai *et al.*[50]
Seed and peel dry weight (β_{Cr})	961.08 kg	Ray *et al.*[51]
Global warming potential for methane (100 year horizon) (ψ_{Cr})	27.9 CO_2-e	Xu *et al.*[52]

reinforces the economic rationale for mitigation. Subsequently, avenues for generating carbon credits are conceptually explored for the litchi supply chain *via* two primary pathways:

(i) Orchard carbon sequestration: the annual CO_2-e sequestered per hectare by litchi orchards, as calculated from the LCA yield data and established sequestration factors, is converted into potential carbon credits (where 1 credit = 1 tCO_2-e).

(ii) Waste valorisation: it shows the potential for carbon credits from circular economy interventions, such as biogas production from litchi waste or compost production:

$$\text{Carbon credit} = C_{\text{CE,c}} \times \text{tCO}_2\text{-e} \tag{7}$$

3.4. Sensitivity analysis

Sensitivity analysis enables the comparison of how several factors influence the litchi supply chain CE across its entire life cycle, providing valuable guidance for implementing effective carbon reduction measures throughout the process.[25] Sensitivity coefficients as estimated using eqn (8) quantify how variations in specific factors affect overall carbon emissions.[53]

$$\omega = \frac{\dfrac{(f(x_1, \ldots, x_i + \Delta x_i, \ldots, x_n) - (f(x_1, \ldots, x_i, \ldots, x_n)))}{f(x_i, \ldots, x_i, \ldots x_n)}}{\dfrac{\Delta x_i}{x_i}} \tag{8}$$

However, conventional sensitivity analysis, being deterministic, captures only the directional influence of parameters and assumes fixed input values, limiting its ability to reflect real-world variability and uncertainty in agricultural systems. Such simplifications may result in biased or incomplete interpretations of emission behaviour, especially in dynamic supply chains affected by climatic and operational fluctuations. To address this, the Monte Carlo simulation was applied to introduce stochastic variations in key parameters. The model performed 20 000 iterations using a log-normal distribution to capture variability in each sub-criterion (*e.g.*, fertilizers, pesticides, and truck fuels), defined by their mean and coefficient of variation (CV) to represent uncertainty in carbon emissions ($kgCO_2$-e per functional unit). This probabilistic approach quantifies uncertainty through repeated random sampling, providing confidence intervals and a more robust understanding of emission variability across the litchi supply chain.[54]

3.5. Emission forecasting framework models

Forecasting models provide insights into future carbon emissions, enabling the development of more targeted strategies to address emerging sustainability demands. The historical data for production, cultivation area, temperature, and rainfall were taken from 1992 to 2024, as given in SI Table S1. Univariate forecasting of CEs was conducted using ARIMA, Prophet, LSTM, and GRU models based on historical litchi production data. For multivariate forecasting, Prophet, LSTM, and GRU models were employed with production data, area, temperature, and rainfall as input variables to enhance the accuracy by capturing the environmental effect on the litchi production. The data partitioning involved an 80% training and 20% testing split to evaluate the accuracy of predictions for litchi production. This robust forecasting of litchi production, in turn, will serve as a crucial input for the subsequent forecasting of associated CEs.

3.5.1. Statistical methods

3.5.1.1. ARIMA model. The ARIMA model was applied to forecast CO_2 emissions by capturing linear trends and autocorrelations in the supply chain data using eqn (9). Stationarity was assessed using the Augmented Dickey-Fuller (ADF) method using eqn (10):[9]

$$\left(1 - \sum_{i=1}^{p} \phi_i L^i\right)(1 - L)^d y_t = \left(1 + \sum_{j=1}^{q} \theta_j L^j\right)\varepsilon_t \tag{9}$$

$$\Delta y_t = \alpha + \beta t + \gamma y_{t-1} + \sum_{i=1}^{p} \delta_i \Delta y_{t-i} + \varepsilon_t \quad (10)$$

where y_t denotes the observed time series at time t, and L is the lag operator such that $L^k y_t = y_{t-k}$. The parameter d represents the number of times the time series must be differenced to become stationary, while p and q indicate the number of autoregressive (AR) and moving average (MA) terms, respectively. The coefficients ϕ_i and θ_j correspond to the AR and MA components, ε_t denotes the white noise error at time t, α is a constant (drift term), βt is the deterministic trend, γ is the coefficient of y_{t-1}, and p is the number of lagged differences.

3.5.1.2. Prophet model. Facebook's Prophet model was used for both univariate and multivariate CO_2 emission forecasting. The univariate prophet model includes three main components, namely, trends, seasonality, and holiday for forecasting the seasonal effects and holidays, as given in eqn (11). The model operates by decomposing time series data into several additive components. For multivariate forecasting, external regressors are incorporated as linear additive terms to the model.[55]

$$y(t) = \overbrace{\overbrace{g(t) + s(t) + h(t)}^{\text{Univariate}} + \sum_{i=1}^{k} \beta_i x_i(t) + \varepsilon_t}^{\text{Multivariate}} \quad (11)$$

where $y(t)$ represents the observed time series at time t, composed of three main components: the trend $g(t)$, which captures non-periodic changes using piecewise linear or logistic functions; the seasonal component $s(t)$, which models recurring patterns like weekly or yearly cycles using Fourier series; and the holiday effect $h(t)$, which accounts for specific events or dates when defined. Additionally, external regressors $x_i(t)$ with corresponding coefficients β_i contribute a linear effect $\sum_{i=1}^{k} \beta_i x_i(t)$ on $y(t)$ during model fitting.

