Carbon Footprint Software for Market Pulp: Kraft and APMP Processes across Twelve Biomass Types with Soil Carbon Sequestration

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Current carbon footprint tools for the pulp and paper industry focus on conventional wood fibers and overlook alternative biomass and soil organic carbon (SOC) sequestration. This study developed a software tool for market pulp production comparing conventional eucalyptus and Northern Bleached Softwood Kraft (NBSK) against alternative non-wood fibers (bamboo, switchgrass, sorghum, rice husk, hemp hurd, sugarcane bagasse, wheat straw, rice straw, banana fiber, and ryegrass straw). The tool models kraft and alkaline peroxide mechanical pulping (APMP), integrates ISO 14040-44 standards, and incorporates SOC sequestration based on cultivar morphology. While applicable to diverse market pulps, tissue production is the primary application. Results identify Brazilian Eucalyptus Kraft (BEK) as the most environmentally favorable option. Specifically, the kraft process delivers lower carbon footprints (504 to 794 kg CO_2eq/ADt) than APMP (1,015 to 1,320 kg CO_2eq/ADt) because lignin combustion provides superior energy self-sufficiency. Energy sources critically affect APMP, with wheat straw ranging from 643 to 1,715 kg CO_2eq/ADt (hydropower versus coal), while NBSK varied minimally (631 to 779 kg CO_2eq/ADt). Across the twelve biomasses, high SOC stabilization factors reduced carbon footprints by up to 86%, while low factors showed less than 1% variation. This tool provides a practical platform for industry decision-making and sustainability education.

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INTRODUCTION

Carbon footprint accounting, the systematic recognition, evaluation, and monitoring of greenhouse gas emissions across value chains, has become a critical business imperative, yet it remains expensive and complex (Stechemesser and Guenther 2012). Companies face costs ranging from \$237,000 to \$677,000 for comprehensive carbon analyses, while grappling with data quality challenges, boundary adjustments, and stakeholder coordination barriers (Lee and Inaba 2004; Brock 2022; Saavedra-Rubio *et al.* 2022; Zargar *et al.* 2022).

Despite these challenges, regulatory mandates are intensifying. California's climate disclosure laws (SB-253 and SB-261) and the U.S. SEC climate disclosure rule now require detailed greenhouse gas reporting, including Scope 3 emissions (Dalton 2024; Naishadham 2024). Market pressures reinforce this shift, with record participation in the Carbon Disclosure Project (CDP) and 86% of S&P 500 firms voluntarily disclosing climate data to meet investor demands (Khan 2024). Carbon transparency has evolved from compliance requirement to strategic asset, fostering stakeholder trust and competitive advantage in the low-carbon economy (Lindell 2025).

Digital transformation offers a solution pathway, with specialized carbon accounting software automating data collection and enabling advanced analytics (Vial 2019). The global carbon footprint software market is projected to grow from $18.52 billion in 2024 to $100.84 billion by 2032 at a CAGR of 23.6% (Fortune Business Insights 2025). However, this growth predominantly serves generic applications, creating opportunities for industry-specific solutions.

Several industry-specific tools have been developed for the pulp and paper industry over the past two decades. Early developments include the GHG Calculation Tools for Pulp & Paper Mills, developed by the National Council for Air and Stream Improvement (NCASI) in 2002, which provide Excel-based models to estimate CO_2 emissions from fossil fuel combustion, methane, and nitrous oxide from combustion processes, and emissions from landfills and wastewater treatment for US and Canadian markets (NCASI 2005). The Paper Calculator, launched in 2005 by the Environmental Defense Fund and now managed by the Environmental Paper Network, is a web-based tool grounded in Life Cycle Assessment (LCA) methodology that enables users to compare environmental performance based on fiber source and recycled content. Version 4.0, released in 2018, evaluates 14 paper grades according to ISO 14044 standards (Schultz and Suresh 2018). In 2006, the GHG protocol adopted the NCASI tool for the Mexican pulp and paper industry (United States-Mexico Foundation for Science (USMFS/FUMEC) 2006).

More recent developments include the FisherSolve® 2018 integration of sustainability modules with carbon-benchmarking capabilities for global pulp and paper mills measuring scope 1, 2, and 3 emissions (FisherSolve® 2025). The World Wildlife Fund (WWF) released the Biogenic Carbon Footprint Calculator for Harvested Wood Products in 2020, which accounts for dynamic forest carbon gaps and storage benefits (Gmünder *et al.* 2020). NCASI introduced the Footprint Estimator for Forest Products (FEFPro™) in 2024, a sector-specific tool enabling pulp and paper companies to estimate product carbon footprints using harmonized data and methods tailored to forest-based value chains (NCASI 2024). VPK Group's Product Carbon Footprint Calculator, announced in 2024, uses the Partnership for Carbon Transparency (PACT) methodology to provide cradle-to-gate carbon intensity data aligned with the GHG Protocol and ISO standards ("vpk" 2025).

Despite these advancements, current industry-specific tools predominantly focus on conventional wood fibers and overlook alternative biomass feedstocks. This gap is particularly significant for the hygiene tissue sector, which is one of the fastest-growing paper categories globally, with a compound annual growth rate (CAGR) of 3.3% (Statista 2026). The tissue industry has emerged as a primary driver for fiber diversification as it seeks to mitigate risks related to the long-term supply and pricing of traditional fibers like Northern Bleached Softwood Kraft (NBSK) (Urdaneta *et al.* 2024a, Urdaneta *et al.* 2025).

Recent research has highlighted the viability of chemi-mechanical pulping processes, particularly alkaline peroxide mechanical pulping (APMP) and chemi-thermomechanical pulp (CTMP), for converting agricultural residues such as wheat straw into tissue-grade pulp (Urdaneta *et al.* 2024a). Furthermore, the utilization of alternative fibers such as bamboo, wheat straw, and miscanthus has shown significant potential for tissue production, offering a pathway for small-scale, low-investment operations that bypass the economic barriers of traditional kraft recovery systems (Urdaneta *et al.* 2025). This shift in processing is fundamentally tied to the physical and chemical characteristics of the biomass. For example, while kraft pulping is the industry standard for dense, resinous softwoods like pine (NBSK) to handle high lignin content (Smook 2016), agro-industrial residues such as rice husk, agricultural residues like wheat straw, and grasses such as miscanthus and bamboo present a vastly different morphology (Mansaray and Ghaly 1997; Urdaneta *et al.* 2025). These materials often possess higher silica content, lower bulk density, and shorter fibers, making chemi-mechanical processes such as APMP more suitable to manage their brittle structure while preserving yield (Urdaneta *et al.* 2025). Beyond APMP and CTMP, recent research has demonstrated the potential of sulfite pulping for alternative fibers (Vivas *et al.* 2024). Moreover, existing tools do not incorporate the potential benefits of Soil Organic Carbon (SOC) sequestration, which recent studies have identified as significantly contributing to climate mitigation (Forfora *et al.* 2024; Lan *et al.* 2024). This gap underscores the need for a specialized tool that compares conventional and alternative fibers while integrating SOC sequestration assessments.

To address these limitations, this study developed a comprehensive carbon footprint software tool to compare the carbon footprint of conventional and alternative fibers processed *via* kraft pulping and APMP from cradle to gate. While the tool is designed for the broader market pulp industry, it is uniquely positioned to support the tissue sector's transition toward alternative biomass by providing the necessary carbon transparency for these emerging supply chains. The tool evaluates twelve biomass types across five categories: tree plantations (eucalyptus), natural forests (northern softwood and bamboo natural stands), dedicated crops (switchgrass and sorghum), agro-industrial residues (rice husk, hemp hurd, sugarcane bagasse), and agricultural residues (wheat straw, rice straw, banana fiber, ryegrass straw). The software incorporates SOC sequestration potential by modeling carbon input based on the root-to-shoot ratios of different cultivars and soil carbon stabilization factors (Forfora *et al.* 2024). This work represents the first comprehensive software tool to simultaneously evaluate diverse biomass types with integrated SOC assessment for pulping applications.

This article presents the methodology for data acquisition and modeling, the model framework and computational modeling, and the software capabilities. The results section demonstrates software validation through comparative analysis against published literature and explores the impact of electricity sources and SOC sequestration factors on process emissions. The findings advance carbon accounting methodologies for the pulp industry while supporting the pulp and paper industry with decision-making tools.

EXPERIMENTAL

This section outlines the systematic approach employed to develop a comprehensive carbon footprint software. The methodology is presented in three subsections. The first subsection, data acquisition and modeling, addresses the procedures for collecting Life Cycle Inventory (LCI) data and developing the mathematical routines that constitute the computational backbone of the tool. The second subsection, the model framework and computational modeling, presents the design and implementation of the software architecture, including database integration, modular coding, and user interface development. The third subsection, software capabilities, describes the validation of the tool and the functionalities that enable scenario analysis, visualization, and recommended carbon comparisons.

Data Acquisition and Modeling

Figure 1 illustrates the comprehensive process of tool development, implementing the ISO 14040/14044 LCA framework within an extended modeling framework for carbon footprint assessment software development.

A systematic literature review of agricultural practices was conducted to extract the LCI data for biomass production, following the methodology described in previous work (Forfora *et al.* 2024). This process considered 187 literature sources, including peer-reviewed articles, government reports, and personal communications. From these sources, a robust dataset of 122 individual data points was compiled, specifically extracted to satisfy the study's twenty carbon footprint equations (S1-S20) as shown in Table 1. These points cover transportation distances, annual productivity, nitrogen application, and market prices. To enable linear correlations, a triad of data points representing the minimum, mean, and maximum values found in the literature characterized key variables. The review encompassed twelve biomass types grouped into five categories: tree plantation (eucalyptus), natural forest (northern softwood and bamboo natural stands), dedicated crops (sorghum and switchgrass), agro-industrial residues (rice husk, hemp hurd, and sugarcane bagasse) and agricultural residues (wheat straw, rice straw, banana fiber, and ryegrass straw). Emissions equations were derived from biomass LCI as a function of biomass yield, nitrogen application rates, transportation distances, fertilizer types and quantities, seed requirements, fuel consumption (Forfora *et al.* 2024). Table 1 summarizes the emission equations by biomass category and the economic and mass allocation factors used for each biomass are described in Table S1.

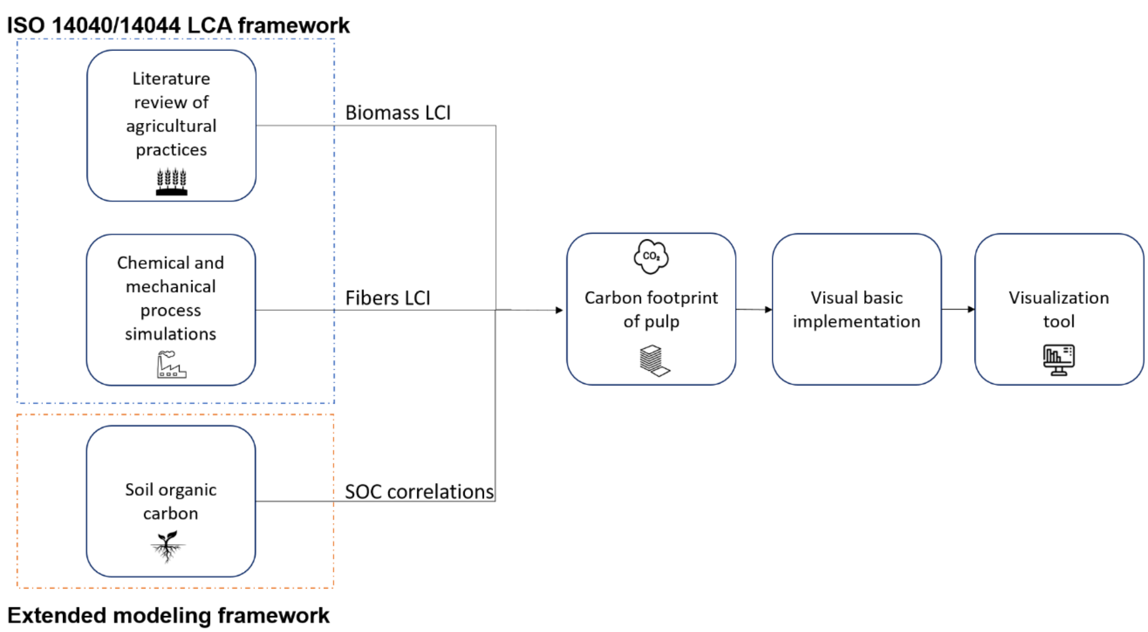

Fig. 1. Data acquisition and modeling framework integrating ISO 14040/14044 LCA principles with extended modeling for carbon footprint software development

Table 1. Emission Equations by Biomass Category

Biomass Category	Specific Type	Allocation Method	Co-products	Equation Reference
Tree plantation	Eucalyptus	N/A	N/A	S1
Natural forest	Northern softwood	Economic	Green lumber, saw dust, bark	S2
		Mass		S3
	Bamboo natural stands	N/A	N/A	S4
Dedicated crops	Switchgrass	N/A	N/A	S5
	Sorghum	N/A	N/A	S6
Agro-industrial residues	Rice husk	Economic	White grain, rice bran, rice straw	S7
		Mass		S8
	Hemp hurd	Economic	Hemp bast fiber, hemp dust	S9
		Mass		S10
	Sugarcane bagasse	Economic	Surplus bagasse, molasses, raw sugar	S11
		Mass		S12
Agricultural residues	Wheat straw	Economic	Wheat grain	S13
		Mass		S14
	Rice straw	Economic	Paddy rice	S15
		Mass		S16
	Banana fiber	Economic	Pseudo-stem, fruit	S17
		Mass		S18
	Ryegrass straw	Economic	Ryegrass grain	S19
		Mass		S20

The upstream data source required for determining the regression parameters in equations S1 to S20 were obtained from the ecoinvent 3.8 database (cut-off) (Wernet *et al.* 2016). Mass and energy balances for pulp production were established using Valmet's WinGEMS software (Valmet 1990) through chemical and mechanical process simulations.

