Desalination 592 (2024) 118092

Contents lists available at ScienceDirect

Desalination

journal homepage: www.elsevier.com/locate/desal

Machine learning framework for wastewater circular economy — Towards smarter nutrient recoveries

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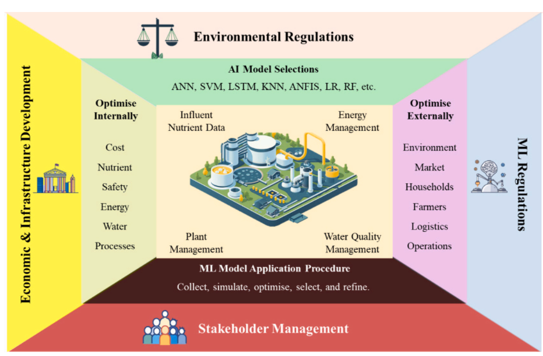
HIGHLIGHTS

- There is a weak utilisation of ML in CE WWTPs.
- Critical material regulations inadequately cover phosphorous circularity for WWTP.
- Further data collections and ML training with WWTP needed for full benefits
- ML an enabler for cost-effective, safer ML CE WWTP commercialisation
- ML utilisation must be strengthened to achieve higher nutrient circularity.

GRAPHICAL ABSTRACT



ARTICLE INFO

Keywords:
Machine learning
Circular economy
Nutrient
Sustainable supply chains

ABSTRACT

As the world's supply chains become disrupted through geopolitical instability and the race towards a net-zero future, policies have been implemented to improve the security of certain minerals and raw materials critical to a country's survival and sustainability goals. Circular economies (CE) are sought to be an ecosystem that will reduce virgin material consumption rates, lower carbon emissions, and decelerate the rate of landfilling. However, cost-effective and commercially attractive substitutes to conventional products are needed for this to be realised. Machine learning (ML) and the explosion of interest in artificial intelligence (AI) have led to growing interests in predictive and generative applications for sustainability. Phosphorous and, nutrients overall, operate on finite reserves essential for food supply chains; while such nutrients are largely present in municipal wastewater streams. Wastewater treatment plants (WWTPs) must then face a transformational force to become nutrient recovery centres, rather than follow a linear treat-for-disposal model. In this framework paper, ML is positioned as an enabler for scaled, cost-effective and safer recovery of nutrients and other valuable products — tying in economic, societal, technical and commercial factors through open data connectivity. Moreover, the paper issues a policy guide for institutions wishing to advance food, energy and water security through machine learning, circular economy wastewater treatment plants (ML CE WWTP).

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https://doi.org/10.1016/j.desal.2024.118092
Received 20 July 2024; Received in revised form 4 September 2024; Accepted 5 September 2024
Available online 7 September 2024

Nomenclature

Symbols	Variables
LFI	linear flow index
F(x)	utility index
V	mass of virgin nutrient. E.g., 14 g of virgin N per kg swine feed.
M	mass of finished product
W	unrecoverable waste
FR	recycled materials
FS	sustainable sourced materials
FD	reused materials
W	e.g., 5.7 g N wasted/kg swine feed produced from recovered N.
C_R	mass fraction of the product that is recycled
C_U	mass fraction of the product that is reused
C_S	mass fraction of the product that is composted
C_E	mass fraction of the product that is incinerated
L	average lifetime of the product
L_{avg}	average lifetime of the product by industry standards
U	functional units consumed
U_{avg}	industry average for this functional consumption

1. Introduction

The European Union (EU) is moving towards replacing inorganic fertilisers with alternative sources to promote a circular economy of critical raw materials given its finite nature [1]. Nutrient recovery technologies are overwhelmingly focused on recovering one set of nutrients and this was cited as a major barrier to achieving nutrient circularity [1]. The EU's response to the war in Ukraine – which disrupted fertiliser and food supply chains – were to roll out a series of policies to encourage nutrient circularity and food security, given the high dependency on nitrogen-based products from third markets [2]. One of the primary methods to recovering phosphorous is through struvite precipitation from wastewater effluents to crystallise and collect phosphorous, but these are highly influenced by chemical compositions and suspended particulates of the waste stream [3]. In addition, N-recovery technologies such as the Haber-Bosch method, are highly energy intensive [2]. Developing economies are heavily agriculturally driven, with India as an example, being the world's second largest consumer of phosphorous [4]. This necessitates a global push for a connected nutrient CE model that ensures all critical nutrients are recovered and recirculated back into food supply chains. Meanwhile, the global fertiliser market was estimated in 2021 to be USD 535.8 million, and WWTP efficacy for nutrient recoveries are dependent on the recovery costs, the product's benefits, and relevancy to the influents being treated — with artificial intelligence (AI) playing a significant role in this [5]. A study in an Italian province showed that 96 % of phosphorous could be recovered from sewage sludge, as currently most of this is disposed of though landfilling [6]. Therefore, there are benefits towards reducing landfilling through nutrient CE practices and converting this organic waste into usable fertilisers. Coinciding with this rapid growth of fertiliser demand, AI is forecasted to grow to $US30.76 billion by the year 2030 [7] across the wastewater and sanitation sectors. The WWTP sector is facing a rapidly changing landscape which continues to face legacy challenges in retrofitting AI, CE technologies and WWTPs together in response to changing regulatory and ML landscapes. Most importantly, recent approvals by the EU (Regulation 2019/1009) [8] on the sale of wastewater precipitated, phosphorous salts and struvite will officially expand revenue sources for WWTP operators.

ML is being applied at a rapid pace to support CE environmental outcomes, especially in securing the integrity of land, agriculture, water bodies and societies [9]. Some key metrics and indexes include ecotoxicity, global warming potential, acidification, and so forth [9] to enhance calculations and simulations made with lifecycle analysis (LCA). Fisher et al. [10] had proposed a framework paper to integrate cross-industry data mining and knowledge discovery with databases approaches through processing parameters for bioprocessing wastewater. However, the paper does not tie ML methodologies to CE outcomes. Recent interests have sparked the use of ML and biological metagenomics to improve water treatment [11], and academic studies have explored combining ML with CE WWTP to varying depths. Nutrient ML framework modelling on the environment [12], effluent quality controls [13] and aeration controls [14] have so far touched base on operating parameters and its impacts on the wider environment, however, none so far have addressed frameworks within the context of CE. Review papers have discussed drinking water safety [15], energy consumption predictions [16], membrane performance predictions [17], contaminant removal, and processes [18] — across both municipal and industrial disciplines [19,20]. Data scrutiny is one concern raised by authors when studying the feasibility of ML for CE bioprocesses [21], however, there is no framework proposed for nutrient ML CE WWTP that addresses data collection, preparation, refinement, ML modelling, post-processing and applications.

The objective of the ML framework paper is to provide further directions and guidelines to help policy makers and business decision leaders navigate and craft sustainable models of operation for commercialising and expanding nutrient recycling capabilities infused with ML to improve its efficacy. Furthermore, there are weak regulations governing the standardisation and safety of consuming recycled nutrients, and even weaker regulations in the presence of ML to manage nutrient CE WWTPs. Given the legacy nature of WWTPs which requires extensive retrofitting for nutrient CE and the explosion in artificial intelligence applications — a framework will help improve the feasibility and viability of nutrient CE WWTP by improving productivity, commercial acceptability, safety, quality, logistic planning, prediction accuracies and transparency to help secure critical fertiliser minerals and food supply chains for generations to come. This framework paper aims to provide a point of reference and guidance on establishing ML for CE across wastewater recovery given the hype surrounding AI.

This framework differs from other studies such as Praveen et al. [22] where the nutrient recovery framework was specific to the farm ecosystem, a focus on digital technologies over ML and not specific to wastewater [23], Smol et al. [24] where the paper was focused more on EU regulations governing circular directives and 9-R principles, and Renfrew et al. [25] explored the framework by establishing plant boundaries and circularity indicators. This paper proposes a broader encompassing of the boundaries extending beyond the treatment plant and into society, regulators, market dynamics, farmers, consumers, infrastructure — with ML being at the core of the CE WWTP.

1.1. PRISMA methodology

Web of Science articles were filtered based on the Topics: "Machine Learning" OR "Circular Economy" AND "Phosphorous" OR "Nitrogen" OR "Potassium". This was then further refined with necessary MUST INCLUDE keywords such as "Machine Learning" and "Circular Economy"; with SHOULD INCLUDE terms containing "Nutrient", "Phosphorous" and "Wastewater" — displaying 182 records.

For SCOPUS, the articles were vetted via Keywords for "Machine Learning" OR "Circular Economy", followed by AND "Wastewater" AND "Phosphorous" OR "Nitrogen" by Keywords. The number of documents found was 190 between the period of 2018 and 2024. Table 1 shows the subject areas based on these keyed criteria. Using RStudio, the combined documents had 2 duplicates removed and a total of 372 entries, and a further 14 were removed during the final revision stage. Given there is very little overlap of the search terms, Keyword assessments were then made.

Table 1
Journal mentions by subject area count.