3.5.2. Deep learning methods. Deep learning methods such as LSTM and GRU are highly effective for capturing complex temporal patterns in sequential data. As a crucial preprocessing step, data scaling was performed using eqn (12) to normalize input features, ensuring stable and efficient training. Scaling helps neural networks like LSTM and GRU converge faster and improves prediction accuracy by bringing all variables to a similar range.

$$x_{\text{scaled}} = \frac{x - \min}{\max - \min} \quad (12)$$

3.5.2.1. LSTM model. The LSTM model excels with sequential data by learning long-term dependencies, crucial for modelling how past agricultural practices influence future emissions. LSTM's ability to retain memory allowed it to capture nonlinear fluctuations and trend shifts, including delayed effects of interventions like circular practices. LSTM uses memory cells that manage information flow through forget (f_t), input (i_t), and output gates (o_t) using eqn (13), (14) and (17). The candidate cell state ($\tilde{c}_t$), cell state update (c_t) and hidden state update (h_t) are determined using eqn (15), (16) and (18). The univariate and multivariate forecasting models for LSTM differ in the input dimensionality, as shown in eqn (19).[56]

$$f_t = \sigma(W_f x_t + U_f h_{t-1} + b_f) \quad (13)$$

$$i_t = \sigma(W_i x_i + U_i h_{t-1} + b_i) \quad (14)$$

$$\tilde{c}_t = \tanh(W_c x_t + U_c h_{t-1} + b_c) \quad (15)$$

$$c_t = f_t \odot c_{t-1} + i_t \odot \tilde{c}_t \quad (16)$$

$$o_t = \sigma(W_o x_t + U_o h_{t-1} + b_o) \quad (17)$$

$$h_t = o_t \odot \tanh(c_t) \quad (18)$$

$$x_t \in \begin{cases} \mathbb{R} \text{ single feature at each timestep : univariate} \\ \Delta\mathbb{R}^n \text{ vector of feature at each timestep : multivariate} \end{cases} \quad (19)$$

where x_t is the input at time t and h_{t-1} is the previous hidden state. The cell state C_{t-1} holds long-term memory. Sigmoid activation σ is used in gates to control information flow, and $\odot$ denotes the element-wise multiplication. The tanh function generates candidate values within [−1, 1]. Weight matrices W and biases b are trainable parameters for each gate: input, forget, and output, and $\mathbb{R}$ is the input feature.

3.5.2.2. GRU model. The GRU model, a computationally efficient alternative to LSTM, was also used to forecast CEs in the supply chain. GRU's simplified structure allows for faster training while effectively capturing both short- and long-term dependencies in emission data.[57] For a given normalized CE data input sequence, $X = \{x_1, x_2, \ldots, x_n\}$, the model parameters were iteratively trained using eqn (20)–(23). The univariate and multivariate function for the model is also governed using eqn (19).

$$z_t = \sigma(W_z x_t + U_z h_{t-1} + b_z) \quad (20)$$

$$r_t = \sigma(W_r x_t + U_r h_{t-1} + b_r) \quad (21)$$

$$\tilde{h}_t = \tanh(W_h x_t + U_h(r_t \odot h_{t-1}) + b_h \quad (22)$$

$$h_t = (1 - z_t) \odot h_{t-1} + z_t \odot \tilde{h}_t \quad (23)$$

where x_t is the input at time t, h_{t-1} is the previous hidden state, z_t is the update gate, r_t is the reset gate, $\tilde{h}_t$ is the candidate hidden state, σ is used in update and reset gates to control information flow, while tanh generates the candidate hidden state. Element-wise multiplication $\odot$ helps regulate retained information. The weights W and biases b are trained for the update, reset, and candidate components.

3.5.3. Performance metrics and criteria. The CE prediction model's performance was measured using statistical metrics, namely, mean absolute error (MAE), mean squared error (MSE), and root mean square error (RMSE), as given in eqn (24)–(26):[9]

$$\text{MAE} = \frac{1}{n} \sum_{i=1}^{n} (\alpha_i - \beta_i) \quad (24)$$

$$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n}(\alpha_i - \beta_i)^2 \tag{25}$$

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\alpha_i - \beta_i)^2} \tag{26}$$

where n represents the total number of observations, α_i denotes the actual CEs for the ith year, and β_i represents the predicted CE for the corresponding year.

The future carbon emission (CE_F) for the predicted data was estimated using litchi production forecast (F_p [kg]) and carbon emission factor (CE_T [$kgCO_2$-e kg^{-1}]), as given in eqn (27):

$$\text{CE}_{\text{Fc}} = F_{\text{p}} \times \text{CE}_{\text{T}} \tag{27}$$

3.6. Cost economics

The cost-economic analysis of waste valorisation and the potential income generated from methane production were conducted to evaluate the potential financial incentives that waste valorisation or bio composting could generate. The initial cost of the biogas plant was estimated at \$1626.41,[58] designed to generate 1.57 m^3 of methane, with a selling price of \$2.10 per kg of methane.[59] The project's return on investment (ROI), net present value (NPV), internal rate of return (IRR), and payback period were evaluated using eqn (28)–(31):[60]

$$\text{ROI} = \frac{\text{net profit}}{\text{initial investment}} \times 100 \tag{28}$$

$$\text{NPV} = \sum_{t=1}^{n}\frac{\text{CF}_t}{(1+r)^t} - I_0 \tag{29}$$

$$I_0 = \sum_{t=1}^{n}\frac{\text{CF}_t}{(1+\text{IRR})^t} \tag{30}$$

$$\text{Payback period} = \frac{I_0}{\text{annual cash flow}} \tag{31}$$

where CF_t is the net cash flow at time t, r is the discount rate (10%), I_0 is the initial investment, and n is the number of years.

4. Empirical results and discussion

4.1. Identifying the carbon emitting hotspots and pathways for decarbonization

Fig. 3 shows the flow of carbon emission throughout the supply chain. Litchi's supply chain possesses a complex CF from orchard to outlet. The CrTH-LCA framework reveals a total environmental imprint of 7305.16 $kgCO_2$-e ha^{-1}, with 1008.02 $kgCO_2$-e ha^{-1} of carbon sequestration. Table 9 shows household waste (seed and peel) as the dominant carbon hotspot, with 40.44% of the total CEs. The carbon emission of cultivation (31.96%) and transportation stage (10.80%) contribute to a total of 42.76% of the total CEs. Even in broader F&V studies, the traditionally scrutinized stages of farming and transportation together account for 36% to 60% of emissions.[19,23,61] The household waste in litchi supply chain as a hotspot of comparable magnitude truly underscores its critical, and perhaps often underestimated, role. Such carbon intensity from post-

