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Fermentelligence – Can AI-optimised fermentation of agri-food side streams deliver the sustainable protein promise?

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Meeting rising global protein demand within planetary boundaries necessitates a shift towards more resilient, circular production models. Fermentation of agri-food side streams offers a promising land-light alternative with possible economic benefits but must overcome significant barriers such as feedstock variability, distributed supply chains, and safety. This article proposes Fermentelligence (AI-optimised fermentation) as the critical enabler to unlock this potential. The article presents how machine learning and digital technologies can manage system-wide variance by highlighting key recent work in this area; including optimising complex feedstock blends, real-time process control, and economic and sustainability-aware decision-making. Furthermore, it highlights the strategic importance of decentralised regional hubs and the retrofitting of legacy assets, such as breweries and wineries, to lower capital costs. Finally, the article outlines a de-risking roadmap emphasising open data ecosystems, food safety evidence, and pilot demonstrations to accelerate the transition from linear agriculture to a flexible, AI-optimised circular bioeconomy.

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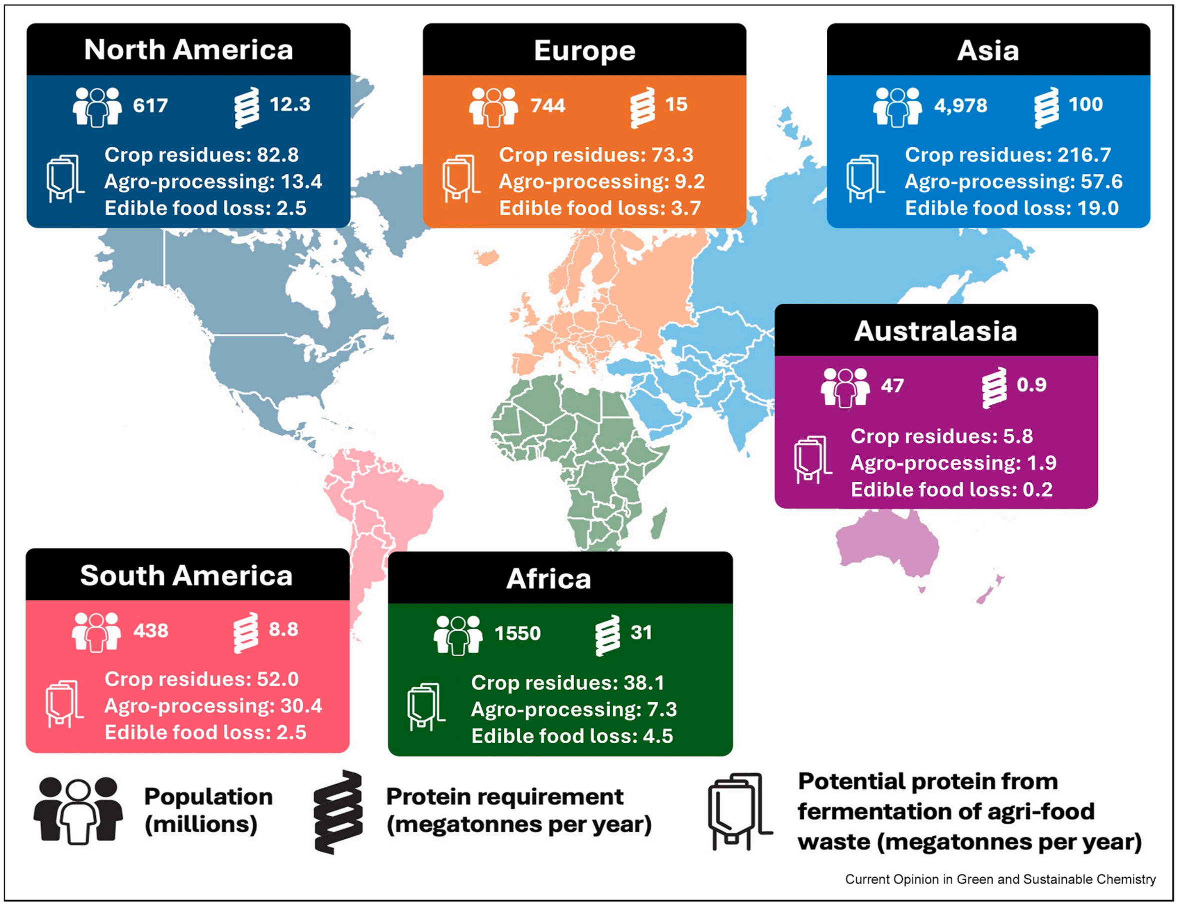
Introduction