LCIs were collected for Bleached Eucalyptus Kraft (BEK) (Ortega *et al.* 2024), NBSK, and Bleached Bamboo Kraft (BBK) (Forfora *et al.* 2025). The APMP process regional selection focused on the southeastern United States (Vivas *et al.* 2024), with the LCI collected from previous research (Urdaneta *et al.* 2024b). Upstream data for fuels, electricity, and chemicals for both processes was obtained from the ecoinvent 3.8 database (cut-off) (Wernet *et al.* 2016).

The LCA framework was implemented following ISO 14040-44 principles, encompassing goal and scope definition with system boundaries from cradle to pulp mill gate, LCI compilation from literature and simulations, life cycle impact assessment executed using openLCA software (Ciroth 2007) and TRACI methodology (Bare *et al.* 2012), and interpretation of results with both mass-based and economic allocation methods applied (Finkbeiner *et al.* 2006). The declared units for analysis were one bone-dry ton (BDt) for biomass and one air-dried ton (ADt, 10% moisture) for pulp fiber.

The extended modeling framework refers to the inclusion of potential soil organic carbon modeling, represented by equations S21 to S23, which was implemented to estimate SOC accumulation by incorporating root-to-shoot ratios with assumptions of uniform soil properties and constant climatic conditions over a 100-year time horizon (Forfora *et al.* 2024). This extended framework enables comprehensive carbon footprint assessment by incorporating carbon sequestration potential alongside emission calculations, providing a more complete picture of the environmental impacts associated with different biomass sources for pulp production.

Finally, the tool development involves the integration of computational models and software implementation. The carbon footprint calculation for pulp production incorporates biomass production emissions, processing energy and material requirements, transportation impacts, and soil organic carbon sequestration potential. The graphical user interface (GUI) was developed using Visual Basic .NET, targeting the .NET Framework 4.7.2 (Microsoft 2018) and Visual Studio 2022 (Microsoft 2022), providing an integrated environment for front-end and back-end coding. The .NET Framework was selected due to its robust performance, ease of integration with Windows-based systems, and extensive library support, which streamlined the development process and facilitated efficient coupling of the computational models with the user interface (Microsoft 2018). The GUI was designed to facilitate user interaction with the models by providing an intuitive platform for data input and visualization of results.

Model Framework and Computational Implementation

The computational framework was developed using a structured sequential process to ensure the rigorous integration of the literature-derived data points and the underlying ISO 14040/14044 LCA principles. This approach, illustrated in Fig. 2, progressed through five primary stages: analysis, design, implementation, testing, and maintenance (Royce 1987).

The analysis phase established the model's core requirements, detailing the purpose and scope of the twenty emission equations (S1 to S20) and soil organic carbon models (S21 to S23). During the subsequent design phase, the software architecture was established, algorithms were developed, and the database schema was designed to manage the complexity of twelve biomass types and multiple allocation methods (Bassil 2012). In the implementation phase, these specifications were transformed into a working executable program, utilizing modular programming to handle diverse computational requirements (Bassil 2012).

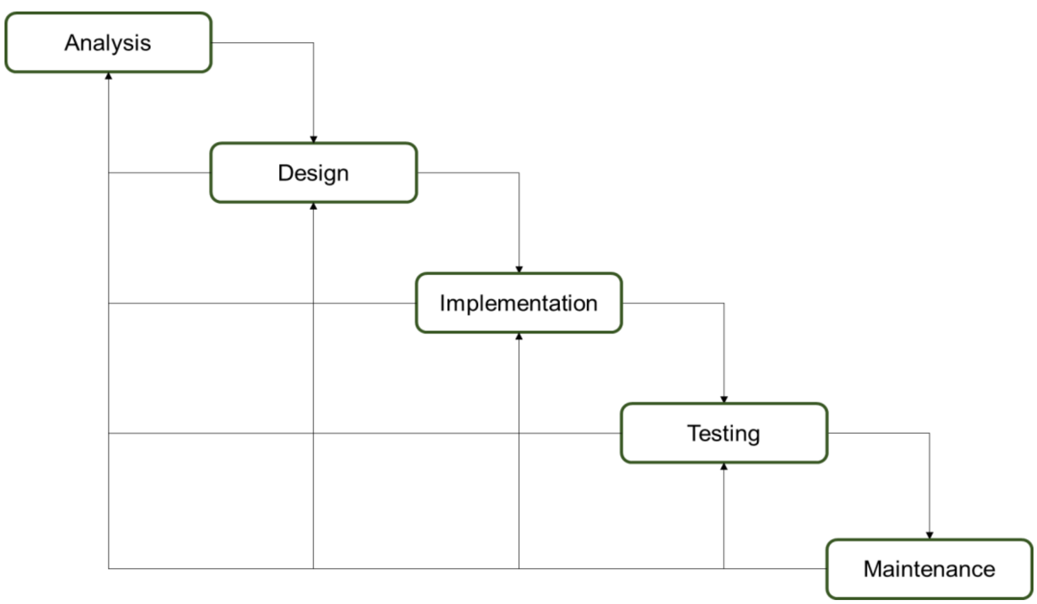

Fig. 2. Sequential framework for model development and computational implementation (Bassil 2012)

The implementation resulted in a comprehensive computational tool incorporating complex repetition structures and algorithmic optimizations to handle the diverse requirements of carbon footprint assessment. The software architecture employed modular design principles to manage the complexity of twelve biomass types and extensive mathematical computations. The codebase utilized object-oriented programming to efficiently process the emission equations while maintaining the flexibility required for various pulping processes.

The testing phase, which incorporated verification and validation processes, ensured that the software met the specified requirements and functioned as intended (Geraci 1991). Finally, the maintenance phase involved iterative modifications to improve accuracy and enhance algorithmic performance (Stellman and Greene 2005).

Over three years, the framework underwent 91 iterations of algorithmic refinement before reaching its current validated state. These refinements focused primarily on optimizing the carbon footprint calculation algorithms and enhancing data integration to accommodate the diverse biomass LCI data.

Key challenges included integrating diverse data sources from the ecoinvent database and literature review, optimizing the accuracy and efficiency of carbon accounting algorithms for the twenty emission equations and three soil organic carbon models, and designing a user-friendly GUI that could effectively visualize results across multiple allocation methods. Continuous feedback from domain experts and stakeholders spurred repeated refinements to both the computational models and the software interface, ultimately ensuring the reliability and effectiveness of the tool. This iterative development process was instrumental in refining the carbon footprint software and ensuring its capacity to perform accurate assessments while maintaining the scientific rigor of the underlying ISO 14040/14044 LCA framework and extended modeling components.

Software Capabilities

Figure 3 illustrates the modular capabilities of the carbon footprint software, demonstrating how the ISO 14040/14044 LCA framework is extended through SOC sequestration modeling. The software comprises six interconnected modules that enable comprehensive comparison of carbon footprint assessments.

Module 1 evaluates the carbon footprint of biomass production across the twelve-biomass types, while Module 2 extends this analysis by incorporating the potential for SOC sequestration to provide a net carbon footprint assessment. Module 3 focuses on the carbon footprint of the APMP pulping process, while Module 4 integrates SOC sequestration potential into the APMP process evaluation. Module 5 assesses the carbon footprint of the kraft pulping process, and Module 6 combines this evaluation with SOC sequestration effects. This modular design allows users to compare conventional LCA results (Modules 1, 3, 5) with extended assessments that account for carbon sequestration benefits (Modules 2, 4, 6), providing a more comprehensive understanding of the environmental impacts across different biomass sources and pulping technologies.

The software incorporates comprehensive input parameters for biomass cultivation, organized by feedstock category. Average input parameters for tree plantations and natural forests are detailed in Table S2. Dedicated crops and agro-industrial residues parameters are presented in Table S3, while agricultural residues are specified in Table S4. The software displays specific system boundaries for each feedstock type, with eucalyptus plantations provided as an illustrative example in Fig. S1.

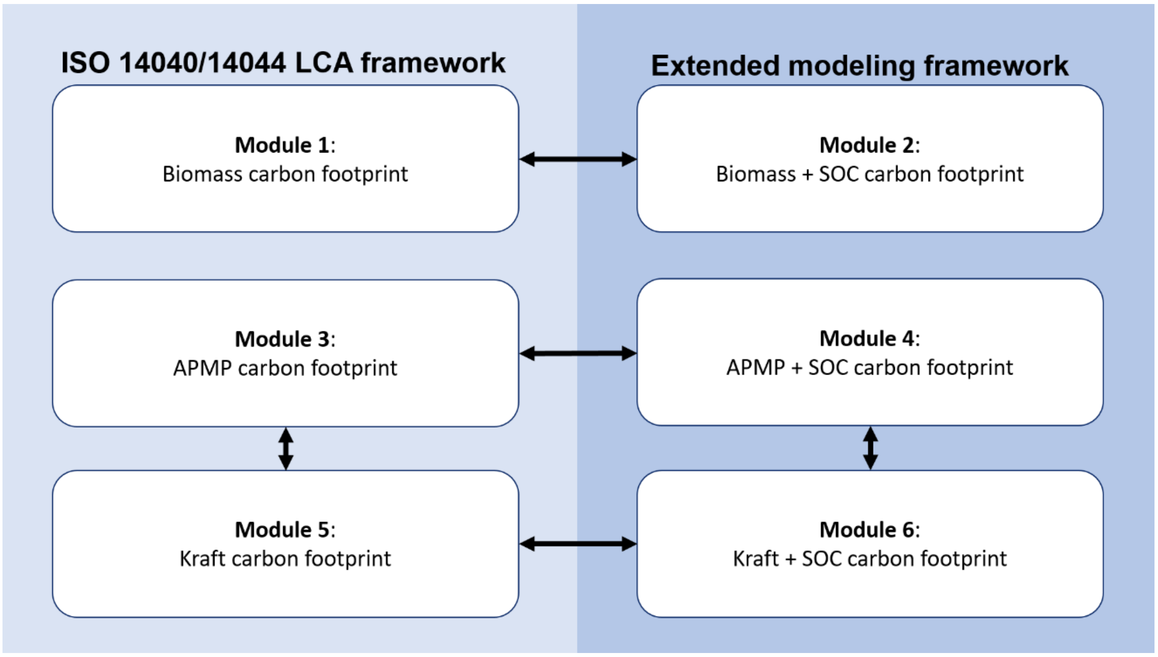

Fig. 3. Modular modeling framework showing ISO 14040/14044 LCA framework integration with extended SOC sequestration modeling capabilities. Arrows indicate recommended comparisons between standard and SOC-inclusive approaches.

The APMP process configuration is detailed in Table S5, showing average inputs with corresponding ecoinvent unit processes described in Table S6. The APMP process system boundary is represented in Fig. S2. Input parameters for APMP encompass production capacity, process yield, power boiler fuel selection, electricity sources, and chemical requirements, facilitating comprehensive comparisons between conventional and alternative fiber processes.

For kraft pulping processes applied to tree plantations and natural forests, LCIs are presented in Table S7, with corresponding ecoinvent unit processes described in Table S8. Each kraft process has its own system boundary description, exemplified by the eucalyptus processing boundary illustrated in Fig. S3. Input parameters for kraft pulping include production capacity, process yield, fuels used in power boilers and lime kilns, electricity sources, and chemical requirements for makeup, bleaching, and chlorine dioxide generation.

The extended modeling framework incorporates morphological properties of cultivars and soil carbon stabilization factors, with input values specified in Table S9. This integration enables the software to account for long-term carbon sequestration effects alongside traditional LCA assessments.