Journal name	SCOPUS subject area count (2018–2024)
Environmental Science	171
Energy	50
Chemical Engineering	45
Engineering	36
Chemistry	22
Biochemistry, Genetics and Molecular Biology	13
Social Sciences	12
Medicine	11
Agricultural and Biological Sciences	9
Computer Science	8
Business, Management and Accounting	7
Pharmacology, Toxicology and Pharmaceutics	5
Physics and Astronomy	4
Materials Science	4
Economics, Econometrics and Finance	4
Mathematics	3
Neuroscience	1

1.1.1. Research footprint

Using the PRISMA approach as seen in other works [26] to sift through review articles, a number of which have been manually excluded and reviewed for relevance to the CE discipline. RStudio was then applied for multidimensional scaling of key terms. Fig. 1 and Fig. 2 demonstrate the interest by geography and keywords. Management, model, prediction and recovery are some of the most searched terms – delineating a focus on combining ML with CE WWTP methodologies.

1.2. Machine learning models

Machine learning algorithms (MLA) are tested for the least R^2 as a measure of its fit. These models include artificial neural networks (ANN), Bayesian neural networks (BNN), support vector machines (SVM), linear regression (LR), kernel nearest neighbour (KNN), deep learning and convolutional neural networks (CNN), random forest (RF) and decision trees (DT) [27,28]. Depending on the type of nutrient recovery technology utilised, inputs will vary, as can be seen in Table 2. For example, the type of microalgae strains and DNA [27], and their relationships to various stressors [29]. However, the inputs used will depend on the correlation analysis that is made to identify variables that are significant for predicting results. The important parameters for predicting WWTP resource recovery include pH, oxygen, and temperature, biomass content (C, H, O, N and S), total suspended solids, chemical oxygen demand, biological oxygen demand, dissolved oxygen, N and P [27,30,31]. However, as can be seen in Table 3, many ML studies were conducted to predict the quality of WWTP effluent. The most important input predictors will depend on outputs desired.

2. Drivers and barriers

When developing an ML CE framework, drivers and barriers are required to shape how ML applications could be applied to WWTPs. Fig. 3 summarises through literature extraction via RStudio the factors that shape CE from economics, societal perceptions, commercial and community participations, technologies, policy, market forces and so on. These challenges and opportunities give WWTP operators a range of CE technologies to recover nutrients such as the use of microalgae, microbes for biogas generation, membranes, thermal and electrochemical technologies. Integrating these technologies with a range of emerging regulations across the world of CE is challenging in itself, when many of these do not thoroughly cover standards governing processes, product purity and safety, and the construction of CE WWTPs.

2.1. Technical drivers

Automation is a driver towards greater connectivity between WWTPs and CE product consumption [86], and an example of this includes ANFIS controllers for TN removals depending on biomass, error rates and nutrient concentrations [87]. Nutrient deposition rates are also predicted based on inputs such as concentrations of nutrients in soil, water and plant pigmentation [88]. Urban environments with high circularity compatibilities fostered greater commercial survivability among businesses [89]. ML applications to use microbes to biodegrade bioplastics and reduce greenhouse gas (GHG) emissions is a significant opportunity to cut down single-use plastics in a time where countries are beginning to implement plastic taxes, however, bioplastic degradation has low commercial feasibility [90] or produce lower quality recycled

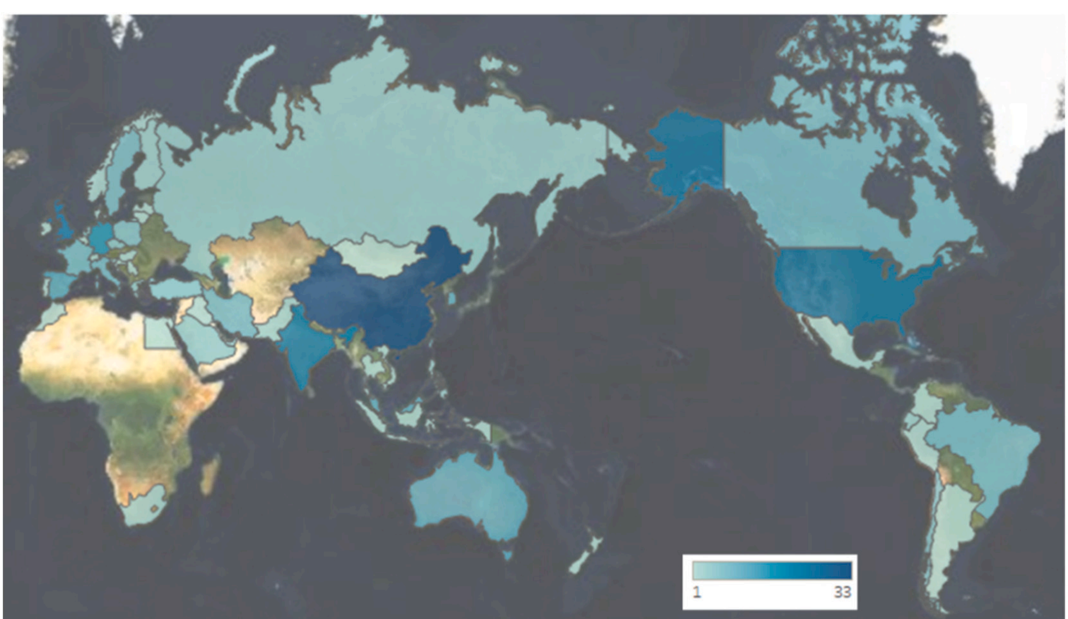

Fig. 1. Web of Science publication counts by country between 2018 and 2023 using the above key term filters.

Fig. 2. Word cloud of the combined article search with article duplicates and keywords omitted across both Web of Science (2018–2024) and SCOPUS (2017–2023). The importance of CE management, business models, and factoring in other sustainability metrics plays a critical role in the sustainable operation of nutrient ML CE WWTPs.

products [91]. Nutrients are consumed during biological processes to support microorganisms in converting waste to useful products. Another application is within biogas and hydrogen gas production using microbes [71], design of biochar characteristics for adsorption [92,93], and verifying recycled sources of nutrients with blockchain [94–96] for sustainable supplier selections.

2.2. Technical barriers

Poor data quality and the lack of training datasets make it difficult to obtain reliable prediction results [88,97] and this is particularly evident across emerging nutrient recovery technologies, and with the lack of sensors to relay this data [98]. Outlier data must also be factored in to increase the accuracy of ML predictions — requiring reprocessing [27]. Environmental elements can alter prediction accuracies [51], requiring larger datasets factoring in adverse challenges to nutrient data, which can hinder ML processing times [26], drive up processing costs [63] and elongate processing times [41]. To simplify and fill in missing data, simulations can be done [99], however, this is not always possible, for example, the lack of urine source separation infrastructure to collect data and train ML for urine nutrient recovery. Simulating microbial performance for both biogas production and CO_2 consumption is also another key area of ML challenges given it is difficult to realistically simulate microbial kinetics and behaviours with large bioinformatics [100,101], trade-offs between biogas production, nutrient consumption and operating costs [52], and predicting the growth of biomasses [102]. Some ML predictions will find it challenging to predict final nanostructure designs and surface morphological features best suited for the final application unless RSM is involved [103].

2.3. Policy drivers

Currently, there is a lack of a virtualised exchange platform for commercialising and linking nutrient CE WWTP products for the broader market. The EU currently has the CIRPASS platform that tracks the recycled material and carbon footprint data of lithium-ion batteries using a blockchain track and trace system that records transactions within a distributed ledger [104–106]. Penalties can be seen as an alternative, coercive driver for compliance on companies to adopt sustainable measures to purchase recycled nutrients [107]. However, such policies should not pigeonhole a company to only one CE technology [108]. However, there are other proposals to drive CE activities throughout the EU such as tax incentives for CE products, liberalised trade of CE products, and virtualised exchange platforms [109]. As regulations begin to encompass carbon neutrality and hazardous waste management policies, CE WWTPs would need to factor these in as a part of their sustainability performance objectives [110]. Policies therefore, become an important driver and guide for CE technology adoption [111].

2.4. Policy barriers

Policies can also work against incentivising purchases or supply of recovered nutrients. Bolivia for example, began prioritising synthetic fertiliser production at the expense of recycled nutrients [112,113]. It is already difficult establishing regulations for emerging nutrient recovery technologies, where thermal and chemical phosphorous recovery technologies would require unique standards and regulations to govern safe output, therefore, a case-by-case and industry specific policy is needed [114]. Policies barring CE implementation should consider economic and financial, managerial implications on organisations, recycling performance indicators, customer sentiment and social acceptance [115]. The handling of the different types of waste and recoverable products challenges how policies work together. For example, whether to separate urine from sewage waste for biogas energy recovery, and the handling of recovered nutrients, metals and hazardous materials [116], and deciding on a policy to encourage the best one to commercialise.

2.5. Social drivers

Populations in highly dense urban centres should see the value and benefits of participating in nutrient CE. Government policies incentivising the implementation for AI across CE WWTPs is critical to technology adoption for improving optimisation and decision making [30,117]. Such data should also be accessible to the general public. Carbon taxes are increasingly becoming an expense many businesses cannot ignore, and nutrient CE must factor in carbon emissions throughout the recovery process. Addressing UN Sustainable Development Goals for responsible consumption and production, combating climate change, decent work and economic wellbeing [118], good health via harm prevention [119] and safe water access [120], are all objectives that CE WWTPs can meet. The consumption of nutrient CE products and participating in waste reuse economies extend beyond WWTPs and into households and the global community, and must mirror the values of the general population wishing to act more on climate change and to transition from a linear to CE.