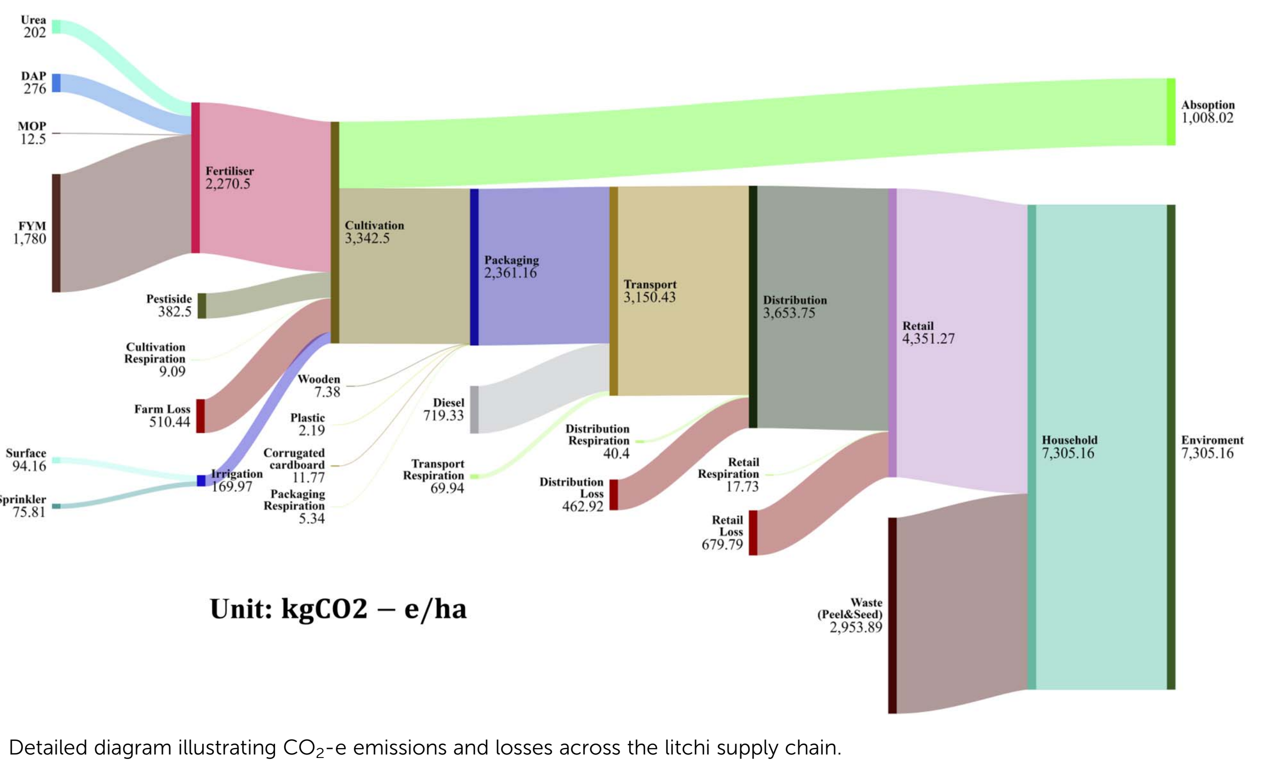

Fig. 3 Detailed diagram illustrating CO_2-e emissions and losses across the litchi supply chain.

Table 9 Carbon emissions by components ($kgCO_2$ ha^{-1}) and their percentage contribution

Emission location	Carbon emission ($kgCO_2$-e ha^{-1})	Percentage (%)
Household waste	2953.63	40.44
Fertiliser	2270.50	31.08
Fuel (vehicle)	719.33	9.85
Loss retail	679.73	9.31
Loss at farm	510.44	6.99
Loss (transportation and distribution)	463.21	6.34
Pesticides	382.50	5.24
Irrigation	169.97	2.33
Transportation respiration	69.94	0.96
Distribution respiration	40.40	0.55
Retail respiration	17.73	0.24
CCB	11.77	0.16
Cultivation respiration	9.09	0.12
Wooden box	7.38	0.10
Packaging respiration	5.34	0.07
Plastic crate	2.19	0.03
Carbon sequestration	−1008.02	−13.80
Total	**7305.16**	**100**

consumption waste is largely due to litchi's substantial inedible fraction, which ends up in landfilling, leading to methane (CH_4) emissions.[19]

Turning upstream, cultivation is the second-largest contributor (31.96%), primarily driven by fertilizer application (31.08%), followed by farm loss (6.99%), pesticides (5.24%), irrigation (2.33%), and field-level respiration (0.12%). The fertilizer hotspot is driven by energy-intensive nitrogen fertilizer (urea, DAP) production and potent nitrous oxide (N_2O) field emissions, making its management critical while field-level respiration acknowledges baseline fruit metabolism.

Mitigating cultivation emissions involves sustainable practices: for fertilization, reusing treated wastewater enhances nutrient cycling.[15] Broader on-farm strategies include organic agriculture, zero tillage, and crop residue farming, improving soil health by reducing greenhouse gas emission.[11] These practices can also enhance soil carbon sequestration, potentially contributing to carbon credit generation under specific agricultural carbon programs. Pest management can shift towards organic principles, such as the application of species-specific pheromones or integrated pest management.[62] Balancing vegetative growth with fruit production is also key for resource efficiency.[11,12] Regarding irrigation energy (influenced by climate, water source, crop demand, and system type), decarbonization is possible *via* solar-powered pumps.[61] Broader integration of renewables like biogas, wind, or hydrogen fuel cells across farm and supply chain stages, alongside biomass-fired boilers or waste-to-energy systems from agricultural materials, offers further footprint reduction.[14,15,61] While cultivation causes notable emissions, litchi orchards provide a natural offset through carbon sequestration, estimated at approximately 1008.02 $kgCO_2$-e ha^{-1}.[33]

The transportation segment contributes 10.80% to total CO_2 emission. Fuel consumption is the principal driver (9.85%), mainly from diesel-powered logistics. Refrigerated transport, vital for litchi quality, intensifies this by increasing fuel for cooling and overall transport emissions.[19] Respiration during transport adds another 0.96%, accelerated due to poor handling and inconsistent cooling exacerbating these emissions.[63]