The software provides flexible energy configuration options to accommodate diverse operational scenarios. Users can evaluate multiple fuel options by selecting from wood waste, coal, fuel oil, and natural gas for various process requirements. The software supports comprehensive electricity selection, enabling users to choose from electricity sources across various regions in the USA and Brazil, as well as average electricity profiles from China, Portugal, Canada, Chile, and Uruguay, as detailed in Table S10. Additionally, users can distinguish between renewable sources (hydro, wind, nuclear, and solar) and non-renewable sources (coal), allowing for detailed assessment of energy source impacts on carbon footprint calculations.

Through the integration of data acquisition, mathematical modeling, and comprehensive software development, the carbon footprint tool can evaluate diverse scenarios and perform detailed comparisons of conventional and alternative fibers produced via kraft pulping and APMP processes. The software enables assessments both with and without SOC sequestration effects, providing flexibility for different analytical approaches. The tool facilitates extensive sensitivity analyses on process parameters and SOC scenarios, allowing users to understand the impact of variable inputs on carbon footprint outcomes.

The software's user-friendly interface provides intuitive access to all analytical capabilities while maintaining the scientific rigor of the underlying computational models. For comprehensive guidance on user engagement with the carbon footprint software, readers are encouraged to refer to Fig. S4, which demonstrates the software's interface and operational workflow.

RESULTS AND DISCUSSION

The results are presented in two subsections. First, the software is validated by comparing calculated GWP values for kraft pulping of eucalyptus plantations in Brazil and natural forests (Northern softwood in Canada and natural bamboo stands in China) against published literature benchmarks. Second, scenario analyses examine how electricity sources (renewable *vs.* non-renewable) influence the carbon footprint of mechanical and chemical pulping processes. The study also evaluates how different soil-carbon stabilization factors affect the carbon footprint of these processes.

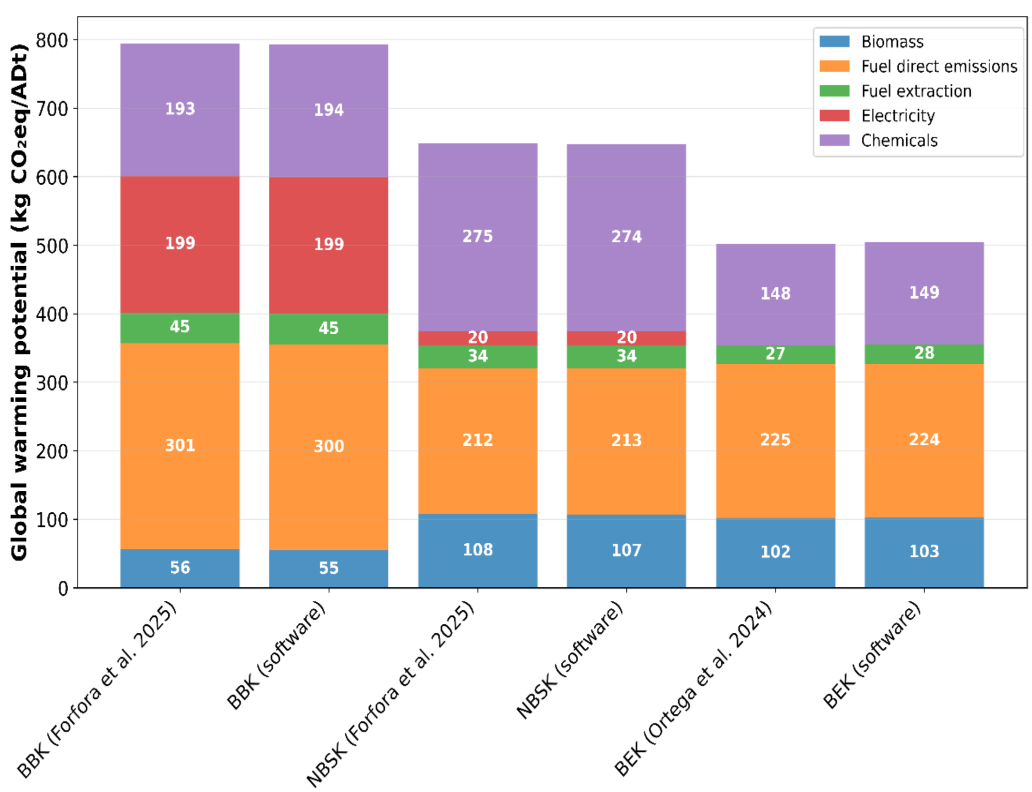

Fig. 4. Validation results of kraft pulping process per ADt of market pulp in the carbon footprint software using economic allocation

Software Validation

The validation results presented in Fig. 4 confirm the accuracy of the carbon footprint software for carbon footprint assessments. The close alignment between software calculated GWP values and published literature benchmarks across all three fiber types (bamboo, northern softwood and eucalyptus) demonstrates the tool's capability to accurately model complex pulping processes.

The software successfully captured the relative contributions of individual impact categories, with fuel direct emissions consistently representing the dominant component (approximately 38% to 44% of total GWP), followed by chemicals (24% to 42%), biomass (7% to 20%), and electricity (3% to 25%), mirroring the patterns reported in peer-reviewed studies. The consistent performance across geographically diverse operations, from eucalyptus plantations in Brazil to northern softwood forests in Canada and bamboo stands in China, validates the software’s robustness in handling varying regional conditions, energy sources, and raw material characteristics.

The validation results have significant implications for industrial decision-making and policy development in the pulp and paper sector. The software's capability to model diverse feedstocks and processing conditions addresses a critical gap in current carbon accounting methodologies, where most existing tools focus on conventional wood-based feedstocks. This comprehensive approach enables pulp producers to make evidence-based decisions about feedstock diversification strategies, particularly relevant as the industry faces increasing pressure to adopt alternative fiber sources to reduce environmental impacts and enhance supply chain resilience.

Scenario Exploration on Processes Energy Consumption and Soil Organic Carbon Sequestration Potential

Figure 5 presents the sensitivity analysis of electricity sources for APMP wheat straw and kraft pulping processes (BBK and NBSK). The results reveal that APMP pulps are highly sensitive to electricity source, demonstrating substantially greater variability in carbon impact compared to kraft processes.

Figure 5 illustrates significant differences between hydropower and coal-based electricity scenarios across different pulp production methods. When hydropower is used, BBK demonstrates the lowest carbon footprint at 597 kg CO_2eq/ADt, followed by NBSK at 631 kg CO_2eq/ADt, and APMP wheat straw at 643 kg CO_2eq/ADt. Under coal-based electricity scenarios, the carbon footprints increase substantially to 779 kg CO_2eq/ADt for NBSK, 1,070 kg CO_2eq/ADt for BBK, and 1,715 kg CO_2eq/ADt for APMP wheat straw. The differences between these two energy scenarios reveal markedly different sensitivities: APMP wheat straw exhibits the most pronounced sensitivity with a range of 1,072 kg CO_2eq/ADt, BBK shows a moderate difference of 473 kg CO_2eq/ADt, while NBSK exhibits the smallest variation at 148 kg CO_2eq/ADt. This substantial variation in APMP wheat straw underscores the critical role of electricity sourcing in APMP operations, where the carbon footprint increases by 167% when switching from hydropower to coal-based electricity. In contrast, NBSK’s carbon footprint increases by only 23% under the same transition, demonstrating how energy source dramatically affects the environmental profile of different pulping processes.

The reduced sensitivity of kraft pulping processes stems from their energy self-sufficiency through black liquor combustion, which provides substantial internal energy generation and reduces dependence on external electricity sources. This inherent characteristic of kraft mills buffers them against variations in external electricity sources, whereas APMP processes, which rely heavily on mechanical refining and external electricity, experience dramatic shifts in their environmental performance based on the energy mix.

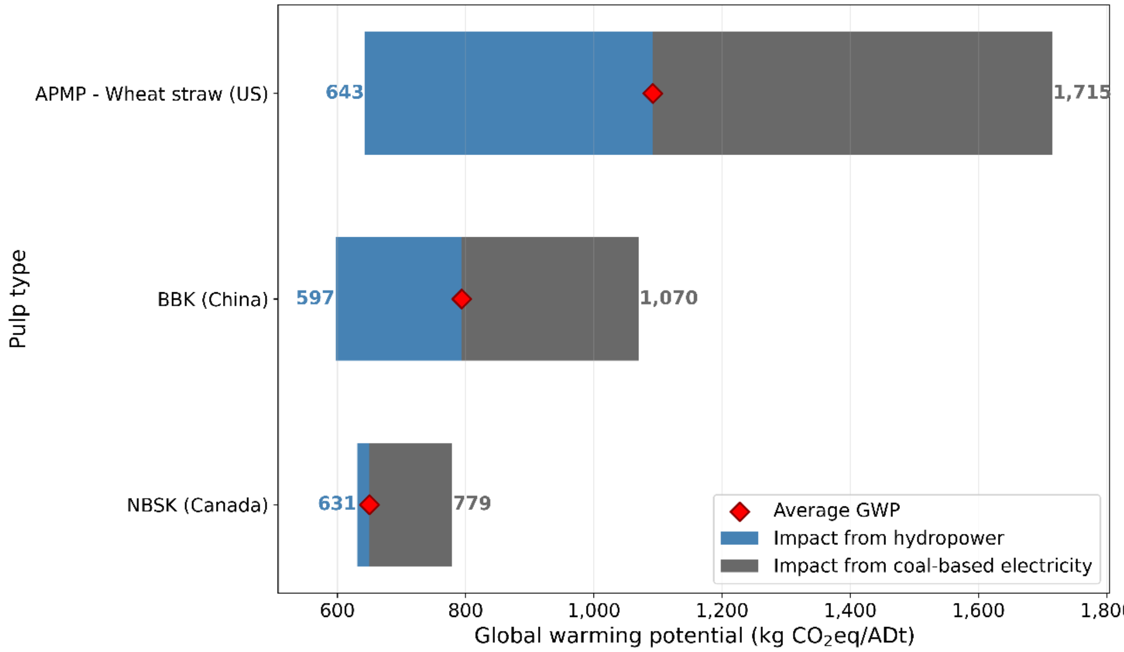

Fig. 5. Carbon footprint sensitivity to electricity source for pulping processes. Blue bars show impact from hydropower; gray bars show impact from coal-based electricity. Red diamonds mark average GWP for each pulp type. Numbers indicate total global warming potential (kg CO_2eq/ADt) for each scenario

The positioning of each process relative to its average carbon footprint baseline (marked by red diamonds) further emphasizes these energy-related impacts. Under hydropower scenarios, both APMP and kraft processes achieve carbon footprints below their respective coal-scenario values. The magnitude of this reduction, however, varies dramatically—APMP processes show large reductions from their baseline, while kraft processes remain relatively stable. Under coal-based electricity scenarios, APMP processes shift dramatically above their average baseline, whereas kraft processes show more modest increases, demonstrating their lower sensitivity to electricity supply source.

These sensitivity patterns are independent of the allocation method employed, as allocation approaches scale absolute values proportionally without altering the relative differences between energy scenarios. This ensures that the observed sensitivity rankings and process comparisons remain robust regardless of whether economic or mass allocation is applied. For a detailed breakdown of the scenario exploration for each process, see Table S11.

Figure 6 presents the scenario exploration for SOC stabilization factors on the carbon footprint for both kraft pulping and APMP processes across the twelve biomasses studied. The results reveal distinct sensitivity patterns among different biomass categories, with dedicated crops and woody biomasses demonstrating substantially higher sensitivity to SOC stabilization factors compared to agricultural and agro-industrial residues.

Figure 6 illustrates significant differences between 5% and 25% SOC stabilization scenarios across different biomass types. Under the 25% SOC stabilization scenario (green bars), BEK (Brazil) demonstrates the lowest carbon footprint at 74 kg CO_2eq/ADt, followed by NBSK at 213 kg CO_2eq/ADt, BBK at 387 kg CO_2eq/ADt, and APMP switchgrass at 539 kg CO_2eq/ADt. Agricultural and agro-industrial residues show higher values, ranging from 815 kg CO_2eq/ADt for APMP bamboo to 1,124 kg CO_2eq/ADt for APMP sugarcane bagasse. Under the 5% SOC stabilization scenario (orange bars), the carbon footprints increase to 404 kg CO_2eq/ADt for BEK, 525 kg CO_2eq/ADt for NBSK, 685 kg CO_2eq/ADt for BBK, and 1,005 kg CO_2eq/ADt for APMP switchgrass, while agricultural residues range from 975 kg CO_2eq/ADt for APMP bamboo to 1,212 kg CO_2eq/ADt for APMP banana fiber.