Global protein demand is expected to rise substantially, driven by population growth, urbanisation, and income-linked dietary shifts. A Europe-focused synthesis of fermentation's role in the protein transition anticipates around a 45% growth in global food demand from 2010 to 2050 and expects protein consumption to follow [1–3]. Policy projections under assumptions of continued economic growth suggest large increases in animal-sourced protein consumption, especially in emerging economies, to 2050 (for example, a 57% increase for meat and 48% for dairy), reinforcing the need for alternative and more resilient protein sources [4]. The urgency is amplified by the scale of current impacts: the global food system is linked to a large share of annual greenhouse gas emissions, land use change (direct or indirect changes in land occupation or conversion linked to food production), and water usage, along with substantial food loss and waste that could be redirected into circular valorisation routes [5]. Microbial protein (Single-Cell Protein, SCP) produced by yeasts, bacteria, fungi, or microalgae has a distinct scaling logic: agriculture scales with land area and is seasonal, while fermentation scales volumetrically and can run continuously or semi-continuously with short residence times [5]. Fermentation-derived proteins can strengthen resilience to shocks by enabling local, land-light production [6], with initial modelling demonstrating the potential of the approach to meet the protein demands across all continents (Figure 1) with the key side streams being crop residues (e.g., straw), those arising during agro-processing (e.g., bagasse), and edible food loss (e.g., overproduction) [7–10].

Achieving economic competitiveness compared with traditional protein sources is most plausible when microbial protein is produced on low-cost side streams rather than refined sugars. However, this shifts the cost burden away from the raw materials towards feedstock handling and pretreatment [11], along with added complexity of high feedstock [12], process [13], and supply chain variability [14]. A United States Department of Energy techno-economic case study shows that changes in media composition can increase or decrease key economic metrics relative to a base case by 10–37%, depending on the metric and direction of media change

Figure 1



Population, annual protein requirement, and potential annual protein production from fermentation of agri-food side streams for each continent [7–10].

[12]. A large evidence base supports converting agro-industrial byproducts and food waste into microbial biomass and protein [15,16]. Circular bioeconomy reviews argue that second-generation substrates (food waste and side streams) are the most credible path to economic competitiveness, especially when SCP production is integrated into zero-waste biorefinery concepts that cascade multiple products and value streams [17]. Beyond SCP, microbial platforms enable bioproduction of diverse value streams, such as organic acids, enzymes, lipids, protein ingredients, pigments, bioactives, and more, strengthening the case for integrated biorefineries [17]. The implication is that side stream-derived protein becomes more economically feasible when embedded in a broader biomanufacturing portfolio.

Furthermore, sector assessments emphasise that meeting projected demand requires rapid access to fermentation capacity and that brownfield development or retrofitting can be attractive where idle, decommissioned, underutilised, excess, or strongly seasonal food-grade fermentation assets exist [6,18,19]. Detailed manufacturing-capacity analysis shows that, where technically feasible, brownfield development and retrofitting can cut up-front CAPEX by over 70% and shorten lead times to months [18]. Assessments of waste-to-feed pathways describe a dominant near-term deployment model of modular, co-located first-of-a-kind plants producing several thousand metric tonnes per year, designed for replication and co-location across dairies, breweries, and distilleries rather than mega-facilities [20]. The same assessment emphasises that transporting bulky, water-rich inputs long distances can undermine viability [20]. To achieve cost competitiveness, this indicates the need for decentralised, regional biomanufacturing hubs located close to side stream sources to reduce logistics, manage heterogeneous supply, and keep shared infrastructure utilised by producing multiple products [19,21–23]. However, active co-utilisation of operating breweries, wineries, or distilleries should be treated as conditional rather than assumed: traditional fermentation facilities are product-quality sensitive and may resist shared use because resident microbiota, spoilage risk, cleaning validation, scheduling conflicts, ownership incentives and hygiene segregation can outweigh the theoretical benefit of shared infrastructure [24,25].