For routes like Muzaffarpur–Delhi, a modal shift from road to energy-efficient rail can reduce carbon emissions.[14] Additional approaches include using hybrid electric vehicles (HEVs), other low-emission alternatives, or sustainably sourced biodiesel;[64] enhancing operational efficiency through fuel-efficient driving and driver training; and adopting comprehensive logistics decarbonisation strategies such as rerouting, network optimisation, and setting carbon reduction targets.[14,63]

Litchi's non-climacteric nature makes it prone to rapid post-harvest degradation and losses across the supply chain; particularly, under ambient conditions, it contributes to a large segment in CE. Farm-level loss contributes to 6.99% emission from market gluts, labour shortages, and inadequate on-farm storage, compounded by field delays.[65,66] Losses at distribution stage (6.34%) are mainly generated due to poor packaging, rough handling, and lack of refrigerated logistics, leading to accelerated pericarp browning. At retail (9.31%) losses accumulate due to microbial decay, worsened by slow turnover and poor demand forecasting, contributing to emissions from unconsumed fruit.

Cold chain circulation (CCC), though it may consume more energy, significantly reduces fruit loss and waste (FLW), resulting in a 34.84% lower CE per effective unit compared to room-temperature circulation, thereby enhancing the overall carbon efficiency.[19] Distribution-stage and retail-stage respiration adds a further 0.55 and 0.07%, respectively, reflecting ongoing metabolism.

Packaging-related emissions were relatively minor with 0.29% from packaging materials used and 0.07% from post-harvest packaging respiration. Reusable packaging (wooden/plastic crates) significantly reduces per-use emissions compared to single-use CCBs, highlighting their environmental advantage over non-biodegradable or single-use options. For litchi transported without refrigeration, corrugated fibre board (CFB) are better than wooden crates. They reduce browning and weight loss by half, cause less damage, keep moisture in, slow down spoilage and ripening, while also costing less.[1] A four-pronged strategy can cut litchi's postharvest packaging CF: (1) bio-based polymers,[67] (2) active/intelligent featuring (O_2/ethylene scavengers with ACC (1-aminocyclopropane-1-carboxylic acid) deaminase, antimicrobial coatings, and RFID (radio-frequency identification) thermo-humidity sensors in CFB cartons) preserve quality and cold-chain integrity, minimizing spoilage emissions,[46] (3) lightweight, reusable RPCs (reusable plastic crate) or ventilated, cushioning-compatible CFB/punnet systems tailored to reduce single-use waste and streamline transport of litchi[40] and (4) compostable cushioning and renewable, edible coatings enhance circularity by replacing synthetics and turning end-of-life packaging into nutrients.[46,68]

4.2. Circular economy for loss and waste

The dominant household waste hotspot is best addressed by valorising all litchi waste streams (including fruit losses, peel, and seed), which collectively amount to approximately 2953.89 kg per hectare, presenting a significant resource. The litchi supply chain releases a total of 165.13 kgCH_4 ha^{-1} which translate to 4607.03 kgCO_2-e ha^{-1} over a 100 year period. The combined CE from waste and loss leads to 63.06% of the total CE. The waste and loss generated from the litchi supply chain can be composted to methane and compost materials, which can be used as biofuels and organic manure, respectively, as shown in Fig. 4. The biocomposting of waste leads to 27.9 times reduction in overall CE with just 165.12 kgCO_2-e ha^{-1}. The organic compost can also help regenerate the soil nutrient, further leading to a lower requirement of fertilisers, which also contributes to 24.37% of total CEs.[11,15,69] These circular economy strategies significantly reduce methane emissions from landfilling, mitigate overall CEs, and hold potential for generating carbon credits.

Therefore, implementing such systemic interventions, potentially supported by carbon financing, is essential for effectively leveraging this biomass and tackling distributed carbon hotspots within the litchi supply chain. The total carbon cost of the litchi supply chain stands at $730.51 per hectare with $100.8 per hectare generated as carbon credit due to CO_2 sequestration.[70] Furthermore, bio-composting of losses and waste generated across the litchi supply chain has the potential to yield carbon credits valued at approximately $444.19. The compost produced can further offset the fertilizer demand in the litchi supply chain, generating additional carbon credits through the retrospective substitution of synthetic fertilizers. Integrating such carbon credit mechanisms can provide tangible financial incentives, accelerating the adoption of sustainable, low-carbon practices throughout the supply chain.[4,11,71]

4.3. Sensitivity analysis

Table 10 shows the sensitivity analysis for the LCA assessment of litchi supply chain. The sensitivity analysis for litchi supply chain was considered at ±20%. The sensitivity analysis revealed that household waste change can lead to an overall CO_2-e change of ±64.10, which is humongous in term of total CE. The potential mitigation can be a hybrid variety of litchi that has smaller seeds, leading to lower waste at household stage, which further clubbed with biocomposting can help reduce CO_2-e emission by 27.9 times. Loss at various stages also leads to a higher variation in the overall CE, which could be controlled with improved transportation and packaging conditions.[19]