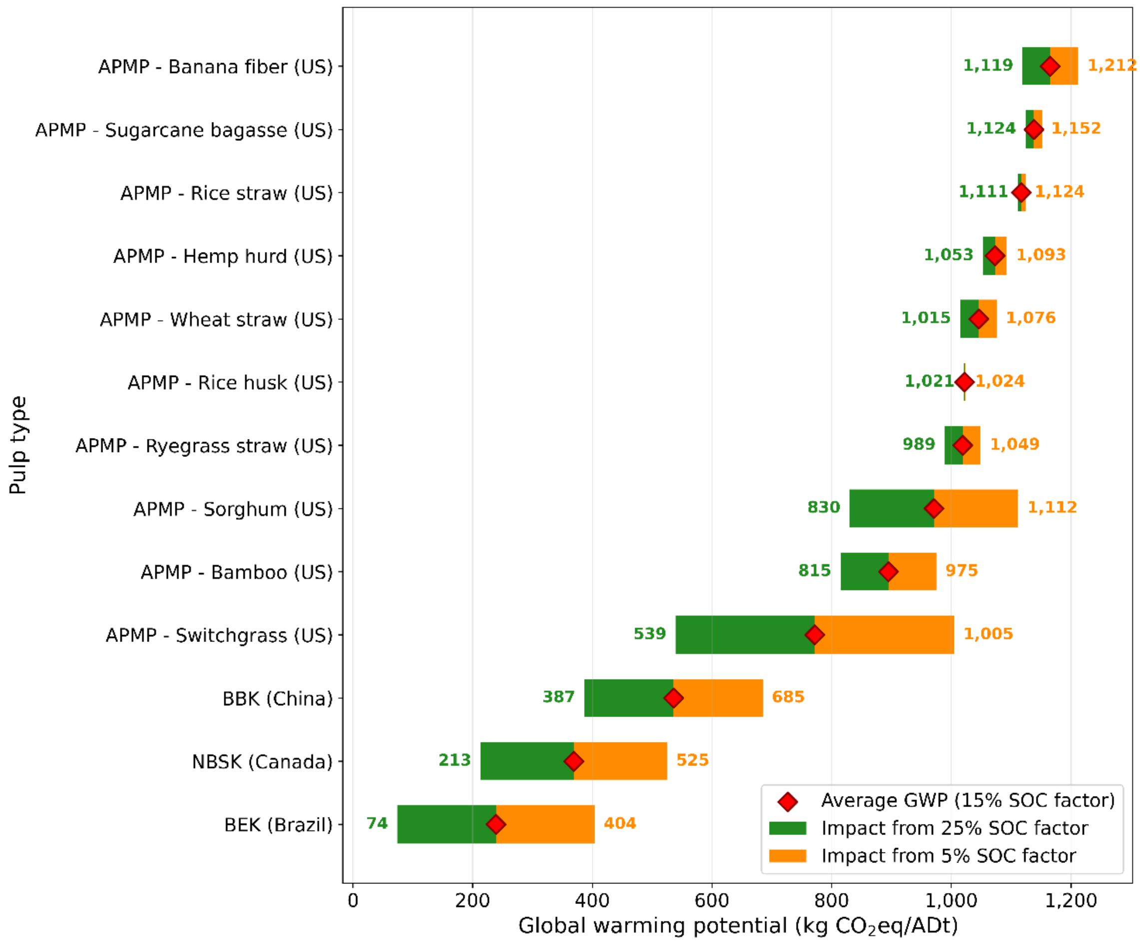

Fig. 6. Carbon footprint sensitivity to SOC stabilization factors for pulping processes across twelve biomass types. Green bars: 25% SOC factor; orange bars: 5% SOC factor; red diamonds: baseline at 15% SOC factor. Values indicate total GWP (kg CO_2eq/ADt) using economic allocation.

The differences between these two SOC scenarios reveal markedly different sensitivities across biomass types. APMP switchgrass exhibits the most pronounced sensitivity with a difference of 466 kg CO_2eq/ADt (from 539 to 1,005 kg CO_2eq/ADt), representing an 86% increase when moving from high to low SOC stabilization. BEK shows a difference of 330 kg CO_2eq/ADt (446% increase), NBSK demonstrates 312 kg CO_2eq/ADt (147% increase), and BBK exhibits 298 kg CO_2eq/ADt (77% increase). In contrast, agricultural and agro-industrial residues show minimal sensitivity: APMP rice husk exhibits the smallest variation at only 3 kg CO_2eq/ADt (0.3% increase), APMP rice straw shows 13 kg CO_2eq/ADt (1% increase), and APMP sugarcane bagasse demonstrates 28 kg CO_2eq/ADt (2% increase). This remarkable contrast underscores the critical importance of soil carbon sequestration potential in dedicated energy crops and woody biomass production compared to agro-industrial and agricultural residues.

The high sensitivity patterns in dedicated crops and woody biomasses reflect the significant root biomass and soil carbon input potential associated with perennial woody species, which typically exhibit higher root-to-shoot ratios and longer growing cycles compared to annual crops. The reduced sensitivity of agricultural and agro-industrial residues stems from the fact that these materials are byproducts of agricultural systems where the primary crop has already been harvested, and the residues themselves contribute minimally to additional soil organic carbon accumulation.

The positioning of each biomass relative to its average carbon footprint baseline (marked by red diamonds) further emphasizes the soil carbon sequestration impacts. Under high SOC stabilization scenarios (25%), dedicated crops and woody biomasses achieve carbon footprints substantially below their baseline values, demonstrating significant climate benefits through soil carbon sequestration. Under low SOC stabilization scenarios (5%), these same biomasses shift above their baseline values, while agricultural residues remain relatively stable near their baseline regardless of the SOC factor applied.

These findings have significant implications for biomass selection in pulp production. Dedicated crops such as switchgrass and woody biomasses such as eucalyptus may offer substantial climate benefits when high soil carbon stabilization is achieved but could show less favorable performance under conservative stabilization assumptions. Conversely, agricultural residues provide more predictable and stable carbon footprints regardless of soil carbon uncertainties. The pronounced sensitivity of woody biomasses and dedicated crops to SOC factors highlights the importance of site-specific soil carbon measurements and long-term monitoring programs to accurately quantify the carbon footprint benefits of these feedstocks in pulp production systems.

These sensitivity patterns are independent of the allocation method employed, as allocation approaches scale absolute values proportionally without altering the relative differences between SOC stabilization scenarios. This ensures that the observed sensitivity rankings and biomass comparisons remain robust regardless of whether economic or mass allocation is applied. For a detailed breakdown of the scenario exploration for each process, see Table S12.

The favorable carbon footprint outcomes for BEK (Brazil) and NBSK (Canada), as illustrated in Fig. 6, are primarily driven by biomass-to-pulp conversion efficiency and mill energy self-sufficiency. BEK mills typically demonstrate a higher degree of power self-sufficiency compared to NBSK operations. By generating a larger share of their energy from biomass-derived black liquor, these mills significantly reduce their reliance on external fossil-fuel-intensive energy.

The outcomes identified in this study are indeed sensitive to the methodology used for biogenic carbon accounting. Following the ISO 14040-44, a biogenic neutrality assumption was applied, treating the CO_2 absorbed during biomass growth as equivalent to the CO_2 released during combustion or decomposition within the same rotation. This approach distinguishes biogenic carbon from fossil-fuel-emitted carbon, which represents a net addition of carbon to the active atmosphere.

Regarding the temporal and ecological assumptions underlying carbon accounting, this study follows the standard attributional LCA approach (ISO 14040-44), which assumes a steady-state biogenic carbon cycle. However, the future ability of the environment to assimilate CO_2 may not mirror recent historical patterns. Factors such as increased frequency of forest disturbances, and the potential saturation of terrestrial carbon sinks introduce a level of non-stationarity into future climate scenarios (Hubau *et al.* 2020; Seidl *et al.* 2017). Nevertheless, even if the net-neutrality of biogenic carbon were to be re-evaluated in future frameworks, the relative performance of the fiber sources analyzed here would likely persist. The fundamental drivers of a low carbon footprint—specifically high biomass-to-pulp conversion efficiency and high mill energy self-sufficiency—are engineering parameters that minimize fossil fuel dependence. These factors remain the primary levers for decarbonization in the pulp and paper industry, regardless of the evolving capacity of the global carbon sink.

The scenario explorations presented in Figs. 5 and 6 demonstrate the robust capability of the carbon footprint software to capture and quantify the impact of key process variables and the intrinsic characteristics of the twelve-biomass types considered. The software successfully demonstrates its capability to simultaneously assess 12 different biomass types across multiple pulping processes (APMP and kraft), maintain methodological consistency across economic and mass allocation methods, generate quantitative benchmarks for carbon footprint variability in pulp production systems, and handle complex interactions between feedstock characteristics and process requirements.

These findings validate the tool's ability to generate scientifically robust carbon footprint estimates when evaluating conventional and alternative fibers in pulp production. The validated software tool provides the pulp industry with comprehensive capabilities to assess alternative fiber strategies while maintaining scientific rigor in carbon accounting methodologies.

Future developments will involve incorporation of additional pulping processes such as CTMP (Chemi-Thermo-Mechanical Pulping) and sulfite processes to provide more comprehensive process coverage across all major industrial pulping technologies. After completing the remaining processes, Techno-Economic Analysis (TEA) capabilities will be included to enable simultaneous evaluation of environmental and economic performance metrics, allowing users to optimize both sustainability and profitability in their decision-making processes. Finally, an intelligent Chatbot interface will be developed to incorporate product-performance data from the SAFI consortium to provide real-time decision support and enhanced user accessibility specifically for tissue products applications.

CONCLUSIONS

1. Validation against published literature benchmarks for kraft pulping of eucalyptus, northern softwood, and bamboo confirmed the software's accuracy.
2. The validated software addresses a critical gap in current carbon accounting methodologies by enabling simultaneous assessment of twelve biomass types across economic and mass allocation methods while maintaining methodological consistency.
3. The carbon footprint software reduces the time and cost of environmental assessments compared to traditional methods.
4. Alkaline peroxide mechanical pulp (APMP) processes demonstrated high sensitivity to electricity sources, with wheat straw showing a difference of 1,072 kg CO_2eq/ADt

between hydropower and coal-based scenarios.

5. Renewable energy adoption for mechanical pulping operations is strongly recommended based on these findings.
6. Kraft pulping processes exhibited greater power self-sufficiency through black liquor combustion, with variations ranging from only 148 to 473 kg CO_2eq/ADt for northern bleached softwood kraft (NBSK) and bleached bamboo kraft (BBK) respectively.
7. Dedicated crops and woody biomasses, particularly switchgrass and eucalyptus, showed substantial sensitivity to soil organic carbon (SOC) factors, with potential swings exceeding 466 kg CO_2eq/ADt between stabilization scenarios.
8. The software capabilities empower the pulp industry to make evidence-based decisions about alternative fiber strategies, particularly relevant as environmental pressures and supply chain resilience concerns drive feedstock diversification.

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Conflict of Interest

The authors declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

REFERENCES CITED

Bare, J., Young, D., and Hopton, M. (2012). *Tool for the Reduction and Assessment of Chemical and Other Environmental Impacts (TRACI) TRACI version 2.1 User's Guide*, U.S. Environmental Protection Agency, Washington, D.C.

Bassil, Y. (2012). "A simulation model for the waterfall software development life cycle," *arXiv* 1205.6904. https://doi.org/10.48550/arXiv.1205.6904

Brock, E. K. (2022). *Costs and Benefits of Climate-Related Disclosure Activities by Corporate Issuers and Institutional Investors*, Sustainability Institute, ERM International Group Limited, London.

Ciroth, A. (2007). "ICT for environment in life cycle applications openLCA – A new open source software for Life Cycle Assessment," *International Journal of Life Cycle Assessment* 12, 209-210. https://doi.org/10.1065/lca2007.06.337

Dalton, A. (2024). "Q&A: Sustainability leaders on preparing for California's climate rules," *WSJ*, (https://deloitte.wsj.com/sustainable-business/q-a-sustainability-leaders-on-preparing-for-californias-climate-rules-7f41f600), accessed Sep. 4, 2025.

Finkbeiner, M., Inaba, A., Tan, R. B. H., Christiansen, K., and Klüppel, H. J. (2006). "The new international standards for life cycle assessment: ISO 14040 and ISO 14044," *International Journal of Life Cycle Assessment* 11, 80-85. https://doi.org/10.1065/lca2006.02.002

FisherSolve® (2025). "Carbon benchmarking," (https://www.resourcewise.com/solutions/carbon-benchmarking#:~:text=FisherSolve's%20Carbon%20Benchmarking%20Module%20provides,and%20identify%20areas%20for%20improvement), ResourceWise, Charlotte, NC, USA, accessed Feb. 17, 2025.