2.6. Social barriers

Poor education and knowledge about circular practices can be to blame for disincentivising consumers from recycling [121]. This would be a barrier to further adoption of urine recovery technologies for

Table 2
ML applications by model type against the types of input variables selected based on a strong R^2 correlation.

Input variables	Microalgae and wetlands	Biochar production	Water effluent quality	Anammox	Nutrient removal from effluent	Hydrothermal treatment/ recovery	Anaerobic digestion/ sewage treatment	Membrane recovery	Gas generation	Sources
pH	DT, ANN, RSM, DT		FFNN, LSSVM, KNN, SVR, ANFIS, ANN, RF, RNN, LSTM GRU	XGB, SVR, SVM, GPR, ANN, TCN, LASSO		XGBDT, RF	GPR	ANN, FFNN, RF, SVM, GPR, GB	ANN, SVM	[32–47]
Light intensity	DT, ANN, RSM									[32,34,47]
TN	DT, RF, ANN, FCNN, SVM		BPNN, LSTM, RF, SVR, RB, RF, KNN, DNN. XGBDT, ANN		BPNN	XGBDT, RF, ANN			RF	[29,32,39,48–57]
TP	DT, RF, ANN, SVM		BPNN, LSTM, RF, SVR, RB, RF, SVR, ANN, ANFIS, KNN		BPNN	XGBDT, RF, ANN				[29,32,41,48–51,53–56]
NH_4/NH_4^+-N	ANN, LR, RF, SVM		KNN, SVR, LSTM, RF, ANN	ANN, BPNN, SVM, LR				ANN, FFNN, RF, SVM, GPR	RF	[35,38,39,51,55,57–61]
Temperature	DT, ANN, RSM, FCNN, SVM, DT		KNN, SVR, RF, RNN	BPNN, SVM, LR, GPR, ANN, TCN		XGBDT, RF	GPR		SVM, ANN, KNN, AdaBoost, DNN, RF	[32,34,36,39,40,44,45,47,49,52,56–58,60,62,63]
CO_2 initial	DT									[32]
COD	RF, ANN, FCNN, SVM, DT		BPNN, LSTM, RF, SVR, RB, RF, SVR, KNN, FFNN, LSSVM, DNN, ANFIS, ANN, RF	SVM, ANN, GPR						[29,39–41,47,48,51,52,55,56,60]
Feed type	DT		ANFIS, SVR, ANN							[32,41]
Volatile solids		LR, DT					GPR		RF	[36,57,64]
Residence time/hydraulic retention time	ANN, SVM	LR, DT	ANFIS, ANN, SVR	XGB, SVR, SVM, BPNN, LR, ANN, GPR		XGBDT, RF	GPR		SVM, ANN, GPR	[33,36,41,44,49,56,58,64,65]
Power input		LR, DT								[64]
Influent–effluent properties	RF, DT		ANFIS, ANN, SVR, RF	SVM, LR, BPNN, ANN, GPR				GB, RF	SVM, ANN	[29,40,41,43,44,47,58,60,65]
Ammonia conc.			BPNN, LSTM, RF, SVR, RB, RF, SVR	XGB, SVR						[48,59]
Heavy metals				XGB, SVR						[33]
Nitrogen or phosphorous removal rate	RF		FFNN, LSSVM	XGB, SVR, SVM, BPNN, LR, ANN, GPR	BPNN, ANN, GPR, SVM					[29,33,40,58,65,66]
Ratios (e.g., N:P, S:N)	ANN, RSM				BPNN					[34,66]
Greenhouse gas emissions					BPNN					[44,50]
Salinity				ANN				GB, RF		[35,43]

(*continued on next page*)

Table 2 (*continued*)

Input variables	Microalgae and wetlands	Biochar production	Water effluent quality	Anammox	Nutrient removal from effluent	Hydrothermal treatment/ recovery	Anaerobic digestion/ sewage treatment	Membrane recovery	Gas generation	Sources
PCR/DNA data	3D-CNN, RF			ANN, LASSO	LR, SVLR, RFR, SVRRBF					[29,35,67–69]
Antibiotics				ANN						[70]
Biomass (C, H, O, S, N, protein, lipids)						XGBDT, RF, ANN				[49,54]
TOC			FFNN, LSSVM			XGBDT, RF				[37,49]
Reactor volume							GPR			[36]
Organic load rate			ANN, SVR, ANFIS				GPR			[36,41]
Operating days	RF		LSTM	BPNN, SVM, LR						[29,58,59]
Ecological databases indexes (soil, hydrological, ecology, rainfall, humidity, wind speed, solar radiation, air quality)	FCNN		FFNN, LSSVM, RNN							[37,45,51]
Electrode design, area or type									SVM, ANN, GPR	[71]
Aeration					ANN, XGB					[72]
Total suspended solids			DNN, RNN, LSTM GRU, ANN							[45,46,52,55,59]
Electrolyte dosage							KRR			[73]
Dissolved oxygen			RF, LSTM GRU							[46,60]
Conductivity				LASSO						[42]
BOD	LR, SVM, RF									[61]
Microbes					XGB					[74]

Notes: RBF = radial based function; FFNN = feed forward neural network, LSSVM = least squares support vector machine, KRR = kernel ridge regression, GB = gradient boosted, SVRL = support vector linear regression with linear kernel, SVRRBF = support vector regression radial basis function kernel, XGB = XGBoost, GRU = gated recurrent unit, FCNN = fully connected neural network, RSM = response surface methodology.

Table 3
Applications of machine learning for circular economies.

ML application	Benefits	
Building materials	Cost maintenance and construction cost estimations, accuracy improvements.	[75]
Plastic circularity	Pinch analysis for CE product quality degradation assessment.	[76]
CE economic feasibility	Sherwood Principle to determine whether it is profitable to recover waste.	[77]
Consumer behaviour	ML to understand consumption patterns for CE products.	[78]
Food waste biogas	Predict methane production from food waste.	[30]
Polymer recycling	Enzyme identification for depolymerisation.	[67]
Predict recoverability rates for building demolition	Predict material recyclability from building demolition.	[79]
Predict mechanical properties	Predict mechanical properties of waste to bricks.	[80,81]
Predict emissions	Predict nitrous oxide emissions from WWTPs.	[82]
Metal sorting	Sorting of ferrous and non-ferrous metals through waste stream.	[83]
Digestate treatment	Cost predictions for payback periods.	[84]
Disaster resilience	Supervised machine learning to improve waste recovery from damaged infrastructure.	[85]

instance, as for example, purchases of property with urine-diversion systems may dissuade customers from using CE technologies. It was shown in Gue et al. [122] that crime, employment, governance and research levels affected the performance of waste management for entire countries or municipalities. This is due to the high levels of communal engagement and cooperation required to facilitate CE practices. Organisational designs and poor regulatory guidelines are to blame for social barriers against CE adoption, particularly in resource-scarce environments [123], while societal acceptance of wastewater reuse is one of the more significant problems facing governments trying to drive widespread waste CE adoption [124]. Despite the openness of transparent data being a driver of public trust [125], ethics committees are required whenever AI is used to process this data [126] to enforce guardrails. The abuse of AI with open data can lead to public distrust, and it becomes important to ensure oversight is established.

2.7. Infrastructural drivers

Waste management can be managed through a centralised municipal system which can connect waste transportation systems with GPS and a range of other sensors for the real-time mapping of waste movements [121] and eliminate the need for individual computers using the cloud [119]. Satellite data can scan and analyse the geography to help plan the construction of circular infrastructures [127] with urban centres. Already, ML data can be further optimised using the Taguchi statistical methods and Analysis of Variance (ANOVA) with RSM to map water distribution networks for energy and hydraulic pressure controls and micro-hydropower recoveries [128]. Given that IoT, blockchain, ML/AI, and Big Data are all critical for the transformation of CE supply chains [129], tying in geospatial methods of data collection with ML, urban CE WWPT design and transportation can help reduce costs in moving nutrient products. When recovering nitrogen and phosphorous, ML can reduce mobility costs by optimising distances travelled [130] to support efficient distribution networks. There are other strategies to reduce costs such as offsetting with energy and biogas recoveries for example, which can reduce payback periods for CE WWTP [131]. A change in how influents are collected by WWTPs, for example, where a 7 % diversion of urine was found to lower electricity consumption by 50 %, and when increased to 75 % urine diversion, corrosion was reduced by 20 % [132]. A combined use of blockchain verifiability of nutrient origins, LCA analysis of the environmental impacts of accepting these CE nutrients, mitigating risks through ML and effectively monitor and distribute these resources in a highly productive way should be implemented to drive seamless ML infrastructure utilisation (Fig. 4).