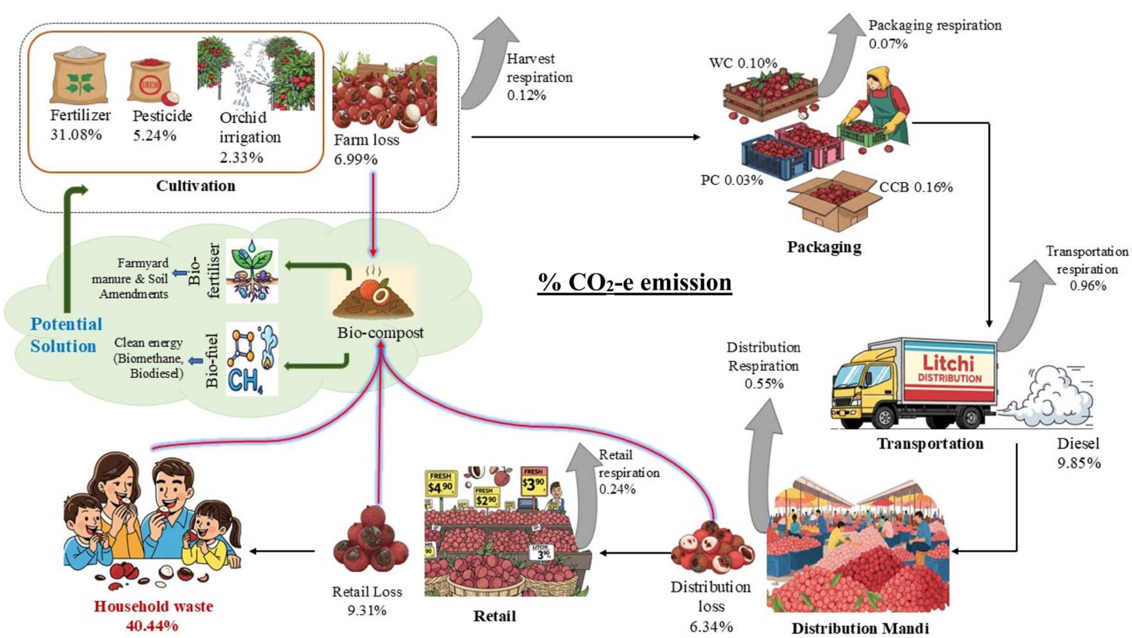

Fig. 4 Potential solution for the loss and waste generated in litchi supply chains.

Table 10 Result of sensitivity analysis

Input variables	Change rate	CO_2 decline rate	Sensitivity coefficient
Cultivation	±20%	±11.08	0.0055
Fertiliser	±20%	$\pm 6.36 \times 10^{-5}$	0.000003178
Pesticides	±20%	$\pm 1.07 \times 10^{-5}$	0.000000535
Irrigation	±20%	$\pm 4.76 \times 10^{-6}$	0.000000238
Respiration	±20%	$\pm 2.54 \times 10^{-7}$	0.000000013
Loss at farm	±20%	±11.07	0.0055
Packaging	±20%	$\pm 7.47 \times 10^{-7}$	0.000000037
Wooden box	±20%	$\pm 2.09 \times 10^{-7}$	0.000000010
Plastic crate	±20%	$\pm 2.42 \times 10^{-8}$	0.000000001
CCB	±20%	$\pm 3.44 \times 10^{-7}$	0.000000017
Packaging respiration	±20%	$\pm 1.7 \times 10^{-7}$	0.000000008
Transportation	±20%	±10.05	0.0050
Fuel	±20%	$\pm 2.29 \times 10^{-5}$	0.000001143
Transportation respiration	±20%	$\pm 2.38 \times 10^{-6}$	0.000000119
Loss	±20%	±10.05	0.0050
Distribution	±20%	±14.75	0.0074
Distribution respiration	±20%	$\pm 1.28 \times 10^{-6}$	0.000000064
Loss retail	±20%	±14.75	0.0074
Household waste	±20%	±64.10	0.0321

The Monte Carlo simulation provides a probabilistic assessment of carbon emissions across the litchi supply chain, capturing variability in each sub-process and overcoming the limitations of deterministic sensitivity analysis. Total emissions across 20 000 simulations are typically right-skewed due to high variability in sub-stages such as fertilizer use, with the median slightly lower than the mean, offering an expected carbon footprint per functional unit. Sub-stages and stage-level boxplots reveal emission ranges and dominant contributors, with fertilizer application, household wastage, and truck fuel consistently exhibiting the largest impacts, while cultivation shows the widest stage-level variability, followed by household, and packaging and distribution demonstrate lower variability (Fig. 5(c and d)).

The Spearman rank correlation-based sensitivity analysis identifies sub-processes and stages that strongly influence total

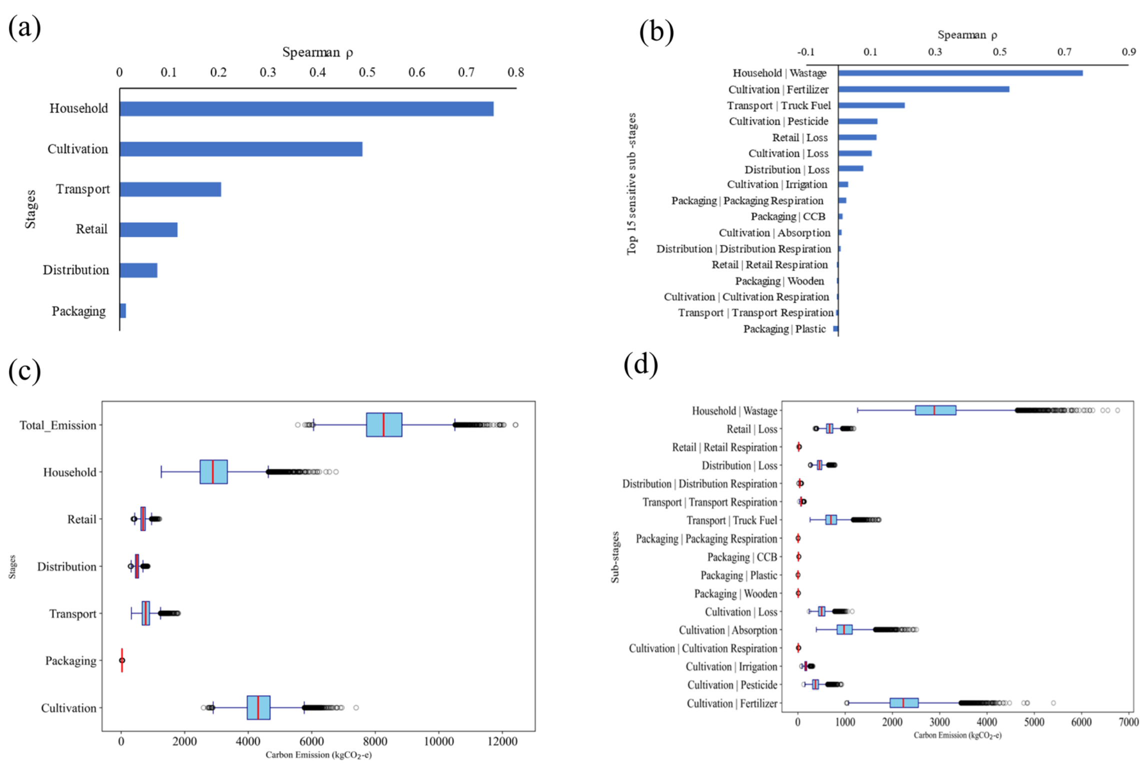

Fig. 5 (a) Sensitivity analysis of stages, (b) sensitivity analysis of sub-stages, (c) carbon emission variation of stages, and (d) carbon emission variation of sub-stages.