Forfora, N., Azuaje, I., Vivas, K. A., Vera, R. E., Brito, A., Venditti, R., Kelley, S., Tu, Q., Woodley, A., and Gonzalez, R. (2024). "Evaluating biomass sustainability: Why below-ground carbon sequestration matters," *Journal of Cleaner Production* 439, article 140677. https://doi.org/10.1016/j.jclepro.2024.140677

Forfora, N., Ortega, R., Urdaneta, I., Azuaje, I., Vivas, K., Jameel, H., Venditti, R., and Gonzalez, R. (2025). "Comparative life cycle assessment of bamboo-containing and wood-based hygiene tissue: Implications of fiber sourcing and conversion technologies," *Cleaner Environmental Systems* 19, article 100337. https://doi.org/10.1016/j.cesys.2025.100337

Fortune Business Insights (2025). *Carbon Accounting Software Market Size, Share & Industry Analysis, By Deployment (Cloud-based and On-premise), By Industry (Energy & Utilities, IT & Telecom, Healthcare, Transportation & Logistics, Retail, Construction & Infrastructure, Food & Beverages, Chemicals, and Others), and Country Forecast, 2024-2032*, (https://www.fortunebusinessinsights.com/carbon-accounting-software-market-107292), Maharashtra, India, accessed October 10, 2025.

Geraci, A. (1991). *IEEE Standard Computer Dictionary : A Compilation of IEEE Standard Computer Glossaries*, Institute of Electrical and Electronics Engineers, Piscataway, NJ, USA.

Gmünder, S., Zollinger, M., and Dettling, J. (2020). *Biogenic Carbon Footprint Calculator for Harvested Wood Products User Manual*, (https://files.worldwildlife.org/wwfcmsprod/files/Publication/file/4f39kysq67_Biogenic_Carbon_Footprint_Calculator_User_Manual_July2020_Quantis.pdf), Quantis, Boston, accessed October 10, 2025.

Hubau, W., Lewis, S. L., Phillips, O. L., *et al.* (2020). "Asynchronous carbon sink saturation in African and Amazonian tropical forests," *Nature,* 579, 80-87. https://doi.org/10.1038/s41586-020-2035-0

Khan, Y. (2024). "Disclosure isn't just about saving the planet, it's a business necessity now, says CDP chief," *WSJ*, (https://www.wsj.com/articles/disclosure-isnt-just-about-saving-the-planet-its-a-business-necessity-now-says-cdp-chief-5577aaa9), accessed Sep. 4, 2025.

Lan, K., Zhang, B., Lee, T., and Yao, Y. (2024). "Soil organic carbon change can reduce the climate benefits of biofuel produced from forest residues," *Joule* 8(2), 430-449. https://doi.org/10.1016/j.joule.2023.12.018

Lee, K.-M., and Inaba, A. (2004). *Life Cycle Assessment: Best Practices of ISO 14040 Series*, Center for Ecodesign and LCA (CEL), Ajou University, (https://www.apec.org/docs/default-source/Publications/2004/2/Life-Cycle-Assessment-Best-Practices-of-International-Organization-for-Standardization-ISO-14040-Ser/04_cti_scsc_lca_rev.pdf).

Lindell, J. (2025). "Carbon transparency: the overlooked competitive advantage," *Normative*, (https://normative.io/insight/carbon-transparency-the-overlooked-competitive-advantage), accessed Sep. 4, 2025.

Mansaray, K. G., and Ghaly, A. E. (1997). "Physical and thermochemical properties of rice husk," *Energy Sources* 19(9), 989-1004. https://doi.org/10.1080/00908319708908904

Microsoft (2018). ".NET Framework 4.7.2," (https://dotnet.microsoft.com/en-

us/platform/why-choose-dotnet), accessed Feb. 17, 2025.
Microsoft (2022). "Visual Studio," (https://visualstudio.microsoft.com/vs/), accessed Feb. 17, 2025.
Naishadham, S. (2024). "SEC approves rule requiring some companies to report greenhouse gas emissions. Legal challenges loom," *AP*, (https://apnews.com/article/climate-change-sec-disclosure-companies-emissions-risks-b5bb510f9167ef396ee2fbc5a02ba1cf), accessed Sep. 4, 2025.
National Council for Air and Stream Improvement, Inc. (NCASI) (2005). *Calculation Tools for Estimating Greenhouse Gas Emissions from Pulp and Paper Mills*, (https://ghgprotocol.org/sites/default/files/2023-03/Pulp_and_Paper_Guidance.pdf), Research Triangle, NC, USA.
NCASI (2024). "Footprint estimator of forest products," (https://www.ncasi.org/resource/footprint-estimator-for-forest-products/), accessed Sep. 4, 2025.
Ortega, R., Forfora, N., Urdaneta, I., Azuaje, I., Vivas, K. A., Vera, R. E., Franco, J., Frazier, R., Abbati, C., Saloni, D., Jameel, H., Venditti, R., and Gonzalez, R. (2024). "Life cycle assessment of Brazilian bleached eucalyptus kraft pulp: Integrating bleaching processes and biogenic carbon impacts," *Cleaner Environmental Systems* 15, article 100234. https://doi.org/10.1016/j.cesys.2024.100234
Royce, W. W. (1987). "Managing the development of large software systems," in: *Proceedings of the 9th International Conference on Software Engineering (ICSE '87)*, pp. 328-338, IEEE Computer Society Press, Washington, D.C.
Saavedra-Rubio, K., Thonemann, N., Crenna, E., Lemoine, B., Caliandro, P., and Laurent, A. (2022). "Stepwise guidance for data collection in the life cycle inventory (LCI) phase: Building technology-related LCI blocks," *Journal of Cleaner Production* 366, article 132903. https://doi.org/10.1016/j.jclepro.2022.132903
Schultz, T., and Suresh, A. (2018). *Life Cycle Impact Assessment Methodology for Environmental Paper Network Paper Calculator v4.0*, (https://c.environmentalpaper.org/pdf/SCS-EPN-PC-Methods.pdf), accessed October 10, 2025.
Seidl, R., Thom, D., Kautz, M., *et al.* (2017). "Forest disturbances under climate change," *Nature Clim Change*, 7, 395-402. https://doi.org/10.1038/nclimate3303
Smook, G. A. (2016). "Handbook for pulp & paper technologist, fourth Ed," *TAPPI Press*, Peachtree Corners, GA. (https://imisrise.tappi.org/TAPPI/Products/02/SMO/0202SMOOK4.aspx)
Statista. (2026). Tissue & Hygiene Paper – Worldwide. Statista. (https://www.statista.com/outlook/cmo/tissue-hygiene-paper/worldwide) accessed January 14, 2026.
Stechemesser, K., and Guenther, E. (2012). "Carbon accounting: A systematic literature review," *Journal of Cleaner Production* 36, 17-38. https://doi.org/10.1016/j.jclepro.2012.02.021
Stellman, A., and Greene, J. (2005). *Applied Software Project Management*, O'Reilly Media, Inc., Sebastopol, CA, USA.
United States-Mexico Foundation for Science (USMFS/FUMEC). (2006). *Guidelines for the Greenhouse Gas Calculation Tool for the Pulp and Paper Sector in Mexico*, Washington, D.C.
Urdaneta, F., Kumar, R., Marquez, R., Vera, R. E., Franco, J., Urdaneta, I., Saloni, D., Venditti, R. A., Pawlak, J. J., Jameel, H., and Gonzalez, R. W. (2024a). "Evaluating

chemi-mechanical pulping processes of agricultural residues: High-yield pulps from wheat straw for fiber-based bioproducts," *Industrial Crops and Products* 221, article 119379. https://doi.org/10.1016/j.indcrop.2024.119379
Urdaneta, F., Meza, L., Marquez, R., Franco, J., Vera, R.E., Urdaneta, I., Parrish, C., Saloni, D., Pawlak, J.J., Jameel, H., and Gonzalez, R. W. (2025). "Comparing the impacts of wood and APMP non-wood fibers on the properties of hygiene tissue paper," *Cellulose* 32, 5021-5034. https://doi.org/10.1007/s10570-025-06529-4
Urdaneta, I., Urdaneta, F., Vera, R. E., and Forfora, N. (2024b). "Evaluating key parameters for carbon footprint estimation of non-wood market pulp produced via mechanical pulping processes," in: *Tappicon24*, Cleveland, OH, USA.
Valmet (1990). "Valmet WinGEMS simulation," (https://www.valmet.com/automation/applications/process-optimization/pulp/wingems/), accessed October 10, 2025.
Vial, G. (2019). "Understanding digital transformation: A review and a research agenda," *Journal of Strategic Information Systems* 28(2), 118-144. https://doi.org/10.1016/j.jsis.2019.01.003
Vivas, K. A., Pifano, A., Vera, R. E., Urdaneta, F., Urdaneta, I., Forfora, N., Abbati de Assis, C., Phillips, R. B., Dasmohapatra, S., Saloni, D., Venditti, R. A., and Gonzalez, R. (2024). "Understanding the potential of bamboo fibers in the USA: A comprehensive techno-economic comparison of bamboo fiber production through mechanical and chemical processes," *Biofuels, Bioproducts and Biorefining* 18(5), 1565-1584. https://doi.org/10.1002/bbb.2652
"vpk." (2025). *VPK Group: Belgium*, (https://www.vpkgroup.com/en/news/vpk-group-launches-product-carbon-footprint-calculator), accessed Feb. 17, 2025.
Wernet, G., Bauer, C., Steubing, B., Reinhard, J., Moreno-Ruiz, E., and Weidema, B. (2016). "The ecoinvent database version 3 (Part I): Overview and methodology," *International Journal of Life Cycle Assessment* 21(9), 1218-1230. https://doi.org/10.1007/s11367-016-1087-8
Zargar, S., Yao, Y., and Tu, Q. (2022). "A review of inventory modeling methods for missing data in life cycle assessment," *Journal of Industrial Ecology* 26(5), 1676-1689. https://doi.org/10.1111/jiec.13305

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APPENDIX

The emissions of eucalyptus plantations in kg CO_2eq/BDt are estimated by Eq. S1,

$$E = \frac{3297.3+10.193*X}{Y*0.47} * 1.12 + 3.0571 + \left(2.44 * \frac{D}{13.2}\right) \quad \text{(S1)}$$

where E is emission (kg CO_2eq/BDt), X is nitrogen application (kg N/ha), Y is yield (m^3/ha), and D is transportation distance (km).

The emissions of northern softwood managed forest in kg CO_2eq/BDt are estimated using Eq. S2 considering economic allocation,

$$E = \left(\left(\frac{1095}{Y} + 18.5\right) * 3.053 + 75.88\right) * \frac{Prc}{Prc+(Pgl*1.61)} + \left(2.44 * \frac{D}{13.2}\right) \quad \text{(S2)}$$

where E is emission (kg CO_2eq/BDt), Y is yield (m^3/ha), Prc is price residual chips ($/BDt), Pgl is price green lumber ($/BDt), and D is transportation distance (km).

The emissions of northern softwood managed forest in kg CO_2eq/BDt are estimated using Eq. S3 considering mass allocation,

$$E = \left(\left(\frac{1095}{Y} + 18.5\right) * 3.053 + 75.88\right) * \frac{1}{1+1.61} + \left(2.44 * \frac{D}{13.2}\right) \quad \text{(S3)}$$

where E is emission (kg CO_2eq/BDt), Y is yield (m^3/ha), and D is transportation distance (km).

The emissions of natural bamboo forest in kg CO_2eq/BDt are estimated using Eq. S4,

$$E = \frac{(8.36+1.28*Y)*0.479}{Y*(1-0.15)} + 17.11 + \left(2.07 * \frac{D}{15}\right) \quad \text{(S4)}$$

where E is emission (kg CO_2eq/BDt), Y is yield (ton/ha/yr), and D is transportation distance (km).

The emissions of switchgrass plantations in kg CO_2eq/BDt are estimated using Eq. S5,

$$E = \frac{(2087.3+10*10.199*X)}{Y*(1-0.184)*10} + 6.75 + \left(2.07 * \frac{D}{15}\right) \quad \text{(S5)}$$

where E is emission (kg CO_2eq/BDt), X is nitrogen application (kg N/ha/yr), Y is yield (ton/ha/yr), and D is transportation distance (km).

The emissions of sorghum plantations in kg CO_2eq/BDt are estimated using Eq. S6,

$$E = \frac{(375.89+10.187*X)}{Y*(1-0.16)} + 6.47 + \left(2.07 * \frac{D}{15.5}\right) \quad \text{(S6)}$$

where E is emission (kg CO_2eq/BDt), X is nitrogen application (kg N/ha/yr), Y is yield (ton/ha/yr), and D is transportation distance (km).