This is where "Fermentelligence" becomes relevant: AI -optimised decision support that could make feedstock -flexible, decentralised fermentation more viable. The claim is not that Artificial Intelligence (AI) makes fermentation economical on its own, but that it can help coordinate and optimise variable inputs, multiple value streams, and multi -objective constraints (cost, carbon, water, safety, reliability) that otherwise prevent side -stream SCP from scaling [26−28]. It may also reduce barriers to entry for non-expert industry to develop fermentation product streams, provided decisions remain validated by process experts and food-safety evidence.

Fermentelligence: AI across a variable, distributed system

Fermentation of side streams is highly variable: heterogeneous feedstocks, diffuse supply, seasonal swings, and bioprocess disturbances are intrinsic. Artificial Intelligence can learn from complex data and make decisions under uncertainty, making it uniquely suited to address current upcycling challenges across six key areas: three operating at individual stages of the upcycling process; economic modelling; and finally, a system level component for connectivity, optimisation and orchestration including data collection for safety, regulation and consumer acceptance aspects.

However, Fermentelligence should be treated as a decision-support architecture, not an autonomous replacement for bioprocess engineering. AI can support feedstock characterisation, media design, soft sensing, blending, scheduling, process control and TEA/LCA scenario analysis, but deployment remains constrained by data scarcity, sensor reliability, model drift, transferability across strains/feedstocks/scales, interpretability, operational-technology cybersecurity, regulatory credibility, model maintenance and validation cost [28−33].

Characterisation of side stream composition

Side stream composition is complex and variable; targeted analysis (e.g., fibre content) can inform which valorisation route is most appropriate and reduce misrouting of streams into low-value processes [34]. Near-infrared (NIR) spectroscopy is increasingly being positioned as a rapid, reagent-free, non-destructive "green" tool for high-throughput biomass characterisation, with portable and miniaturised NIR enabling decentralised inline and at-line monitoring [35]. Combined with AI, sensor measurements can determine acceptance or rejection of side streams, blending ratios, and pretreatment selection, reducing variability before it reaches the fermenter.

Side streams should therefore be treated as feedstock classes rather than as a single waste category. Sugar- and starch-rich streams, lignocellulosic residues, protein-rich residues and mixed food wastes differ in moisture, C/N ratio, fermentable carbon release, fibre/ash/mineral content, inhibitor formation, resident microbiota and solids loading. These differences affect organism choice, pretreatment, nutrient supplementation, oxygen transfer, contamination control, downstream dewatering/drying and final biomass composition, and so directly influence product consistency [15−17,34,36].

Side stream blending and pretreatment optimisation

Once the side streams are characterised, the decision is how to blend them into a useable feedstock that can smooth seasonal supply risk and stabilise fermentation inputs. Mixture design combined with Machine Learning (ML) has been applied to optimise fermentable sugar recovery from mixed agricultural wastes during thermochemical pretreatment, explicitly motivated by logistics and seasonal constraints of single feedstocks [37]. Reinforcement Learning (RL) has also been proposed for dynamic blending under uncertainty, where the controller selects flow rates and blending ratios of multiple waste feeds to stabilise and optimise process performance despite variable composition [14].