Table 11 Performance metrics of forecasting models

Model	Error metric	MAE	MSE	RMSE
ARIMA	Univariate	15.38	360.25	18.98
Prophet	Univariate	77.32	6048.01	77.76
	Multivariate	86.67	7621.95	87.3
LSTM	Univariate	72.18	5515.98	74.26
	Multivariate	34.92	1268.96	35.62
GRU	Univariate	92.72	8715.52	93.3
	Multivariate	50.15	2609.52	51.08

emissions: high positive correlations for fertilizer and wastage increase emissions, whereas absorption processes reduce them, with stage-level ranking typically following cultivation > household > transport > retail > packaging > distribution (Fig. 5(a and b)). This integrated approach combining probabilistic simulation, variability analysis, and sensitivity quantification provides a robust framework for pinpointing high-impact sub-processes and stages, enabling targeted mitigation strategies and supporting sustainable supply chain management.[54]

4.4. Litchi production forecasting: model performance and selection

Table 11 indicates that the multivariate LSTM model demonstrated the strongest overall performance for litchi production forecasting.[56] It yielded the lowest MAE (34.92) and RMSE (35.62) compared to other models. The superior performance suggests that the LSTM architecture, when augmented with relevant exogenous variables (area, temperature, rainfall), was exceptionally well suited for capturing the complex, non-linear patterns, and temporal dependencies inherent in the litchi production. Fig. 6 shows the model's predictions, which adequately captured the recent dynamic shifts in production during the test phase, unlike some models that produced flatter or more lagging forecasts like ARIMA and Prophet. Comparing across frameworks, the multivariate LSTM significantly outperformed its univariate counterpart (RMSE 35.62 *vs.* 74.27). The multivariate GRU model also showed improved performance with external variables (RMSE 51.08) compared to its univariate version (RMSE 93.36), positioning it as a strong multivariate approach, though second to multivariate LSTM.

The univariate ARIMA model was robust, with an MAE value of 15.38 and a competitive RMSE value of 18.98. Notably, it

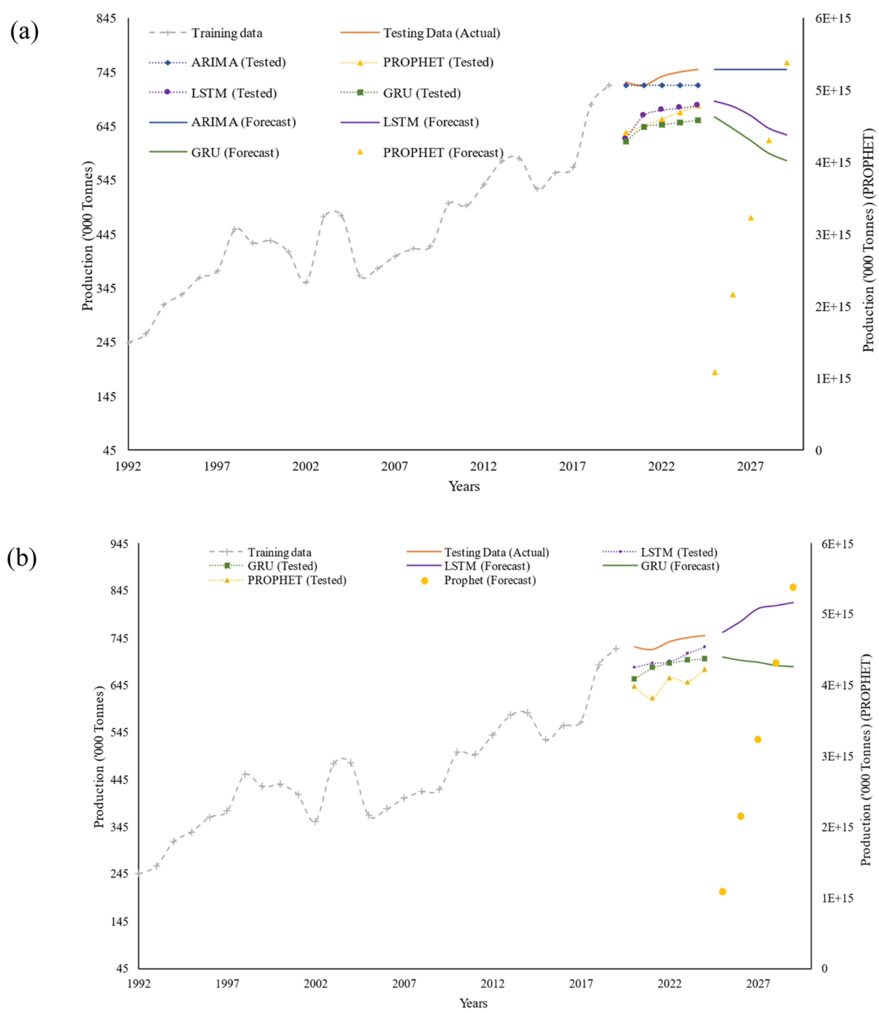

Fig. 6 Forecast of litchi production using (a) univariate and (b) multivariate time series methods.

consistently predicted 721 tonnes during the 2020–2024 test period, even as actual production rose from 726 to 750.8 tonnes. This flat predictive output indicates that ARIMA captured a stable baseline from training data but missed recent upward trends and yearly variations, offering robustness for noisy series but implying less responsiveness to dynamic shifts. The Prophet model, in both configurations, generally exhibited higher errors. When considering Prophet's utility, its performance was primarily assessed on the test set, as its longer-term future forecast stability was less reliable for this specific application. Thus, the multivariate LSTM model was found as the most accurate and appropriate for subsequent CE projections due to its superior ability to learn from historical patterns, integrate external factors, and model dynamic production trends.