The emissions of rice husk in kg CO_2eq/BDt are estimated using Eq. S7 considering economic allocation,

$$E = \left(\left(\left(\left(\left(\frac{6.4939*X+1018.4+27.124*RSIF*(1-0.08)-0.0084+\left(\left(160*1.586*\left((1+0.29*RSR*(1-0.08))^{0.59}\right)\right)*25\right)}{Y*(1-0.2)}\right)*\left(\frac{PRG*Y}{PRG*Y+PRS*RSR}\right)\right)+5.72\right)*5+356.2\right)*\left(\left(PRH*\frac{0.2}{(PRH*0.2)+(PWG*0.7)+(PRB*0.1)}\right)\right)+3.28+\left(2.07*\frac{D}{10.3}\right) \quad \text{(S7)}$$

where E is emission (kg CO_2eq/BDt), X is nitrogen application (kg/ha), $RSIF$ is rice straw incorporated in field (ton/ha), RSR is rice straw removed (ton/ha), Y is rough grain yield (ton/ha), PRG is price rough grain ($/ton), PRS is price rice straw ($/ton), PRH is price rice husk ($/ton), PWG is price wheat grain ($/ton), PRB is price rice bran ($/ton), and D is transportation distance (km).

The emissions of rice husk in kg CO_2eq/BDt are estimated using Eq. S8 considering mass allocation,

$$E = \left(\left(\left(\left(\left(\frac{6.4939*X+1018.4+27.124*RSIF*(1-0.08)-0.0084+\left(\left(160*1.586*\left((1+0.29*RSR*(1-0.08))^{0.59}\right)\right)*25\right)}{Y*(1-0.2)}\right)*\left(\frac{Y*(1-0.2)}{Y*(1-0.2)+RSR*(1-0.08)}\right)\right)+5.72\right)*5+356.2\right)*(0.2)+3.28+\left(2.07*\frac{D}{10.3}\right) \quad \text{(S8)}$$

where E is emission (kg CO_2eq/BDt), X is nitrogen application (kg/ha), $RSIF$ is rice straw incorporated in field (ton/ha), RSR is rice straw removed (ton/ha), Y is rough grain yield (ton/ha), and D is transportation distance (km).

The emissions of hemp hurd in kg CO_2eq/BDt are estimated using Eq. S9 considering economic allocation,

$$E = \left(\left(\frac{11.459*X+548.78}{Y*(1-0.13)}\right)*1.66+97.89\right)*\left(0.6*\frac{PHH}{0.3*PHB+0.6*PHH}\right)+4.46+\left(2.07*\frac{D}{12}\right) \quad \text{(S9)}$$

where X is nitrogen application (kg/ha/yr), Y is hemp fiber yield (ton/ha/yr), PHH is price hemp hurd ($/ton), PHB is price hemp bast ($/ton), and D is transportation distance (km).

The emissions of hemp hurd in kg CO_2eq/BDt are estimated using Eq. S10 considering mass allocation,

$$E = \left(\left(\frac{11.459*X+548.78}{Y*(1-0.13)}\right)*1.66+97.89\right)*0.667+4.46+\left(2.07*\frac{D}{12}\right) \quad \text{(S10)}$$

where X is nitrogen application (kg/ha/yr), Y is hemp fiber yield (ton/ha/yr), and D is transportation distance (km).

The emissions of sugarcane bagasse in kg CO_2eq/BDt are estimated using Eq. S11 considering economic allocation,

$$E = \left(\left(\frac{10.177*X+2686.3}{Y*(1-0.7)}+13.12\right)*14.12+45.17\right)*\left(\frac{PSB}{PSB+5.42*PRS+2.06*PM}\right)*1.44+38.3+11+\left(2.07*\frac{D}{6.2}\right) \quad \text{(S11)}$$

where X is nitrogen application (kg/ha/yr), Y is sugarcane yield (ton/ha/yr), PSB is price surplus bagasse ($/BDt), PRS is price raw sugar ($/ton), PM is price molasses ($/ton), and D is transportation distance (km).

The emissions of sugarcane bagasse in kg CO_2eq/BDt are estimated using Eq. S12 considering mass allocation,

$$E = \left(\left(\frac{10.177*X+2686.3}{Y*(1-0.7)}+13.12\right)*14.12+45.17\right)*\left(\frac{1}{1+5.42+2.06}\right)*1.44+38.3+11+\left(2.07*\frac{D}{6.2}\right) \quad \text{(S12)}$$

where X is nitrogen application (kg/ha/yr), Y is sugarcane yield (ton/ha/yr), and D is transportation distance (km).

The emissions of wheat straw in kg CO_2eq/BDt are estimated using Eq. S13 considering economic allocation,

$$E = \left(\frac{(10.285*X+389.56)+(78.502*(WSR*(1-0.098))+0.0638)}{WSR*(1-0.098)}\right)*\left(\frac{WSR*PS}{WSR*PS+Y*PWG}\right)+5.18+\left(2.07*\frac{D}{10.6}\right) \quad \text{(S13)}$$

where X is nitrogen application (kg/ha), WSR is wheat straw removed (ton/ha), PS is price straw ($/BDt), Y is wheat grain yield (ton/ha), PWG is price wheat grain ($/ton), and D is transportation distance (km).

The emissions of wheat straw in kg CO_2eq/BDt are estimated using Eq. S14 considering mass allocation,

$$E = \left(\frac{(10.285*X+389.56)+(78.502*(WSR*(1-0.098))+0.0638)}{WSR*(1-0.098)}\right)*\left(\frac{WSR*(1-0.098)}{WSR*(1-0.098)+Y*(1-0.15)}\right)+5.18+\left(2.07*\frac{D}{10.6}\right) \quad \text{(S14)}$$

where X is nitrogen application (kg/ha), WSR is wheat straw removed (ton/ha), Y is wheat grain yield (ton/ha), and D is transportation distance (km).

The emissions of rice straw in kg CO_2eq/BDt are estimated using Eq. S15 considering economic allocation,

$$E = \left(\frac{(6.4939*X+1018.4)+\left(\left(160*1.586*\left((1+0.29*RSIF*(1-0.08))^{0.59}\right)\right)*25\right)+(27.124*RSR*(1-0.08)-0.0084)}{RSR*(1-0.08)}\right)* \left(\left(\frac{RSR*PRS}{RSR*PRS+Y*PRG}\right)\right)+5.98+\left(2.07*\frac{D}{10.3}\right) \quad \text{(S15)}$$

where E is emission (kg CO_2eq/BDt), X is nitrogen application (kg/ha), $RSIF$ is rice straw incorporated in field (ton/ha), RSR is rice straw removed (ton/ha), Y is rough grain yield (ton/ha), PRG is price rough grain (\$/ton), PRS is price rice straw (\$/ton), PRH is price rice husk (\$/ton), PWG is price wheat grain (\$/ton), PRB is price rice bran (\$/ton), and D is transportation distance (km).

The emissions of rice straw in kg CO_2eq/BDt are estimated using Eq. S16 considering mass allocation,

$$E = \left(\frac{(6.4939*X+1018.4)+\left(\left(160*1.586*\left((1+0.29*RSIF*(1-0.08))^{0.59}\right)\right)*25\right)+(27.124*RSR*(1-0.08)-0.0084)}{RSR*(1-0.08)}\right)* \left(\left(\frac{RSR*(1-0.08)}{RSR*(1-0.08)+Y*(1-0.2)}\right)\right)+5.98+\left(2.07*\frac{D}{10.3}\right) \quad \text{(S16)}$$

where E is emission (kg CO_2eq/BDt), X is nitrogen application (kg/ha), $RSIF$ is rice straw incorporated in field (ton/ha), RSR is rice straw removed (ton/ha), Y is rough grain yield (ton/ha), and D is transportation distance (km).

The emissions of banana fiber in kg CO_2eq/BDt are estimated using Eq. S17 considering economic allocation,

$$E = \left(\frac{10.199*X+2892.3}{FP*(1-0.1)}\right)*\left(\frac{FP*PBF}{PBF*FP+FrP*PFr}\right)+6.12+\ 0.1717*1.11*D \quad \text{(S17)}$$

where E is emission (kg CO_2eq/BDt), X is nitrogen application (kg/ha/yr), FP is fiber production (ton/ha/yr), PBF is price banana fiber (\$/ton), FrP is fruit production (ton/ha/yr), PFr is price fruit (\$/ton), and D is transportation distance (km).

The emissions of banana fiber in kg CO_2eq/BDt are estimated using Eq. S18 considering mass allocation,

$$E = \left(\frac{10.199*X+2892.3}{FP*(1-0.1)}\right)*\left(\frac{FP*(1-0.1)}{FP*(1-0.1)+FrP*(1-0.7366)}\right)+6.12+\ 0.1717*1.11*D \quad \text{(S18)}$$

where E is emission (kg CO_2eq/BDt), X is nitrogen application (kg/ha/yr), FP is fiber production (ton/ha/yr), FrP is fruit production (ton/ha/yr), and D is transportation distance (km).

The emissions of ryegrass straw in kg CO_2eq/BDt are estimated using Eq. S19 considering economic allocation,

$$E = \left(\frac{12.683*X+307.24}{RSR*(1-0.13)}\right)*\left(\frac{PRS*RSR}{PRS*RSR+PG*Y}\right)+6.25+\ 2.07*\frac{D}{15.6} \quad \text{(S19)}$$

where X is nitrogen application (kg/ha/yr), RSR is ryegrass straw removed (ton/ha/yr),

PRS is price ryegrass straw (\$/ton), Y is ryegrass grain yield (ton/ha/yr), PG is price grain (\$/ton), and D is transportation distance (km).

The emissions of ryegrass straw in kg CO_2eq/BDt are estimated using Eq. S20 considering mass allocation,

$$E = \left(\frac{12.683*X+307.24}{RSR*(1-0.13)}\right)*\left(\frac{RSR*(1-0.13)}{RSR*(1-0.13)+Y*(1-0.425)}\right)+6.25+\ 2.07*\frac{D}{15.6} \quad \text{(S20)}$$

where X is nitrogen application (kg/ha/yr), RSR is ryegrass straw removed (ton/ha/yr), Y is ryegrass grain yield (ton/ha/yr), and D Transportation distance (km).

The SOC sequestration potential was included for each biomass, considering the morphological properties of each cultivar, following the methodology developed by (Forfora *et al.* 2024), which is described in equations S21 to S23, as follows,

$$C_{R\_PP} = AGB * RSR * X_C * X_{PP} \quad \text{(S21)}$$

$$Total\ C_{input} = \sum_1^n C_{input_i} = \sum_1^n C_{R_{PP_i}} * S_{R_i} + C_{E_{PP_i}} * S_{E_i} \quad \text{(S22)}$$

$$C_{input} = \frac{Total\ C_{input}}{Rotation\ time} \quad \text{(S23)}$$

where C_{R_PP} is carbon in coarse roots (ton C/ha), AGB is aboveground biomass (ton C/ha), RSR is root-to-shoot ratio (dimensionless), X_C is carbon mass fraction (dimensionless), X_{pp} is allocation factor (dimensionless), $Total\ C_{input}$ is total carbon input to soil (ton C/ha), n is rotation time, i is iteration index, S_{R_i} is fraction of the coarse roots that are returned to the soil=1 (dimensionless), $C_{E_{ppi}}$ is carbon associated with rhizodeposition of extra roots = 0.65*C_{R_PP} (ton C/ha), S_{E_i} is fraction of the extra roots that are returned to the soil=1 (dimensionless), and C_{input} is total carbon input normalized by year (ton C/ha.yr).