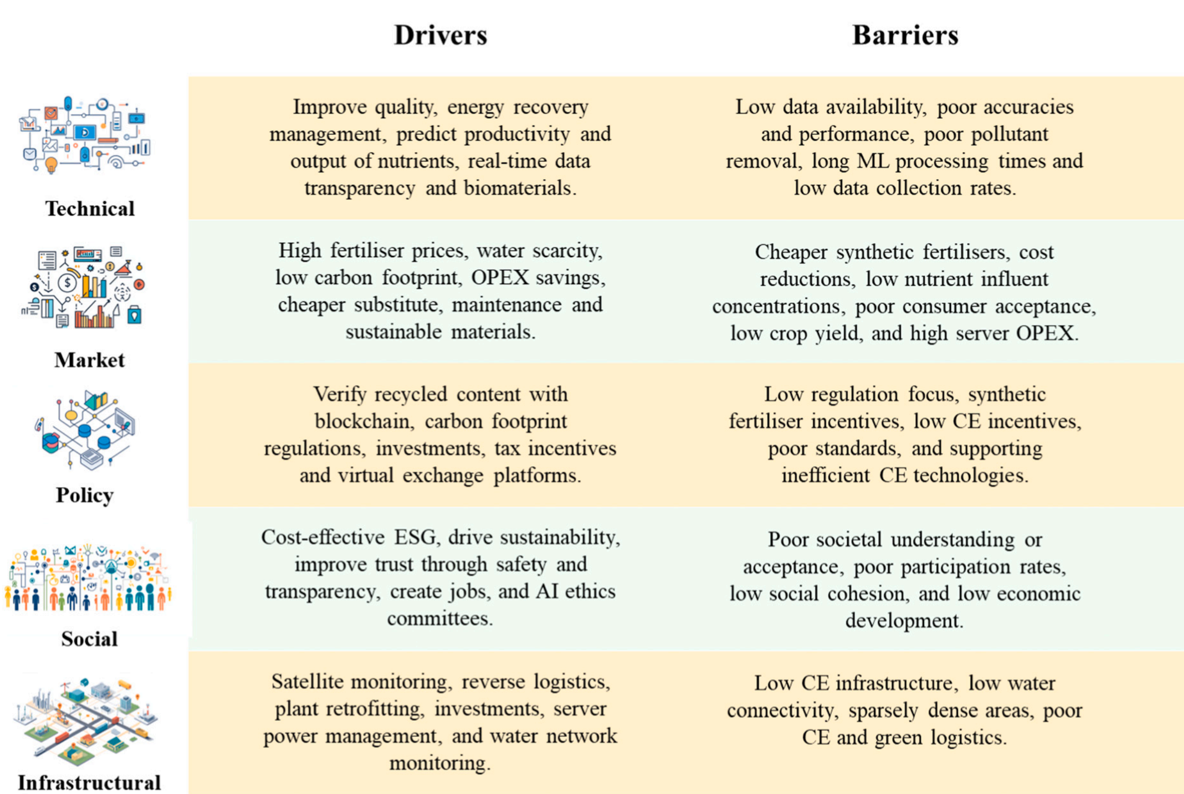

Fig. 3. A range of technical, market, policy, social and infrastructural forces that can accelerate and hamper developments in the nutrient CE WWTP space.

2.8. Infrastructural barriers

Lack of digitised connectivity between WWTPs and households are to blame for poor data collection rates where an example is seen in the healthcare sector [133]. City policies do not incentivise enough digitisation [134] and this can drive up implementation costs in the future as it becomes more difficult to overcome existing barriers [133,135]. Not to mention that servers consume large amounts of power that ML can optimise with CE activities [136]. Nutrient CE supply chains are not well established and this poses a challenge to farmers, WWTPs and households within cities. This also applies to centralised and decentralised WWTPs given the barrier of either connectivity or transportation [4,137]. The lack of green transportation options makes it even more challenging when keeping the carbon footprint of CE logistics low [97,138]. The lack of green transportation from CE WWTP to farms is a challenge during a time where governments are moving towards decarbonising their economies, and the value of the nutrients being transported plays a key deciding variable justifying its collection economics.

2.9. Market barriers

Nutrient recovery technologies are not fully commercially available [139] and the EU is currently piloting several plants on its potential applications. Cost of operation factoring in energy, water, insufficient breakeven for the market sale of recovered nutrients, biofuels and biogases, can make or break the nutrient recovery CE WWTP [140]. Cost barriers was the most significant hindrance to the widespread adoption of CE. A suggestion is to optimise CE supply chains to run as responsively and efficiently as possible through ML and big data mining [141]. Capital and operating costs are the biggest predictors that ML can reliably conclude for payback periods, as well as operating costs such as chemical consumption on the concentration of nutrients that can be recovered within influent streams [142]. Sufficient fertile land area is needed to produce high crop yields [143], but not all WWTPs are located close to farmlands, and some technologies may work better than others to help produce an acceptable product [144,145], and these technologies should be compared to similar readiness levels. The success of nutrient CE products depends on a range of factors such as waste-population density, market prices, product demand, and crop productivity. However, all of these would not work if consumer awareness is low [146].

2.10. Market drivers

A high demand and low supply of nutrients and its equivalent CE substitutes will pressure governments to act and stabilise the supply of critical farming nutrients by adopting CE WWTP [147]. Alternative foods grown with recovered nutrients can be derived from fungi [101], and other products can be made such as animal feeds, biofertilisers, nutraceuticals, food colouring and cosmetics from microalgae [148]. Sustainable biofuels created by microalgae and biomass waste can provide alternatives to fossil fuels. Food scarcity and insecurity will also have price pressure ramifications, and the high price of mined phosphate rock can add pressure to source from alternative supply chains (Fig. 5). Cost reductions on food prices by increasing the supply of CE nutrients into the supply chain can economically persuade customers to choose food grown using CE products with ML [101,149]. By using a CE supply chain, logistics can be shortened for these nutrients and improve food security and resiliency. However, financial incentives to entice customers to adopt and participate in a nutrient CE is important [149], for example, nutrients recovered in apartments can be used to reduce ongoing strata costs. A combination of product value, costs, financial incentives and applications can drive nutrient CE WWTPs to become more widespread.

3. Framing the circular economy ecosystem with machine learning

Authors such as Walzberg et al. [151] have attempted to frame the limits of the CE system by thermodynamic, system boundary, physical scale economies, technology lock-ins, and governance and management.

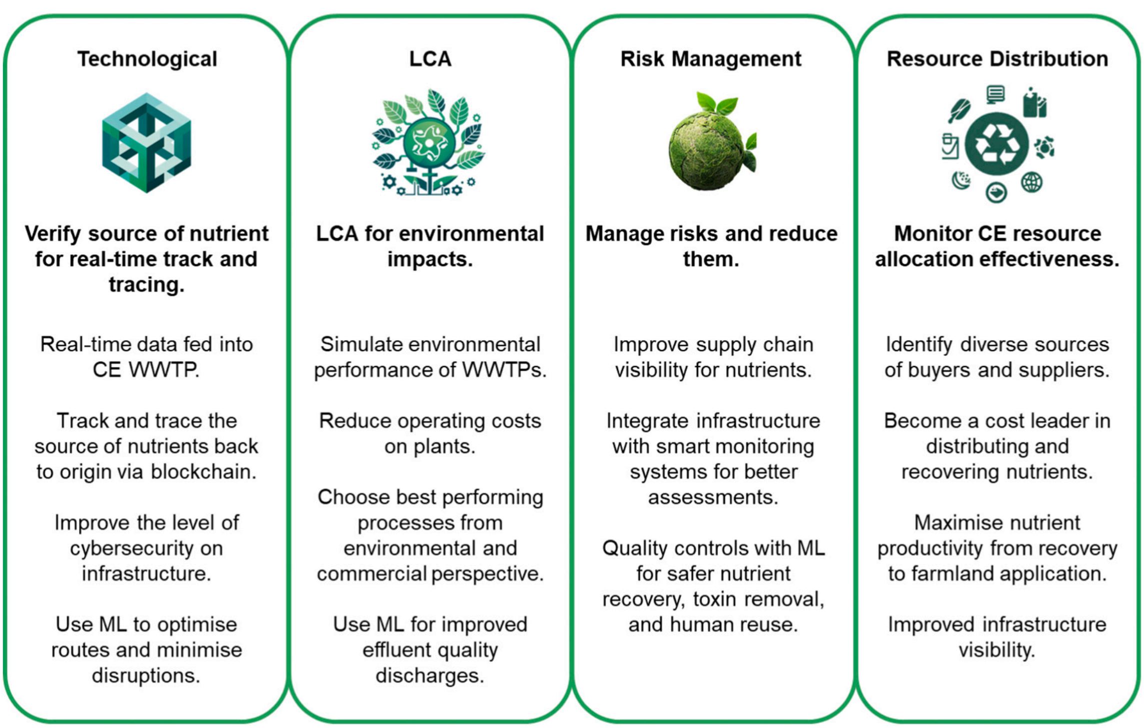

Fig. 4. For a complete end-to-end smart CE WWTP infrastructure, ensuring that trust is built into verified data throughout the network and fed into ML for WWTPs is crucial for effective, predictive nutrient recoveries.

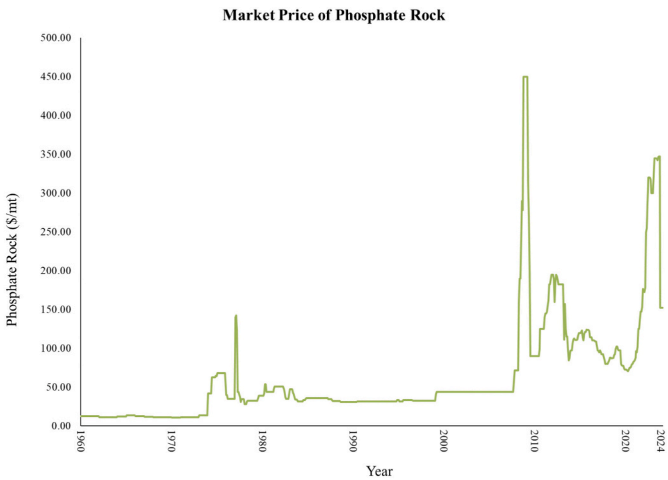

Fig. 5. Taken from the World Bank Commodity Price Data (The Pink Sheet) [150].