Leveraging the litchi production forecasts using the multivariate LSTM model, the associated total CEs from the supply chain were subsequently projected. This translation relies on the comprehensive CF intensity established from the LCA data, where the emission intensity is approximately 0.94 kg CO_2-e kg^{-1} of litchi produced. Using the production forecasts from the multivariate LSTM model, the anticipated annual CEs were found to be approximately 7205.52, 7422.62, 7686.12, 7746.35, and 7809.77 kgCO_2-e ha^{-1} for 2025, 2026, 2027, 2028, and 2029, respectively.

Linked to the multivariate LSTM model's forecasted litchi production growth, these projected CEs signal an escalating environmental burden, challenging climate targets if current emission intensities persist. This highlights the urgent need for the earlier mentioned decarbonization strategies, especially strong actions to reduce emission intensity (EI) as litchi production continues. The CrTH-LCA-based projections offer a crucial baseline for policymakers to set targeted emission reduction goals and prioritize mitigation investments in the litchi sector.

4.5. Economic assessment of waste valorisation

The economic feasibility of waste valorisation in the litchi supply chain was assessed at two levels: farmer and whole supply chain. The analysis used forecasted production data over five years combined with the current year, representing a six-year project lifespan. The evaluation considered potential financial incentives from methane generation and composted farmyard manure (FYM). Due to the high initial investment for biogas plants, a community-based investment covering a cumulative 10 hectares was assumed. Table 12 shows the economic performance assessed using ROI, IRR, NPV, payback period, and cumulative revenue per hectare.

Table 12 Economic performance

Parameter	Farmer level	Entire supply chain
ROI (%)	164.01	1232.22
IRR (%)	84	288
NPV (USD)	1472.19	13 997.62
Payback period (months)	28	5.6
Cumulative revenue per hectare (USD)	428.60	2162.83

The study also highlights that, at the farmer level, methane production alone generated a cumulative revenue of $428.60 per hectare, with an ROI value of 164.01% and a payback period of 28 months. At the whole supply chain level, financial returns were substantially higher, with an ROI value of 1232.22% and a cumulative revenue of $2162.83 per hectare, emphasizing the economic advantage of a community-based biogas plant strategy. The additional revenue from composted FYM further enhances the financial incentives at both levels. These findings underscore the importance of government support through subsidies, infrastructure development, and farmer training to facilitate efficient waste collection and biogas adoption. Implementing such measures can significantly improve the financial viability for farmers and other stakeholders while promoting sustainable waste management and circular economy practices within the litchi supply chain.

The economic feasibility of farm- and community-level waste valorisation is mainly influenced by initial investment, scale, and market access. High upfront costs often limit smallholder adoption, even for profitable technologies which require government policy modification and community-based development. Optimized pyrolysis of vegetable waste can yield an ROI value of 29% with a payback period of 3.4 years under ideal conditions, though high-moisture fruits like litchi reduce the ROI value to below 10% and extend payback periods beyond ten years without costly pre-drying, as observed in the present study.[72] Post-harvest loss reduction through improved handling and cold chain infrastructure offers higher returns, reducing losses of up to 30% at the farmer level and 35–44% across the supply chain.[73] Low-cost, small-scale processing of rejected litchi into juice, jams, wine, canned fruit, or dried pulp provides positive ROI and a short payback period, indicating economic viability. The economic performance improves further with operational efficiency, diversified revenue streams, shared infrastructure, and government support, including subsidies and technical assistance.[74] Context-appropriate interventions combining loss prevention, processing, and cooperative action can make litchi waste valorisation profitable while promoting sustainable horticultural practices. Thus, the hybrid CrTH-LCA framework, combined with advanced forecasting methods, not only projects future carbon emissions but also informs policy frameworks, strengthens the economic viability of farmers, and encourages adoption of sustainable waste management practices by providing data-driven insights for targeted interventions.

5. Conclusion

The study evaluated an innovative circular tiered hybrid life cycle assessment (CrTH-LCA) framework, combined with deep learning-based time series forecasting techniques, to comprehensively assess the litchi supply chain's CF and future emission trajectories. The key findings identified household waste (40.44% of total CEs) and cultivation (31.96%, primarily from fertilizers) as the most significant CE hotspots, with a total supply chain footprint of 7305.17 $kgCO_2$-e ha^{-1} and an emission intensity of approximately 0.94 $kgCO_2$-e kg^{-1}. The Monte Carlo simulation further revealed the variability in emissions across sub-processes, highlighting fertilizer use, household waste, and transport as consistently high-impact contributors, while absorption and composting processes help mitigate total emissions. This probabilistic assessment provided robust insights for targeting interventions at both sub-process and stage levels.

The research demonstrated substantial mitigation potential through circular economy (CrE) strategies, particularly valorising the 4656.37 kg ha^{-1} available litchi waste biomass into biofuel and biocompost, alongside 1008.02 $kgCO_2$-e ha^{-1} $year^{-1}$ from orchard sequestration, with conceptual pathways for carbon credits. Economic assessment of waste valorisation at the farmer and supply chain levels underscores the financial viability of such strategies: community-based biogas plants yield high ROI (164.01% at the farmer level; 1232.22% at the supply chain level), short payback periods, and additional revenue from composted FYM. Post-harvest loss reduction, small-scale processing of rejected fruits, and operational efficiency further enhance the economic outcomes. The multivariate LSTM model proved most accurate for litchi production forecasting. Based on LSTM projections, gross CEs are forecasted to rise significantly, while net emissions remain substantial.

The study provides a robust integrated methodology for carbon management in ASC, offering data-driven insights for interventions. Crucially, the modular CrTH-LCA frameworks and sector-agnostic design are applicable to supply chains of agriculture,[75] vegetables and fruits,[76] and grains,[77] systematically analysing cultivation, post-harvest, transportation, distribution, and consumption waste streams, enabling its adaptation to other supply chains and supporting broader scalability in CF assessment and predictive modelling across the global fruit sector.