Table S1. Economic and Mass Allocation Factors of Biomass Used

Biomass	Economic allocation factor	Mass allocation factor
Eucalyptus	-	-
Northern softwood	0.18	0.38
Bamboo	-	-
Switchgrass	-	-
Sorghum	-	-
Rice husk	0.02	0.72
Hemp hurd	0.23	0.68
Sugarcane bagasse	0.04	0.19
Wheat straw	0.13	0.43
Rice straw	0.07	0.33
Banana fiber	0.38	0.47
Ryegrass straw	0.14	0.82

Table S2. Inputs to the Carbon Footprint Software to Produce one BDt of Biomass from Tree Plantations (Eucalyptus) (Ortega *et al.* 2024) and Natural Forests (Northern Softwood and Natural Bamboo Stands) (Forfora *et al.* 2025)

Functional Unit: 1 BDt of biomass				
	Unit	**Eucalyptus**	**Northern softwood**	**Bamboo**
Inputs				
Nitrogen application	kg/ha	70.6	0	0
Yield	m^3/ha	256.2	335	0
Yield	ton/ha/yr	0	0	4.8
Price Residual Chips	$/BDt	0	118	0
Price Green Lumber	$/BDt	0	325	0
Transportation distance	km	61.2	100	65
Outputs				
Biomass	BDt	1	1	1

Table S3. Inputs to the Carbon Accounting Software to Produce one BDt of Biomass from Dedicated Crops (Switchgrass, Sorghum) and Agro-industrial Residues (Rice Husk, Hemp Hurd, and Sugarcane Bagasse) (Forfora *et al.* 2024)

Functional Unit: 1 BDt of biomass						
	Unit	**Switchgrass**	**Sorghum**	**Rice**	**Hemp**	**Sugarcane**
Inputs						
Nitrogen application	kg/ha/yr	69.5	140.5	207	92.8	196.4
Yield	ton/ha/yr	11.9	15.9	0	11.9	76.4
Rice straw removed	ton/ha	0	0	3.85	0	0
Rice straw incorporated into the field	ton/ha	0	0	3.85	0	0
Rough grain yield	ton/ha	0	0	9	0	0
Price rough grain	$/ton	0	0	308	0	0
Price rice straw	$/ton	0	0	54.7	0	0
Price rice husk	$/ton	0	0	7	0	0
Price white grain	$/ton	0	0	616	0	0
Price rice bran	$/ton	0	0	191	0	0
Price hemp bast	$/ton	0	0	0	1,190	0
Price hemp hurd	$/ton	0	0	0	168	0
Price raw sugar	$/ton	0	0	0	0	352
Price molasses	$/ton	0	0	0	0	220
Price surplus bagasse	$/BDt	0	0	0	0	44
Transportation distance	km	75	50	40	120	20
Outputs						
Biomass	BDt	1	1	1	1	1

Table S4. Inputs to the Carbon Accounting Software to Produce one BDt of Biomass from Agricultural Residues (Wheat Straw, Rice Straw, Banana Fiber, and Ryegrass Straw) (Forfora *et al.* 2024)

Functional Unit: 1 BDt of biomass					
	Unit	**Wheat**	**Rice**	**Banana**	**Ryegrass**
Inputs					
Nitrogen application	kg/ha/yr	86.4	207	358.8	86.9
Grain yield	ton/ha/yr	4.76	0	0	1.91
Wheat straw removed	ton/ha	3.27	0	0	0
Percentage straw removed	%	50	0	0	0
Price wheat grain	$/ton	256.7	0	0	0
Price straw	$/ton	52.8	0	0	0
Rice straw removed	ton/ha	0	3.85	0	0
Rice straw incorporated into the field	ton/ha	0	3.85	0	0
Rough grain yield	ton/ha	0	9	0	0
Price rough grain	$/ton	0	308	0	0
Price rice straw	$/ton	0	54.7	0	0
Fiber production	ton/ha/yr	0	0	14.9	0
Fruit production	ton/ha/yr	0	0	60	0
Price banana fiber	$/ton	0	0	1,000	0
Price fruit	$/ton	0	0	420	0
Ryegrass straw removed	ton/ha/yr	0	0	0	4.94
Percentage of straw removed	%	0	0	0	50
Price grain	$/ton	0	0	0	694.4
Price ryegrass straw	$/ton	0	0	0	35.7
Transportation distance	km	120	64.3	40	195
Outputs					
Biomass	BDt	1	1	1	1

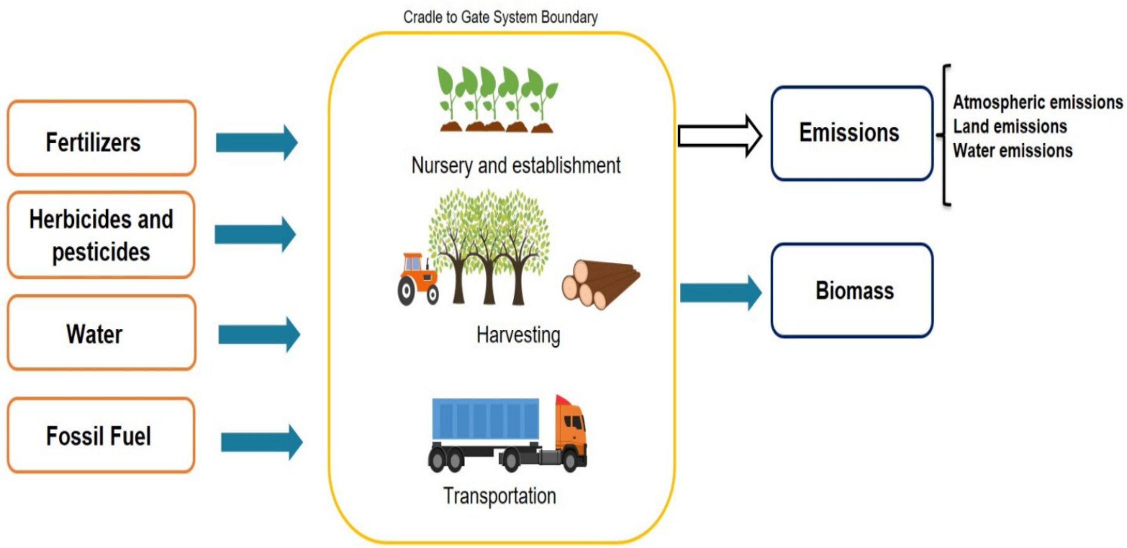

Fig. S1. System boundary for biomass cultivation (Forfora *et al.* 2024)

Table S5. LCI of Inputs to Produce one ADt of Market Pulp from Natural Forest (Bamboo), Dedicated Crops (Switchgrass and Sorghum), Agro-industrial Residues (Rice Husk, Hemp Hurd, and Sugarcane Bagasse), and Agricultural Residues (Wheat Straw, Rice Straw, Banana Fiber, and Ryegrass Straw) using the APMP Process (Urdaneta *et al.* 2024b)

Functional Unit: 1 ADt of market pulp (sold at 90% consistency)							
Process: APMP							
	Unit/ ADt	Wheat straw	Hemp hurd	Switchgrass	Sorghum	Bamboo	Other
Inputs							
Process yield	%	75.3	79.8	75.5	71.6	75.9	75
NaOH	kg	70.2	70.2	70.2	70.2	70.2	70.2
H_2O_2	kg	70.2	70.2	70.2	70.2	70.2	70.2
DTPA	kg	5.8	5.8	5.8	5.8	5.8	5.8
Natural gas	m^3	142	142	142	142	142	142
Purchased electricity	kWh	875	875	875	875	875	875
Outputs							
Pulp fiber	ADt	1	1	1	1	1	1

Other: Rice straw, rice husk, sugarcane bagasse, banana fiber, ryegrass straw
DTPA: Diethylene-triaminepentaacetic acid

Table S6. Ecoinvent Unit Processes Selected for Each Inputs to Produce One ADt of Market Pulp from Natural Forest (Bamboo), Dedicated Crops (Switchgrass and Sorghum), Agro-industrial Residues (rice husk, hemp hurd, and sugarcane bagasse), and Agricultural Residues (Wheat Straw, Rice Straw, Banana Fiber, and Ryegrass Straw) using the APMP Process (Urdaneta *et al.* 2024b)

Ecoinvent unit process	APMP (USA)
NaOH	Market for sodium hydroxide, without water, in 50% solution state | sodium hydroxide, without water, in 50% solution state | Cutoff, U – Global
H_2O_2	Market for hydrogen peroxide, without water, in 50% solution state | hydrogen peroxide, without water, in 50% solution state | Cutoff, U – RoW
DTPA	Market for DTPA, diethylenetriaminepentaacetic acid | DTPA, diethylenetriaminepentaacetic acid | Cutoff, U – RoW
Natural gas	Market for natural gas, high pressure | natural gas, high pressure | Cutoff, U - US
Purchased electricity	Electricity, high voltage, production mix | electricity, high voltage | Cutoff, U – SERC

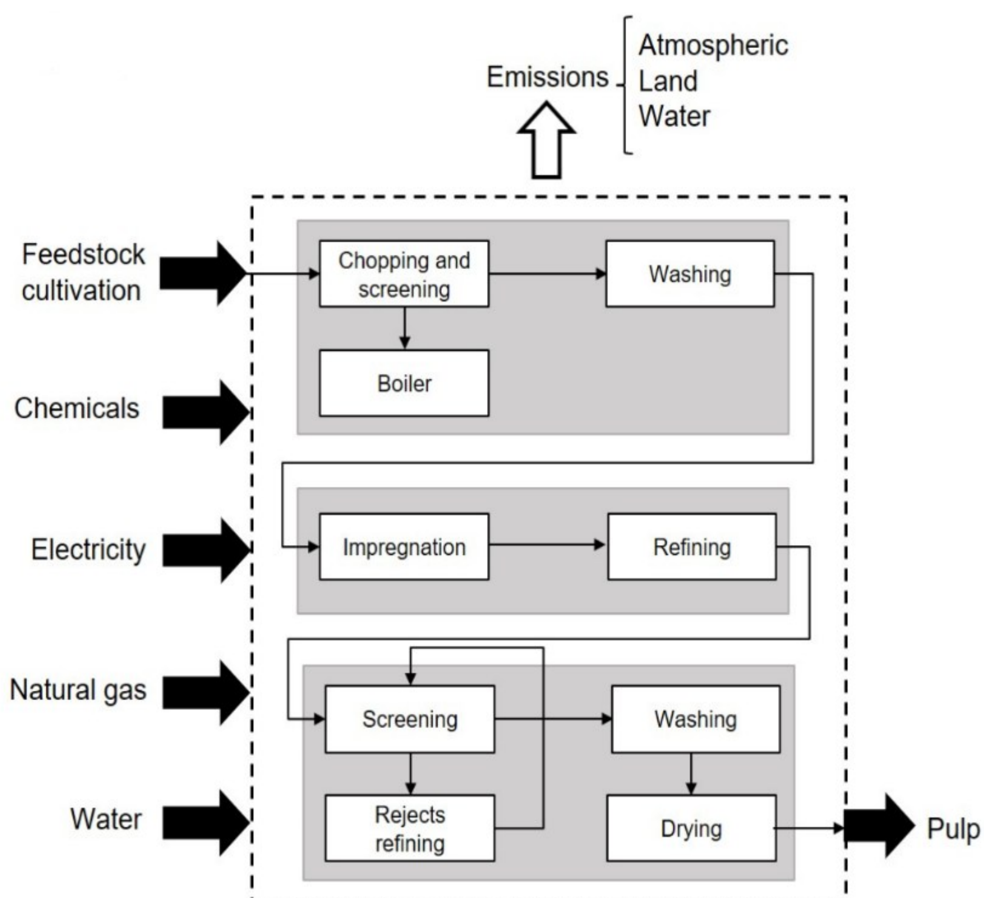

Fig. S2. System boundary for APMP process (Urdaneta *et al.* 2024b)

Table S7. LCI of Inputs to Produce one ADt of Market Pulp from Tree Plantations (Eucalyptus) (Ortega *et al.* 2024) and Natural Forests (Northern Softwood and Bamboo) using a Kraft Pulping Process (Forfora *et al.* 2025)

Functional Unit: 1 ADt of market pulp (sold at 90% consistency)				
	Unit/ADt	**BEK (Brazil)**	**NBSK (Canada)**	**BBK (China)**
Inputs				
Biomass	kg	2,120	2,400	2,440
Woodwaste	kg	155	73.6	0
NaOH	kg	20.25	40.2	26.8
Na_2SO_4	kg	0	0.8	2
H_2O_2	kg	6.40	1.9	1.8
CaO	kg	14.5	18.7	18.1
$NaClO_3$	kg	15.8	38.2	21
Cl_2	kg	1.16	0	0
CH_3OH	kg	1.65	3.7	2.2
O_2	kg	30.7	24.6	35.8
H_2SO_4	kg	10.2	28	15.3
$MgSO_4$	kg	1.63	1.9	1.9
Natural gas	m^3	32.7	96.1	22.6
Biogas	m^3	4.45	0	0
Fuel oil number 6	kg	21.4	3.6	21.1
Fuel oil number 2	kg	2.28	0	0
Coal	kg	23.7	5.92	0
Purchased electricity	kWh	0	122.5	386.6
Outputs				
Pulp fiber	ADt	1	1	1

BEK: Bleached Eucalyptus Kraft, NBSK: Northern Bleached Softwood Kraft, BBK: Bleached Bamboo Kraft

Table S8. Ecoinvent Unit Processes Selected for Each Process of Inputs to Produce One ADt of Market Pulp from Tree Plantations Eucalyptus) (Ortega *et al.* 2024) and Natural Forests (Northern Softwood and Bamboo) using a Kraft Pulping Process (Forfora *et al.* 2025)