Institutional forces and regulations have been proposed as shaping CE policies which influence consumption and production of CE products [77,152]. However, ML can also support the monetisation of waste informally for consumers but can be challenged by poor data to train ML algorithms [153]. Rarely, if ever, do CE ecosystems operate without social and economic supports in place [154].

Incorporating ML requires layered consideration for application, control, transport, and perception [155]. In particular, considerations for lifecycle assessment data, material flow analysis, social network analysis will require digital systems to manage all aspects of CE flow from energy, materials and water across these layers from input, process, output and end-of-life waste management [156]. Furthermore, ML model accuracies are affected by noise [48]. Datasets for ML should be collected from Big Data to predict adsorption performance against micropollutants [157]. Nutrient deficiency analysis by countries and regions is becoming a popular method for managing the flow and deposition of recycled nutrients [112]. However, there is a lack of end-to-end connectivity to measure and optimise the flow of CE products [119]. Furthermore, ML model accuracies are affected by noise [48].

CE WWTP should be designated as green suppliers for helping buyers procure recovered nutrients, who are connected through IoT and transport management systems [158]. This can also be combined with ML and digital twins to simulate entire supply chains [159]. However, procuring CE nutrients is unattainable due to the fragmented nature of CE supply chains [159] and the lack of supplier segmentations available [160]. This poses a challenge when distinguishing between green and non-green WWTPs. There are opportunities for ML to identify sustainable suppliers and products that can encourage farmers to purchase from CE sources.

3.1. Products

Given WWTPs are operated by companies, financial incentives are needed to justify the adoption of CE technologies. Some products of valuable interest include the use of biochar as nutritious soil conditioners [161] and to produce more P-recovery electrodes [162]. For example, high concentrations of useful materials in heterogenous waste must be present to justify the economics of CE [77], and consumer behaviours can be studied with ML to determine better commercial CE outcomes [78]. Biochar can also be used to absorb contaminants within wastewaters [163]. Hydrochar contains significant caloric value that can be combusted as a source of fuel [164]. Advanced materials can be manufactured from waste recovered from WWTP [165] and combined with ML to design nano-scale materials to maximise performance outcomes [166] or sturdier construction materials [167]. Sustainable materials such as bioplastics can be produced through microalgae [142,168], however doubt is raised across the quality of these materials when remanufactured from wastewater [167].

Alternative food proteins can be made with microalgae to address food insecurity and encourage sustainable alternatives to food cultivation, but are currently too costly with safety data still lacking [169]. Additionally, the concentration of valuable nutrients or other products has always been a significant cost contributor to CE [170]. Therefore, ML incorporation into influent nutrient concentration detections and predictions are critical. There exists a trade-off between nutrient, water consumption when sustaining resilient food supply chains [171]. Besides food supply chains, waste reuse is touted as an alternative to absorb nutrients [172], as feed source for producing alternative foods [169]. ML can be combined with waste products to design nano-scale materials to maximise performance outcomes [166].

Current research into nutrient recovery product commercialisation is incongruent with profitable needs due to the poor scalability of technologies [139]. This leads to an uncertainty around the pricing of CE products for end consumers. Commercial sector entities are wary of investing in unproven nutrient recovery technologies. A challenge here is the limited products that can be made with recovered nutrients such as that of feedstock, and the knowledge gaps that exist within current research [1], that add to these commercial hesitancies. Demand economics will always play a key role in whether the recovered products will become successful on the market. For example, biochar electrodes correlating with the maturity of microbial fuel cell technology compared with straight P-recovery for fertiliser products. Therefore, it is posited that the maturity of the economic application of the product will play a key demand role in driving the success of CE WWTP.

3.2. Recyclability metrics

Compared to conventional CE dealing with plastics where some plastics reach finite recovery recycles before quality degrades [76], nutrient reusability is infinite, provided that the technologies have high selectivity for recovery. Increasingly, other metrics such as carbon emissions and renewable power are being factored into CE [143,173], and there has been a strong correlation between biological nutrient removals and carbon emissions [50,174]. CE forms a strong relationship with deforestation and renewable power consumption which aids in decarbonisation [175]. Carbon emissions become a key justifying factor for why CE should be preferred over virgin-material extraction methods given its lower carbon intensity. Fig. 6 shows the range of metrics covering financial, CE performance, supplementary value-added products besides nutrients, and the wider environmental benefits the WWTP will have. CE metrics for nutrients will depend on purity, contaminant removal for safety, and recovery rates. Second level down, operating costs and the market resale value of these nutrients become important, followed by other product recoveries used to offset costs or expand revenue streams. Meanwhile, external environmental metrics become important for policy makers to gauge the effectiveness of their sustainability targets. ML can increase the value being added to these end CE products by raising chemical complexities, eliminate contaminants, predict optimal product qualities, best technology selections and better manage CE WWTP processes.

ML recovery and removal predictions were affected by the presence and concentrations of heavy metals and pollutants [33,70]. Predicting how specific genes impact recyclability and recoverability of wastewater resources through microorganisms is gaining traction [30,35]. Certainly, in the processing of organic waste, biogas production predictions are widely applied with ML [30,31]. These correlations can be assessed on the relative abundance genus level depending on changes in water quality and operating efficiencies [74]. The resiliency of ML models to predict nutrient removal or recovery processes should play a significant safety role when CE product recovery and human consumption is involved. The Ellen Macarthur Foundation devised a Material

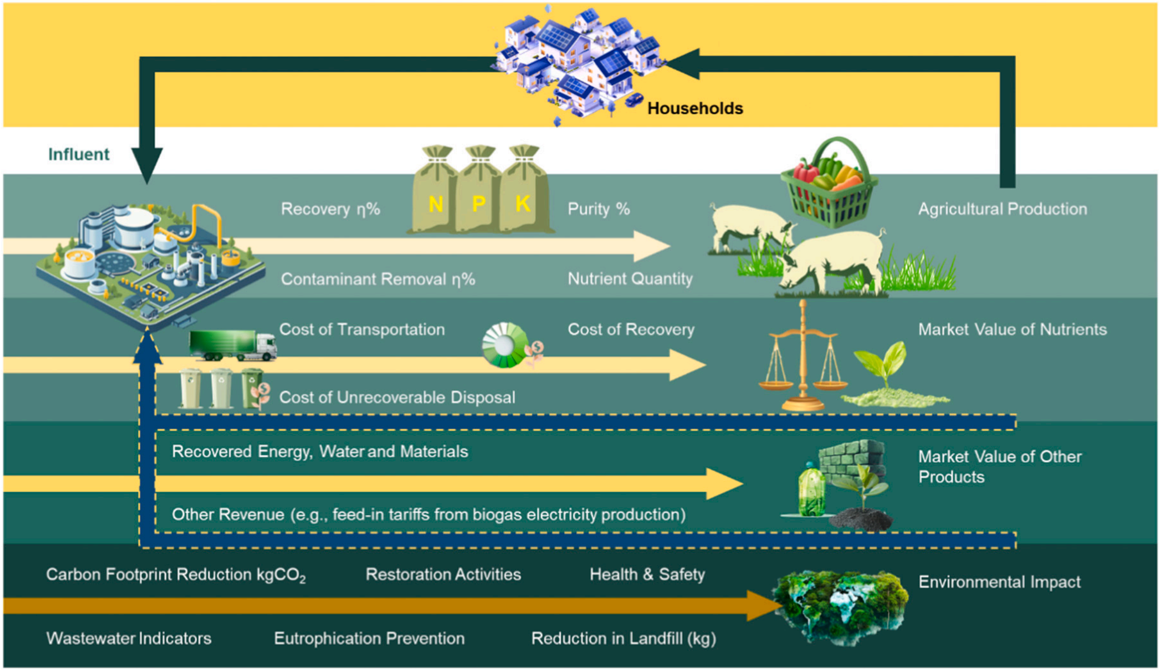

Fig. 6. Waste generated by households will be processed and have its nutrients and other products recovered for market resale to the agriculture and other sectors. There are non-financial benefits ton also consider such as lower carbon footprints, reversing environmental damage and ecological preservation.

Circularity Indicator (MCI) to determine the circularity of a product. When dealing with nutrients, circularity is a bit more difficult to define (Table 4).

3.3. Environmental and social governance

With the reduction in virgin material consumption comes lower GHG emissions. Governments globally are mandating companies to disclose GHG emissions [178]. Policies designed around ML can improve the efficiency of supply chains through lowering of GHG emissions [97]. CE WWTP technologies can predict carbon footprint reductions through ML-assisted organic waste treatment through mainly chemical and processing parameters [36]. Carbon footprints in several EU countries, will require assessments and reporting, and the high energy consumption and GHG emissions from WWTPs are a significant concern [142]. There are ample opportunities to decarbonise WWTPs using CE given the positive treatment and carbon reduction impacts for recovering nutrients would have on the environment [179]. When integrating AD with biogas production, carbon reductions can be aided through ML predictions, but these are complicated by the complex nature of wastewater [36]. There are also nutrient emissions to consider for CE WWTP implementations. Currently, the decomposition of sewage sludge accounts for 40 % of total GHG emissions, and its disposal 50 % of the total WWTP cost [180], but opportunities to use microalgae to capture these emissions and produce biofertilisers is possible [181]. ML can be inserted throughout these nutrient CE WWTP processes to optimise energy and GHG emissions management [182,183]. Widespread use of the Haber Bosch process for ammonia and N-recovery is energy intensive, and renewable power is offered as a solution [144].