Fermentation monitoring and control

Side stream fermentations face disturbances that challenge classical PID and sparse sensing, necessitating advanced control strategies. Industrial validation work reports RL-based control trained offline on PID controller trajectories and then adapted to drifting dynamics via periodic retraining, demonstrating a realistic pathway for RL in bioprocess settings [38]. Quantitatively, the study reported simulated reductions in integral absolute error of 8%, 6% and 5% relative to PID, classical MPC and standard off-policy RL, respectively; control-effort reductions of 54%, 11% and 7%; and 8-day experimental validation under changing environmental conditions [38]. Soft sensor work has used ML to infer variables of interest (e.g., product concentration or quality proxies) from available measurements but emphasises that real-time prediction systems need end-to-end architectures covering development, deployment, monitoring, and retraining, not just optimisation of offline accuracy [29]. For turbid fermentations where optical probes struggle, ultrasound-based monitoring combined with neural networks has been used to predict cell count noninvasively [39]. Fermentation reliability also requires contamination detection: ML-based contamination detection can be framed as anomaly detection with scarce contaminated data and highly asymmetric costs from false negatives; this motivates unsupervised learning approaches trained on normal batches [13]. Bayesian RL has been applied to predict harvest timing under limited data, explicitly modelling biological variability and model risk [40]. Bayesian optimisation is a sample-efficient approach that adapts sequentially and uses uncertainty to guide experiments. It has been recommended as a method that can outperform fixed experimental designs in noisy, nonlinear bioprocess spaces [41]. Hybrid modelling approaches can combine mechanistic structure with ML components to reduce model—process mismatch; industrial fermentation case studies show how hybrid models can replace time-consuming offline measurements with online signals as steps toward operational digital twins [42].

Economics as the gating constraint: embedding techno-economics and sustainability early

As economic performance depends on coupled choices (feedstock, pretreatment, organism, fermentation mode, downstream processing) and fragmented R&D focus can miss system-level trade-offs, Techno-Economic Analysis (TEA) and Life Cycle Assessment (LCA) are needed to guide design and iteration from the start [26]. A techno-economic report for fermentation-derived ingredients notes that many techno-economic models are proprietary or inconsistent, limiting transparent learning [11]. Open and surrogate approaches are changing this landscape to enable rapid analysis. BioSTEAM provides a community-led, open-source platform for biorefinery design, simulation, and TEA under uncertainty [43]. BioProcessNexus enables ML surrogate techno-economic models trained on Monte Carlo outputs from proprietary TEA tools, allowing fast screening without sharing the proprietary simulator itself [44]. Related surrogate TEA work shows how ML can compress detailed economic evaluations into fast early-stage screening tools [45]. For LCA, reviews highlight persistent data challenges: incomplete inventories, limited representativeness across geographies, and difficulty reflecting temporal dynamics; ML can support gap filling and uncertainty quantification [46]. A LCA perspective proposes a taxonomy for ML contributions: surrogate screening, ML to inform model construction and interpretation, and decision support via multi-objective optimisation and ranking [27].

The economic question is therefore not whether side streams are cheap at the gate, but whether they remain cheaper than refined or sugar-industry substrates after conversion to a safe, consistent ingredient. Cleaner substrates such as sucrose or molasses can have higher purchase prices but lower pretreatment, sterility, filtration and QA burden, whereas heterogeneous side streams can add collection, sorting, storage, testing, contamination control, sterilisation, pretreatment/hydrolysis, enzymes, nitrogen and micronutrient supplementation, aeration, downstream recovery, drying, wastewater treatment, regulatory compliance, logistics and under-utilised CAPEX [11,12,26,47,48]. AI can reduce uncertainty in blending, routing, scheduling and scenario screening, but it cannot remove these physical and regulatory costs. Environmental benefits are similarly conditional. While microbial protein can displace land-intensive ruminant meat or feed, total environmental performance can move upward or downward by category if pretreatment energy, drying, transport, nutrient inputs, wastewater treatment, electricity mix or low plant utilisation dominate [26,27,46].

System level connectivity, orchestration, and optimisation

Digital twins provide the software layer linking sensing, forecasting, and decision-making for either an individual unit operation or cluster of equipment or facilities. Food-industry reviews define a digital twin as a living model linked to a physical system and continually updated with incoming data to monitor and forecast behaviour for decision support [49]. Transfer learning can then adapt twins to new strains, substrates, or sites with minimal new data [50]. A Bioprocessing 4.0 review frames digital twins, active learning, and Bayesian optimisation as pillars of self-driving process development, with value measured in reduced experimental burden and faster iteration cycles [51]. At the knowledge layer, emerging multi-agent LLM architectures use retrieval-augmented generation to retrieve relevant literature and extract structured fields to support microbial protein R&D workflows [52].