Achieving a sustainable transition requires concerted efforts: farmers and cooperatives should adopt integrated nutrient management, improve post-harvest handling, and engage in waste valorisation; supply chain intermediaries must invest in efficient logistics and sustainable packaging, while consumer awareness on responsible consumption and waste management is vital. Complementing these actions, supportive policy frameworks and market-based mechanisms such as clean development mechanism (CDM)[78] allow investments in emission-reducing projects, though agricultural participation remains limited. National and regional systems such as Canada's Alberta Emission Offset System, the EU Carbon Farming Initiative, Australia's Emission Reduction Fund,[79] and India's Carbon Credit Cell[80] enable farmers to generate credits through practices like conservation cropping, organic farming, agroforestry, and micro-irrigation.[74,79] Financial incentives including subsidies, tax benefits, and blended finance encourage adoption of climate-smart practices, while carbon valuation at global market prices provides measurable outcomes.[81,82] Digital platforms, blockchain systems, and tools like the Cool Farm Tool and COMET-Farm improve transparency, traceability, and verification of emission reductions.[83,84] Despite these efforts, challenges such as high transaction costs, regulatory uncertainty, low adoption, and carbon leakage persist.[84] Overall, integrated policies, market mechanisms, and technological platforms are essential to reduce emissions, incentivize sustainable practices, and support climate resilience in agriculture. The actions will aid in aligning the litchi sector with national and global climate action goals (SDGs 2, 12, and 13).

Future research should prioritize economic feasibility studies for valorisation pathways, developing dynamic emission intensity models, expanding the CrTH-LCA to include socio-economic indicators, investigating consumer behaviour, and further refining advanced forecasting techniques.

Overall, this study provides a replicable data-driven framework for carbon management that can guide sustainable practices and policy interventions across fruit supply chains, supporting the transition toward low-carbon and circular agricultural systems.

6. Implications of the study: practical and policy framework

The present research advances theoretical understanding in environmental science and agricultural sustainability while providing actionable insights for policy and practice aimed at decarbonizing the litchi supply chain and supporting key SDGs. The study makes several theoretical contributions: it develops a novel circular tiered hybrid life cycle assessment (CrTH-LCA) framework that integrates tiered emission sources from cultivation to post-consumption with circular economy loops, providing a robust and replicable tool as compared to the previous existing circular LCA framework.[27] A comparison of statistical and deep learning models ARIMA, Prophet, LSTM, and GRU was performed, followed by validation highlighting that multivariate LSTM models with exogenous variables provide more dynamic and adaptable emission projections. The framework also aids toward fulfilment of SDGs 2 (food security planning), 12 (responsible consumption and production) and 13 (climate action). The empirical finding that post-consumption household waste accounts for 40.44% of total CE challenging conventional production-centric views and emphasizes the importance of consumption-based circular strategies. Linking LCA data with predictive forecasts enhances anticipatory environmental management, while the conceptual exploration of carbon credits from waste valorisation and sequestration form the ground for circular bioeconomy. Below are the practices and policy frameworks across different stages of the supply chain, focusing on waste reduction and resource recovery.

6.1. Farm-level practices (SDGs 2, 12, and 13)

Adoption of soil health practices, improved post-harvest handling, and collective waste valorisation, supported by training, financing, and micro-leasing of low-cost equipment, helps reduce losses and overcome financial barriers.[80]

6.2. Supply chain interventions

Investment in energy-efficient transport, cold chains, sustainable packaging, and optimized inventory, along with crop loss and valorisation (CLV) centres, mobile cold storage, and cooperative waste-to-energy or composting units, enables waste reduction and resource recovery.[73]

6.3. Consumer engagement

Promotion of responsible consumption patterns and household food waste management, including proper disposal or composting, is complemented by digital/IoT-enabled inventory tracking platforms to minimize spoilage and losses.[85]

6.4. Policy and governance

Integration of climate projections into agricultural planning, incentivization of circular packaging through fiscal measures and R&D support, and adoption of life cycle perspectives are necessary. Subsidized or bundled climate insurance schemes can reward smallholders who adopt high-impact practices (*e.g.*, integrated nutrient management), mitigating financial and climate-related risks.[86,87]

By explicitly addressing feasibility constraints, financial barriers, and technical limitations, this study provides actionable context-sensitive pathways for smallholder adoption and system-wide decarbonization. The integration of LCA with predictive forecasting outputs ensures interventions that are data-driven, targeted, and capable of supporting scalable, sustainable transformations in horticultural supply chains globally.

Abbreviations

ACC	1-Aminocyclopropane-1-carboxylic acid
ADF	Augmented dickey fuller
AR	Autoregressive
ARIMA	Autoregressive moving average
ASC	Agricultural supply chain
BCR	Benefit-cost-ratio
CCB	Corrugated cardboard
CCC	Cold chain circulation
CDM	Clean development mechanism
CE	Carbon emission
CF	Carbon footprint
CFB	Corrugated fibre board
CH_4	Methane
CO_2	Carbon dioxide
CO_2-e	Carbon dioxide-equivalent
CrE	Circular economy
CrTH-LCA	Circular tiered hybrid life cycle assessment
CV	Coefficient of variation
DAP	Diammonium phosphate
EU	European union
F&V	Fruit and vegetable
FLW	Food loss and waste
FU	Functional unit
FYM	Farm yard manure
GHG	Green-house gas
GI	Geographical indication
GRU	Gated recurrent unit
h	Hour
HEV	Hybrid electric vehicles
IPCC	Intergovernmental panel on climate change
ISO	International standard organisation
kg	Kilogram
LCA	Life cycle assessment
LSTM	Long short-term memory
MA	Moving average
MAE	Mean absolute error
MJ	Mega joule
MLP	Machine learning program
MOP	Muriate of potash
MSE	Mean squared error
N_2O	Nitrous oxide
O_2	Oxygen
PB	Payback period
PC	Plastic crate
RFID	Radio-frequency identification
RMSE	Root mean square error
RNN	Recurrent neural network
ROI	Return on investment
RPC	Reusable plastic crate
SDG	Sustainable development goals
SETAC	Society of environmental toxicology
SVM	Support vector machine
t	Tonnes
WC	Wooden crate

Conflicts of interest

There are no conflicts to declare.

Data availability

No new data were generated in this study. All data analysed were obtained from previously published sources, which are cited in the reference list.

Supplementary information (SI): the historical datasets used for training the time-series forecasting models. See DOI: https://doi.org/10.1039/d5fb00519a.

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