There are growing applications of using urine as an electrolyte to produce hydrogen gas [184], however, ML has not explored its applications for improving hydrogen gas production with the characteristics of urea and urine. In the study [184], a city of 160,000 inhabitants and a hydrogen production of 430 kg, the net energy produced was 2500 kWh/day — potentially the datapoints of 160,000 people could form a part of data inputs to help increase the production of hydrogen. Given the large municipality, plenty of datapoints can be captured to train ML models. Similarly, for micropollutant removal of pharmaceuticals [185] captured across entire populations. It is well known that there is a strong link between economic activity, waste generation and GHG emissions [186,187].

Other indicators used in ML correlation analysis for assessing CE effectiveness include industrial zoning densities, population densities, topography, hydrometeorology, soil conditions, rainfall, construction zones, water consumption, and other environmental terrains to predict the concentration of nutrients in rivers [188]. This measure is done to assess the nutrient leakage into the ecosystem, or could be used to identify any nutrients that have escaped CE WWTP treatment, given that phosphorous depletes overtime due to rain runoffs and erosion [6]. ML model impacts on the external environment would be important when considering the full extent of the benefits that CE ecosystems have.

Table 4
CE metrics conventionally applied to physical material sorting and recycling.

Metric	Recyclability metrics	Source
Material circularity indicator	$MCI = 1 - LFI * F(x)$	[176,177]
Linear flow index	$\frac{V + W}{2M}$	[176,177]
Mass of virgin material	$M (1 - F_R - F_U - F_S)$	[176,177]
Waste	$M (1 - C_R - C_U - C_S - C_E)$	[176,177]
Utility factor	$\frac{0.9}{\frac{L}{L_{avg}} + \frac{U}{U_{avg}}}$	[176,177]

3.4. Technical risks

Poor datasets for training the ML model, with lack of research data cited as a major barrier [50]. Missing data is also another, which is addressed through mean imputations [36], and there are challenges to setting system boundaries, evaluating prediction accuracies with poor data, and data availability [10]. This is resolved through a series of approaches such as imputations, interpolations and combining algorithms to reduce generalisations [39]. Some datasets are incomplete or unreliable for use in managing waste and resources, particularly when dealing with time series [125]. It is proposed to ensure that data is centralised and open access across different regions to improve the prediction accuracies of ML WWTPs to fill in these missing data gaps [125], but depending on the plant operator's preferences, edge computing for higher responsiveness may be desired. This difficulty is compounded by the heterogenous nature of wastewater, and ML predictions vary wildly depending on the influent nutritional and organic loading content [27,36]. ANN could be used to study the complex compositions of the waste before making performance predictions, such as thermal degradation curves for the conversion of biomass into useful products and fuels [189]. However, process knowledge was important in improving the accuracy, for example, it is well established that ammonia concentrations contribute to the accuracy of N_2O due to the nitrogen source [63].

It is no secret that cybersecurity and privacy issues are a great concern for ML CE WWTPs [104,130] — or anything involving digitised systems. To build trust in CE WWTP with ML: data verifiability, high ML model accuracies and robustness, encryption using blockchain, big data, real-time data visibility and traceability systems are some tools CE WWTP operators can use to encourage commercialisation of their own products. To overcome concerns for greenwashing, displaying verifiable traceability of recovered nutrients is a key disseminator of trust that sustainable purchases are made that suffice cost points for consumers.

3.5. Benefits of machine learning

ML can predict quantities of products to be collected [190], is most popularly used for transportation and communication — particularly for autonomous delivery systems [26,135]. Transportation is one of the largest costs for CE waste management. ML technologies can help with optimising waste or nutrient product collections by factoring in population, socioeconomic, contamination rates and household incomes for waste predictions [191]. Population was the most important input contributor for waste ML [191,192]. Population concentrations determine the economic feasibility of nutrient CE. In Deng et al. [77] SVM was used to predict which waste streams would have enough valuable concentrations of materials to be recovered to make it economically worthwhile. With this being said, forecasting is a core strength of ML with applications for plant lifecycle assessments from construction to demolition [193], WWTP effluent quality [48,194], maintenance [27,195], waste characteristics [30], and the best enzymes from microalgae in creating compounds and minimising carbon emissions [135].

Another area of ML is waste classification. Phosphorous is a critical raw material according to the EU. Zocco et al. [196] studied material flow analysis at the country level to measure the total amount of critical minerals circulating throughout an economy for monitoring energy and food securities. ML analysis of critical agricultural minerals would be important to ensure that food security is gauged on the amount of nutrients being circulated throughout a glob or country. Waste classification is a laborious task, and will drive up recovery costs. Therefore, another strength of ML is its coupling with automation systems [197]. Automated nutrient recovery, sorting and data collection systems will play a large role in driving CE WWTP costs down.

3.6. Model robustness

Methods are followed to ensure that proper data collection, optimisation techniques before and after processing and refinements lead to highly accurate predictions. Some models can tolerate high variations in data predictions using probabilistic methods compared with non-probabilistic approaches [36]. However, human intervention is still required to improve the prediction accuracies. Refinement processes can still use optimisation procedures that train ANN models such as data normalisation, number of hidden layers, cost and activation functions [55]. These procedures are particularly useful for monitoring the quality of water systems and designing CE WWTPs. Sometimes, factors outside of the plant's control is considered in the prediction process, such as in Li et al. [51] where rainfall, solar radiation and temperature had significant effects on the prediction accuracies for TN, TP, COD and ammonia. However, robustness of the model will reside in the selection of the ML type [51].

Not all nutrient prediction performances are equal, and may require factoring in contingency variables impinging the accuracy of the results. FCNN TP predictions in Li et al. [51] worked less effectively for the model compared to ammonia, COD and TN. In this constructed wetland study, rainfall, solar radiation and temperature had significant effects on the prediction accuracies for TN, TP, COD and ammonia. Adverse conditions can alter the ML model's prediction, despite the incorporation of accurate sensors for pH, temperatures, wastewater flow rate, chemical probes are important measurement appliances in collecting data. When a time variable is involved with another changing metric of interest, LSTM with RNN is used [198]. Despite sensors collecting data, they are pointless if the ML model is not adaptable to changing conditions of the measured environment.

Future propositions are to hybridise ML models to improve the robustness of the predictions. From the study [199], agent-based modelling can complement ML models in new hybrid approaches to improving the accuracy of ML models. The agent-based model provides enriched data for ML, meanwhile ML can refine the simulations of the agents [199]. Hybrid approaches in ML predictions can help establish digital twins of CE WWTPs that can fill in and optimise data inputs to improve prediction model behaviours. These agents could include customers, retrofitters, operators, recyclers, and CE nutrient resellers. Meanwhile, lower costs of recovering valuable resources have led to a slight increase in recycling uptake for photovoltaics, however, social factors in this case have not been factored [200]. Agent-based models do not always factor in randomised human behaviours affecting prediction accuracies, but attempts to hybridise ML models could improve its robustness (Table 5).

3.7. ML approaches in WWTP

An ML model's development begins through data collection and using correlation approaches to determine which variables contribute

Table 5
The various steps studies have taken to train and refine ML models.

Simulate/ analyse	Optimise	Predict	Refine	Source
	Adam, SGD	LSTM		[59]
Data generation	Fuzzy clustering algorithm	ANN	NSGA-II	[52]
	KNN	TCN	MOTPE Bayesian optimisation	[62]
GPS-X/Mantis		RF		[201]
ANOVA	RSM	ANN, ANFIS		[103]
	Variational mode decomposition	RNN	Bayesian Optimisation	[45]
Grid search algorithm, maximum relevance minimum redundancy feature selection	Mahalanobis distances, parametric multivariate outlier removal	KNN, DNN and AdaBoost		[63]
	Linear regression, stochastic gradient descent, ridge regression	SK-Learn Python 3.6 Linear Regression		[202]
Agent based modelling/ virtual simulation		ML models		[199]

significantly to prediction performance. For example, using the Spearman, redundancy and SHAP analysis [33,50,66,70]. For DT, mutual information, Pearson correlation and F-regression are some relevance calculation methods for selecting features contributing to high prediction accuracies across ML models.

Sometimes, not all data is available. Here, imputations are done to fill in the missing data and can be univariate or multivariate [37]. These can include filling in the missing data using mean, median and mode approaches [37]. In multivariate approaches, Bayesian ridging and randomised trees can be used but they are subject to biases [37]. Probabilistic approaches therefore appear to show higher accuracies factoring in a wider range of values that could happen. Probabilistic data imputations are used alongside k-fold analysis to stress test prediction models for accuracy, with Bayesian methods optimising the ML algorithms [39,58,203]. A typical value of 5-fold is used for cross validation [39]. Depending on the modeller, test and training data ratios are on the order of respectively, 30 % and 70 % [33], 20 % and 80 % [35,49], and 75 % training and 25 % testing data [38].