Distributed hubs add a coordination challenge: routing side streams to the optimal facility and deciding which products to make. Digital industrial symbiosis tools provide a template: matchmaking platforms can rank exchange opportunities using stream volumes, material concentrations, prices and recipient demand rates [53]. Agent-based modelling suggests such platforms create value mainly by reducing transaction costs and coordinating exchanges under uncertainty [54]. Economic nonlinear model predictive control and scheduling across multiple fed-batch fermenters has been demonstrated as a way to allocate variable feeds and maximise profit under composition disturbances [55]. When coupled to open TEA and LCA surrogates and simulators, these systems can enable rapid screening and prioritisation.

Safety, regulation and consumer acceptance

Food-grade side-stream SCP also requires a product-specific safety, protein-quality and regulatory case. Relevant evidence includes organism and strain identity, production process, substrate provenance, contaminants, toxins/mycotoxins where relevant, allergens, nucleic-acid/RNA levels, amino—acid profile, nutritional quality, digestibility, toxicology, microbiological specifications, intended use levels and batch-to-batch consistency [56,57]. AI and big data can help organise provenance, process and batch records for dossier preparation and risk-based monitoring, but they cannot substitute for controlled manufacturing data or experimental safety evidence. Consumer acceptance is another deployment constraint: by-product-derived ingredients can benefit from circularity framing, but "waste-derived" positioning may also raise concerns about naturalness, safety, contaminants and processing intensity; communication must therefore emphasise controlled upcycling, verified safety and nutritional value [58].

De-risking roadmap

Four enabling actions would materially reduce risk.

Curated, open datasets

Curated datasets of side stream composition, fermentation trajectories, and downstream yields could underpin benchmark ML tasks and reduce duplicated effort. Data-infrastructure perspectives argue that the bottleneck has shifted from model architecture to data quality, standardisation, interoperability, and low-latency ingestion across the design—build—test—learn cycle; FAIR (Findable, Accessible, Interoperable, Reusable) practices and structured capture are prerequisites for scalable optimisation [30]. Data management and sharing is required across biomanufacturing to provide AI with the high-quality training data needed to enable scale-up and competitiveness [31].

Open TEA and LCA toolchains

Open simulation and TEA platforms [43], TEA surrogates [44,45], and integrated TEA and LCA guidance [26,27,46] would lower barriers for SMEs and regional consortia to evaluate configurations and embed sustainability and cost constraints directly into optimisation.