Ecoinvent unit process	BEK (Brazil)	NBSK (Canada)	BBK (China)
NaOH	Market for sodium hydroxide, without water, in 50% solution state | sodium hydroxide, without water, in 50% solution state | Cutoff, U - Global	Market for sodium hydroxide, without water, in 50% solution state | sodium hydroxide, without water, in 50% solution state | Cutoff, U - Global	Market for sodium hydroxide, without water, in 50% solution state | sodium hydroxide, without water, in 50% solution state | Cutoff, U - GLO
Na_2SO_4	-	Market for sodium sulfate, anhydrite | sodium sulfate, anhydrite | Cutoff, U - RoW	Market for sodium sulfate, anhydrite | sodium sulfate, anhydrite | Cutoff, U - RoW
H_2O_2	Market for hydrogen peroxide, without water, in 50% solution state | hydrogen peroxide, without water, in 50% solution state | Cutoff, U - RoW	Market for hydrogen peroxide, without water, in 50% solution state | hydrogen peroxide, without water, in 50% solution state | Cutoff, U - RoW	Market for hydrogen peroxide, without water, in 50% solution state | hydrogen peroxide, without water, in 50% solution state | Cutoff, U - RoW
CaO	Market for quicklime, milled, packed | quicklime, milled, packed | Cutoff, U - RoW	Market for quicklime, milled, packed | quicklime, milled, packed | Cutoff, U - RoW	Market for quicklime, milled, packed | quicklime, milled, packed | Cutoff, U - RoW
$NaClO_3$	Market for sodium chlorate, powder | sodium chlorate, powder | Cutoff, U - RoW	Market for sodium chlorate, powder | sodium chlorate, powder | Cutoff, U - RoW	Market for sodium chlorate, powder | sodium chlorate, powder | Cutoff, U - RoW
Cl_2	Market for chlorine, gaseous | chlorine, gaseous | Cutoff, U - RoW	-	-
CH_3OH	Market for methanol | methanol | Cutoff, U - Global	Market for methanol | methanol | Cutoff, U - GLO	Market for methanol | methanol | Cutoff, U - GLO
O_2	Market for oxygen, liquid | oxygen, liquid | Cutoff, U - RoW	Market for oxygen, liquid | oxygen, liquid | Cutoff, U - RoW	Market for oxygen, liquid | oxygen, liquid | Cutoff, U - RoW
H_2SO_4	Market for sulfuric acid | sulfuric acid | Cutoff, U - RoW	Market for sulfuric acid | sulfuric acid | Cutoff, U - RoW	Market for sulfuric acid | sulfuric acid | Cutoff, U - RoW
$MgSO_4$	Market for magnesium sulfate | magnesium sulfate | Cutoff, U - Global	Market for magnesium sulfate | magnesium sulfate | Cutoff, U - Global	Market for magnesium sulfate | magnesium sulfate | Cutoff, U - Global
Natural gas	Market for natural gas, high pressure | natural gas, high pressure | Cutoff, U - RoW	Market group for natural gas, high pressure | natural	Market for natural gas, high pressure | natural gas, high

		gas, high pressure | Cutoff, U - CA	pressure | Cutoff, U - RoW
Biogas	Treatment of biowaste by anaerobic digestion | biogas | Cutoff, U - RoW	-	-
Fuel oil number 6	Market for heavy fuel oil | heavy fuel oil | Cutoff, U - RoW	Market for heavy fuel oil | heavy fuel oil | Cutoff, U - RoW	Market for heavy fuel oil | heavy fuel oil | Cutoff, U - RoW
Fuel oil number 2	Market for heavy fuel oil | heavy fuel oil | Cutoff, U - RoW	-	-
Coal	Market for hard coal | hard coal | Cutoff, U - RoW	Market for hard coal | hard coal | Cutoff, U - RoW	Market for hard coal | hard coal | Cutoff, U - CN
Purchased electricity	-	64.2 kWh electricity, high voltage, production mix | electricity, high voltage | Cutoff, U - CA-BC 4.8 kWh electricity, high voltage, production mix | electricity, high voltage | Cutoff, U - CA-NB 22.6 kWh electricity, high voltage, production mix | electricity, high voltage | Cutoff, U - CA-ON 16 kWh electricity, high voltage, production mix | electricity, high voltage | Cutoff, U - CA-AB 14.9 kWh electricity, high voltage, production mix | electricity, high voltage | Cutoff, U - CA-QC	207.4 kWh electricity, high voltage, production mix | electricity, high voltage | Cutoff, U - CN-SC 55 kWh electricity, high voltage, production mix | electricity, high voltage | Cutoff, U - CN-CQ 124.2 kWh electricity, high voltage, production mix | electricity, high voltage | Cutoff, U - CN-GZ

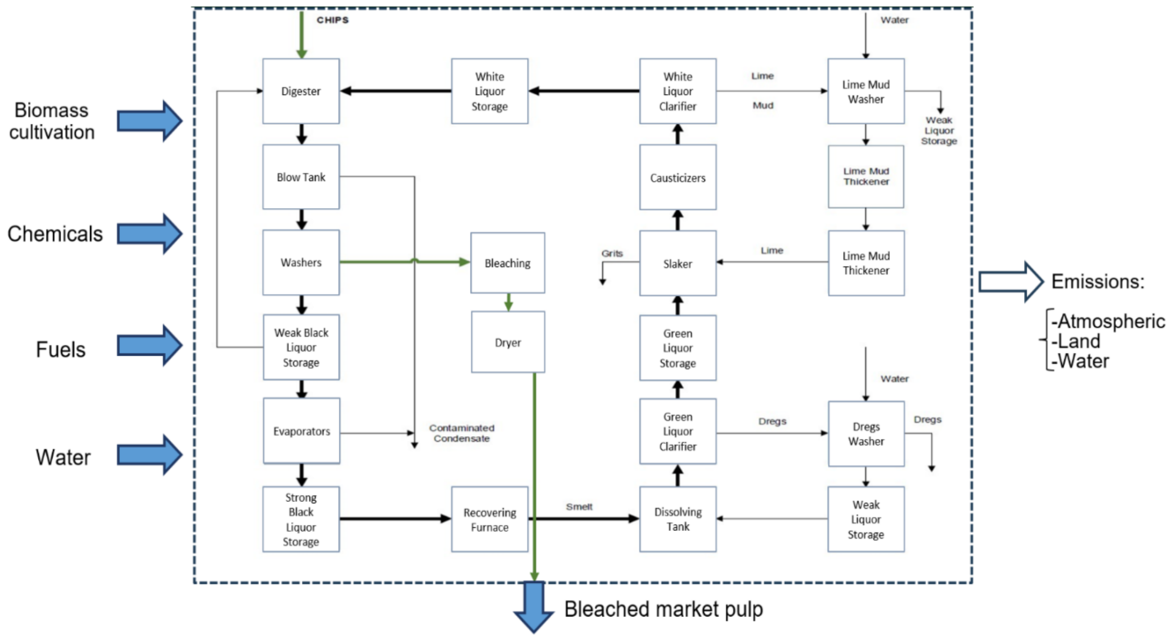

Fig. S3. System boundary for eucalyptus kraft pulping process (Ortega *et al.* 2024)

Table S9. Average Root-to-Shoot Ratios of Biomasses and Soil Carbon Stabilization Factor (Forfora *et al.* 2024)

Biomass	Root-to-shoot ratio	Soil carbon stabilization factor over 100 years (%)
Eucalyptus	0.21	15
Northern softwood	0.32	
Bamboo natural forest	0.46	
Switchgrass	1.5	
Sorghum	0.353	
Rice husk	0.14	
Hemp hurd	0.18	
Sugarcane bagasse	0.16	
Wheat straw	0.21	
Rice straw	0.14	
Banana fiber	0.11	
Ryegrass straw	0.322	

Table S10. Energy Regions Considered in the Carbon Footprint Software (Ortega *et al.* 2024; Urdaneta *et al.* 2024b; Forfora *et al.* 2025)

Country	Grid region
USA	WECC
	MRO
	RF
	TEXAS RE
	NPCC
	SERC
Brazil	Northern
	North-eastern
	Mid-eastern
	South-eastern
	Southern
Chile	Country average
China	Country average
Portugal	Country average
Uruguay	Country average
Canada	Country average

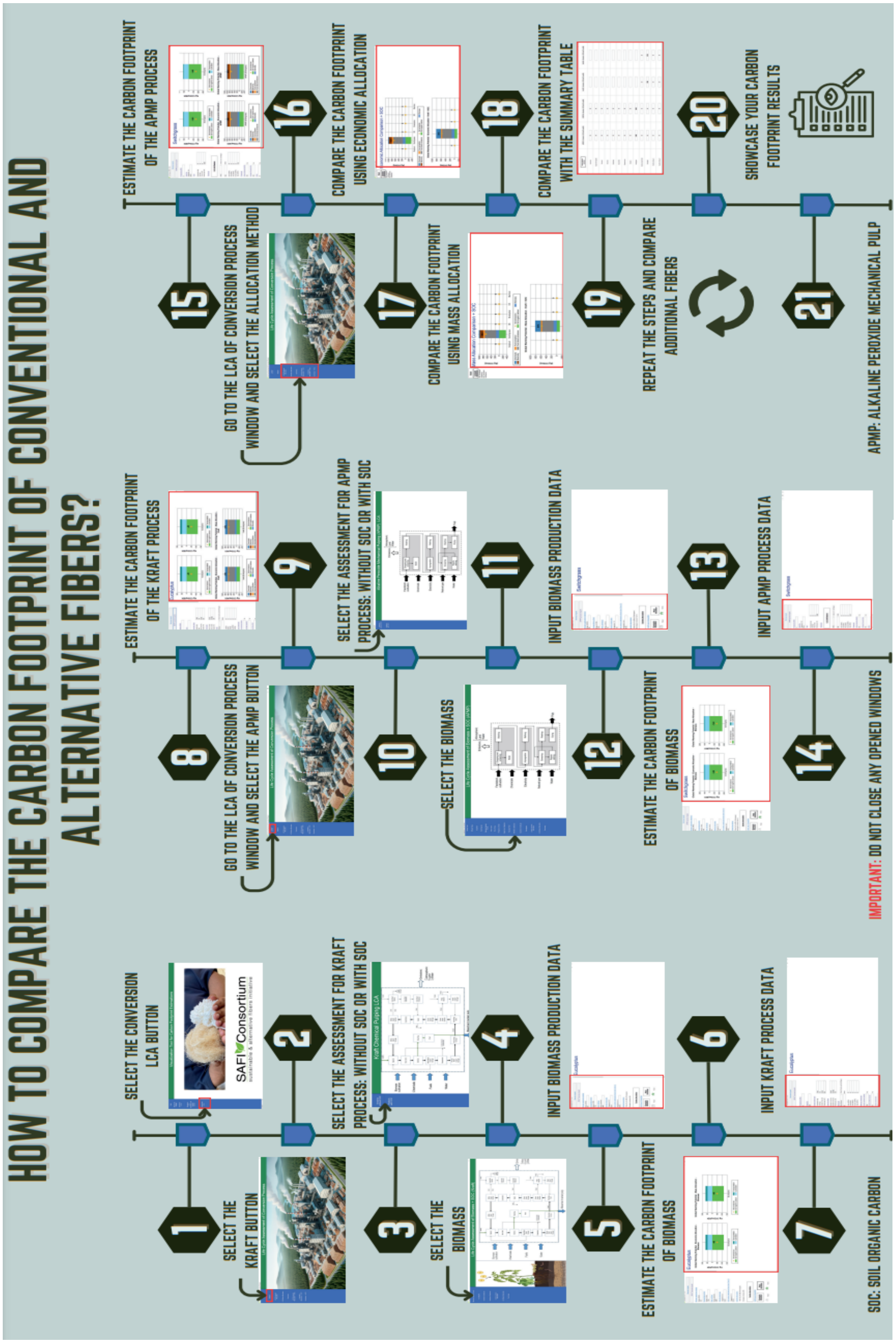

Fig. S4. Software user manual

Table S11. Scenario Exploration of Carbon Footprint for Kraft Pulping and APMP Processes Under Different Electricity Sources Using Economic Allocation

Process	Carbon footprint impact from hydropower (kg CO_2eq/ADt)	Carbon footprint impact from coal energy (kg CO_2eq/ADt)
NBSK	-19	129
BBK	-197	276
APMP	-449	623

Table S12. Scenario Exploration of the Carbon Footprint for Kraft Pulping and APMP Processes under Different Soil Carbon Stabilization Factors Using Economic Allocation

Biomass category (process type)	Biomass	5% soil carbon stabilization factor (kg CO_2eq/ADt)	25% soil carbon stabilization factor (kg CO_2eq/ADt)
Agro-industrial residue (APMP)	Rice husk	2	-1
Agricultural residue (APMP)	Rice straw	7	-6
Agro-industrial residue (APMP)	Sugarcane bagasse	14	-14
	Hemp hurd	20	-20
Agricultural residue (APMP)	Ryegrass straw	30	-30
	Wheat straw	30	-31
	Banana fiber	47	-46
Natural forest (APMP)	Bamboo	80	-80
Dedicated crop (APMP)	Sorghum	141	-141
Natural forest (Kraft pulping)	Bamboo	149	-149
	Northern softwood	156	-156
Tree plantation (Kraft pulping)	Eucalyptus	165	-165
Dedicated crop (APMP)	Switchgrass	233	-233