Processing follows after data collection and cleaning up is done. Process iterations in training the model could reach 5000 times [35], combinations of data inputs in some instances have reached 2058 different combinations of inputs are experimented with design and operating parameters for electrodes in gas production provided in the supplementary data [203], and hidden layer sizes could be 1 to 100 [35] and even more depending on the processing time and power required. Ensemble methods improve the prediction accuracies of non-linear models: simple averaging, weighted averaging and neural network ensemble techniques with ANFIS [204] are some techniques to improve data usability.

When time-series data collection is involved, LSTM is used for ML model processing. Online and offline learning approaches, compared to batch ML methods where a training and test dataset is used, uses sequential learning approaches to correct the ML model after every prediction to improve accuracy over time using real-time data [205]. Under LSTM, accuracy improvements were found by aggregating timestamps to which data was collected to 1-h intervals during inactive periods [59]. Accuracies for using LSTM to measure and predict effluent qualities could be above 96 % [46] when similarly sampling intervals were done. There is growing popularity in hybrid ML models [60] that provide far greater accuracies compared to single ML methods. RF and LSTM analysis were shown to raise biogas prediction accuracies by 20 % and reduced calculation times for identifying key input factors by 28 % [206]. Data could be skewed due to seasonal and operational changes to the WWTP [63], and collecting more data could slow the performance of the ML model. Spearman and other feature selection practices may not be appropriate for lower cost ML models dealing with multicollinearity, which is common with wastewater. Applications for LSTM appears to hold high value given the heterogenous, dynamic characteristic of WWTP influents required for an accuracy.

On top of this, data simplification and trust in the prediction results are paramount for ML emissions modelling [63]. The more data is collected, the slower the performance of the ML model. Spearman and other feature selection practices may not be appropriate for lower cost ML models dealing with multicollinearity, which is typical with wastewater. With poor data availability, ML models may have to generalise predictions. Overfitting is also an issue given the ML model can make predictions matching too closely with datasets [10], but this challenge could be overcome through improved feedforward neural networks and optimising genetic algorithms [207]. Generalising datasets can raise scepticism across those using the model, given it is already a challenge identifying accurate ML algorithms with given datasets [50], using non-actual data can slightly alter accuracies in these predictions.

A pinch analysis can be done to reduce the consumption of energy and water where thermal leakages can be identified and recovered during thermally-driven, nutrient recovery processes [208]. Variations of this analysis include water and cascade pinch analysis to reduce water consumption by analysing mass flows [209,210]. These are also being tied to carbon emissions as a result of reducing virgin material processing. Currently, ML WWTP CE do not factor in carbon emissions as a part of the recovery performance, mainly focusing on ML metrics such as Root Mean Square Error (RSME), Mean Relative Absolute Error (MRAE), Mean Squared Error (MSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), Relative Bias (RB) and Mean Absolute Relative Error (MRAE) [37,60]. Table 6 shows that studies were applied from a material conservation and environmental simulation standpoint.

3.8. Plant retrofitting

Many WWTPs operate off legacy infrastructure without smart sensors and connectivity to the cloud. Plant integration for data collection from sensors with smart cloud systems would require further data refinement processes, furthermore, lifecycle databases for circularity assessments will also become crucial [216]. Digital twins can support the simulation of nutrient circularity performance [217], however, these studies are mostly confined to material sorting and waste management [218]. The IoT and connected appliances can collect large datasets for automated waste management [119] at scale and in some cases with minimal human effort [205]. When retrofitting plants, ML models should factor in safety, economics, product specification goals, and meeting regulations on product quality controls [10]. There are regulatory requirements to the storage and encryption of sensitive plant data, while simultaneously being shared to systems and databases for ML applications [10]. Out of all the nutrient recovery technologies, AD is the most promising [140].

3.9. Sustainable modes of operation

For sustainable ML operation, Fisher et al. [10] through von Stoch et al. [219], suggested that to improve ML robustness, models should complement, correct, embed within, integrate output-to-input, and inspire one another. This will lead to much more accurate setups for CE WWTP. The process must be affordable, resilient, and be accessible to servers and input data types such as images and log files. In one study [140], the most promising large-scale commercial application of nutrient recovery combines urine separation technologies, pyrolysis and algal biomass cultivation – with a potential revenue potential of $US0.2 billion. Given ML urine nutrient recovery has not been studied extensively, there are gaps within academia to determine ML algorithms specific to nutrient recovery performance effectiveness. In the beginning stages of ML, various data inputs should be collected and feature

Table 6
Methodologies other ML WWTP studies were applied for conservation and environmental simulations.

Method frameworks	Goal	Source
Pinch analysis	Applicable to water and energy consumption minimisation.	[209,210]
Sherwood principle	Determine economic viability of recovering end of life products based on concentration of waste and economic value.	[170]
Water quality cascading	Alleviate water scarcity through water quality analysis.	[211]
Sustainable circular index	Substituting physical elements with virtual ones which factor in social, environmental, economic, performance and circular indexes.	[212]
European platform on LCA	Provisions frameworks on material and emissions. ISO 14044 and International Reference Life Cycle Data System was used to model the circular flow of nutrients in the LCA analysis in the study.	[213,214]
LSTM RNN influent data generator	Simulate influent data to fill in missing data gaps to train ML models. For example, missing TSS, COD and ammonia nitrogen concentration data.	[215]

selections depending on their contributions to the final output (Fig. 7).

Nutrient recovery technologies are highly energy intensive and renewable power sources have become a method of cutting down on-grid energy [220]. This connectivity to solar and wind power sources for example, could be integrated into the wider ML ecosystem for day-ahead solar weather forecasting [221] and wind near-weather predictions [222] to improve the reliability of renewable power sourcing for CE WWTP.

The management of dangerous goods and chemicals will also be required given stringent regulations surrounding its disposal and treatments. Waste management 4.0 can help predict quantities of dangerous waste for collection [223]. Data collection on hazardous materials in the construction sector will play a huge role [224], one where it could also be applied in CE WWTP influent for hazardous chemicals prediction, detection and removal. The data must also be verifiable for the ML model to predict effluent qualities or water reuse safety that can be trusted by stakeholders — something that is important when wastewater can contain fatal chemicals and contaminants. However, nutrient discharge impacts on the environment with ML are most commonly studied in the absence of a CE focus.

Big Data is proving to be decisive in evaluating the sustainable performance of countries, organisations and companies. The development of the United Nations (UN) Sustainable Development Performance Indicators, helps companies measure their sustainability progress covering activities such as CE, the Green and Sharing Economy, and other climate change impacts [225]. The collection of operating, environmental and market data for ML CE WWTPs can help meet these objectives towards safety, sustainability and industry compliance (Fig. 7). Data democratisation allows improved access to environmental benchmarks where operators can compare their own sustainability performances with other metrics. Different CE WWTPs can get real-time performance data to determine how well nutrient recovery processes remain within safe and standard limits that also support CE decision making for all participants [226].

3.10. Stakeholder inclusion

Forums are opened up to stakeholders through online channels that help to shape sustainability frameworks and regulations. Website and intake platforms are developed to capture stakeholder voices on the development of CE WWTP technologies [227]. An example of this platform is its ease of comprehension to its viewers, and the compilation of nutrient recovery technologies is presented in an easily navigable way to public stakeholders to drive progress and implementation across WWTP. Experienced stakeholders can recommend best input data as predictors for supervised ML [228], which can help shape the way data is collected, processed to predict or automate for certain outcomes.

There are a lack of tools enabling sustainable supplier selection throughout CE ecosystems mainly due to the infancy of such technologies [229]. ML use with best-worst methods and fuzzy inference systems can optimise the sustainability scores of fertilisers and other upstream suppliers [229]. This scoring of sustainable suppliers against critical fertiliser products requires extensive supplier and producer engagement to collect verifiable and reliable sustainability data. The metrics will vary depending on the niche traits. Big data analytics will play a crucial role in providing information to all stakeholders [226]. Economists and researchers for example, are more concerned about environmental regeneration, while administrators expect job creation and economic growth utilising bottom-up approaches led by companies and consumers [111]. It is important to consider the diversity of voices, particularly when CE nutrient WWTP policies have an impact on everyone.