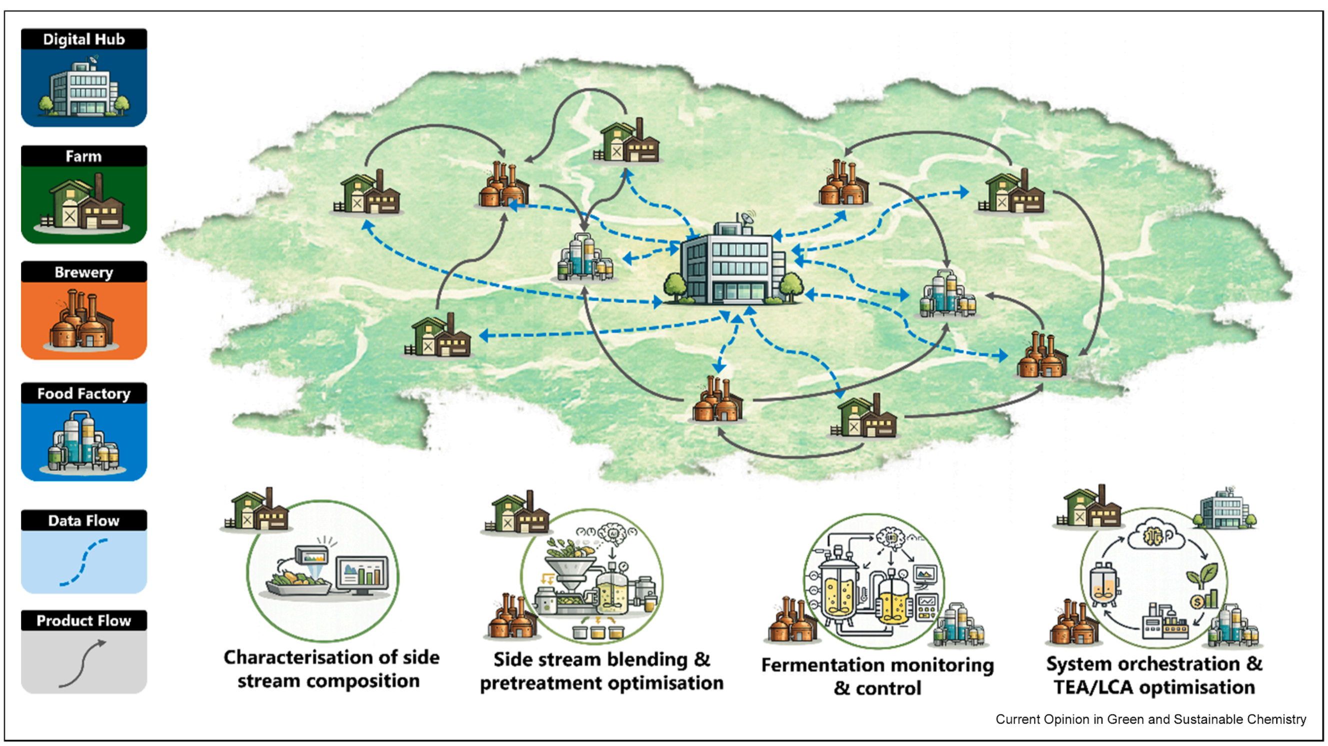
Safety, quality and regulatory data

Pilot studies should generate the data needed for safety and regulatory review, including substrate provenance, contaminant control, nucleic-acid reduction, amino—acid profile/protein quality, digestibility, allergenicity, nutritional quality, toxicology and batch consistency [56—58].

Pilot retrofit demonstrations

Pilot projects should test the retrofit-hub thesis only where existing infrastructure is idle, underutilised, decommissioned, or seasonally available, and should

Figure 2



The different connected AI components of Fermentelligence and the organisations that would utilise them for a regional system.

explicitly measure contamination control, cleaning validation, product-quality protection, oxygen-transfer needs and economics [18,19,24,25]. For example, a brewery-side demonstration could ferment spent grain and spent yeast (and imported local side streams) into SCP only with physically segregated operations, validated hygiene controls and targeted oxygen transfer and monitoring upgrades [18,19].

Conclusions

Producing microbial protein from agri-food side streams is therefore a combined biological, engineering and systems -integration challenge, featuring variable feedstocks, distributed logistics, contamination risk, strain robustness requirements, substrate utilisation limits, protein-quality, product-quality and food-safety constraints, and narrow margins across the value chain. A scalable pathway may be modular regional biomanufacturing hubs, ideally built around retrofitted food-grade assets potentially where suitable idle, excess or seasonal capacity exists, and configured as multi-product circular biorefineries to keep infrastructure utilised and spread risk. In this context, Fermentelligence (AI decision support and orchestration) acts as the key missing ingredient, translating heterogeneous inputs into predictable operations and investment-grade performance. Progress now depends less on new algorithms than on shared datasets, interoperable data pipelines, food-grade safety evidence, and pilot retrofit demonstrations that validate end-to-end performance (cost, carbon, safety, reliability) and repeatability.

Declaration of AI use in the manuscript preparation process

During the preparation of this manuscript Nik Watson used Gemini 3 Pro to review sections of text and propose edits to improve readability and highlight key messages and to generate some of the icons used in Figure 2. Alex Bowler used ChatGPT 5.3 for editing text. After using these tools, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

Declaration of competing interest

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

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Data availability

Data will be made available on request.

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