4. Discussion

Nutrient ML CE WWTPs are an emerging technical area of wastewater resource recovery for phosphorous, nitrogen and ammonia from wastewater streams. The hesitancy in its widespread adoption arises from the unknown prediction accuracies and reliabilities from using ML models to manage WWTPs to ensure safe resource reuse and its incompatibility with many outdated treatment plants. Pilot WWTPs throughout the world have implemented large-scale, struvite

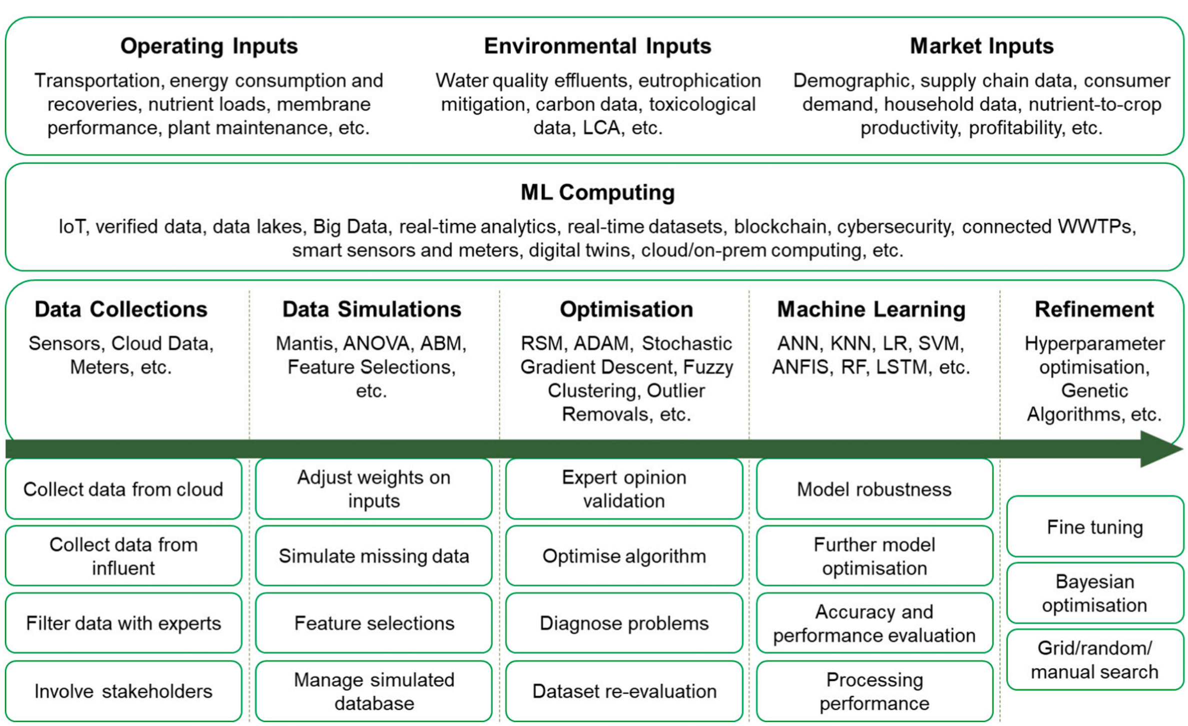

Fig. 7. CE WWTP will integrate a wide range of data beyond influent collection to provide the most optimal mode of operation to include market, environmental and operating parameters to improve operating efficiencies, economies of scale, and cost-effective nutrient recovery.

precipitation technologies, but none so far have incorporated ML. There are opportunities for using ML to optimise and manage nutrient, energy, water and other material recoveries to cost-effectively increase CE productivity. ML with open-data sources can work with other treatment plants to coordinate an effective nutrient supply and demand planning network which is responsive to the needs of farmers while encouraging trustworthy participation from consumers and households, and help manage nutrients in a way that maximises crop productivity and monitors the wider environment against eutrophication. It can be interpreted that ML drives nutrient CE productivity and success by connecting all of these drivers and overcoming limitations in a space that is still developing in response to EU directives declaring phosphorous as a critical raw mineral.

Blockchain offers opportunities to track and trace nutrients and waste throughout CE WWTPs while maintaining anonymity, and aid in supplier evaluation and management [230,231]. The technology can support in decarbonisation of waste management operations by tracking the carbon footprint and origins of CE products throughout the nutrient CE supply chain — allowing buyers to determine whether the CE product comes from a mined or recycled source. Verifiable data is a core part of the ML trust building process given the sensitive nature of reusing processed waste for fertiliser applications given ML models can only be as good as the data being ingested (Fig. 8). The inclusion of various stakeholders across different forums can shape the determination of significant data points for ML models for high accuracy predictions, however, there is no standardised guideline governing the selection of inputs and training of ML models for CE WWTPs.

ML is still lacking in studies for optimal value realisation between nutrient recovery, processes and market distribution to agriculture and meeting environmental targets. For example, ML use for biochar application in soils and fertilisers, and optimising processes against emissions reductions. There presently is a lack of digital literacy to aid in decision-support applications for ML nutrient management [232], which highlights a barrier to ML implementation for nutrient CE WWTP given its recentness for a largely legacy-based, WWTP industry. The study of ML for microalgae biofuel production is still in its infancies [233], while bioplastic recycling with wastewater nutrients and microorganisms has yet to see ML applications [234]. ML hindrance is worsened by the lack of maturity in some recycling technologies besides nutrients. Even in the presence of regulations, it will be impossible for CE WWTP to operate on an ongoing loss. Subsidies and other economic levers may need to be introduced to soften operating losses while the technology achieves

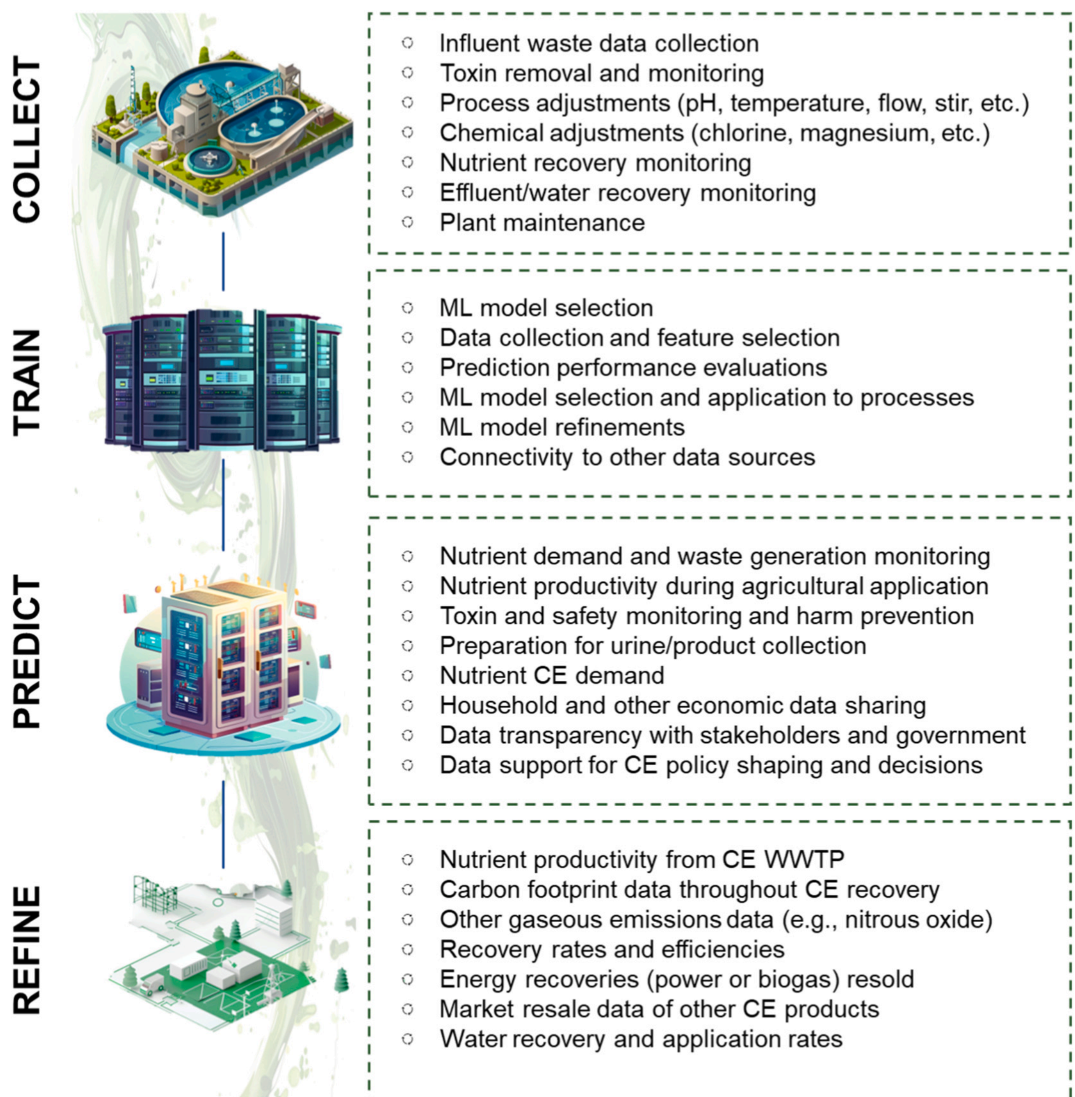

Fig. 8. The ML CE WWTP framework will be based on a continuous learning model to refine and improve the safety of recovered nutrients for agricultural applications, while auxiliary data is consumed to refine the recovery of other products to increase the circularity of a wide range of waste types, and to improve CE WWTP connectivity with wider society.

profitability. Meanwhile, the recovered nutrients are subject to market spot prices for phosphorous.

5. Conclusion

The emergence of ML technologies has the potential to revolutionise the way nutrients are recovered from wastewater streams. The intersection between nutrient influent data, the environment, farmers, stakeholder, consumer and household trends are a reflection of a growing need to integrate ML to improve the performance and viability of CE. Predictions for CE quality, safety, energy recoveries and management, nutrient supply and demand planning, improved crop productivity and environmental pollution monitoring are all important benefits that ML can produce within nutrient CE. Policies, technologies, infrastructure, societal attitudes and market forces moderate the efficacy and success of nutrient CE programs with wastewater. Besides the EU, very few jurisdictions outside have regulated standards governing the resale of precipitated phosphorous from waste sources, and even less so with ML. Whereas water quality reuse standards are effectively developed across most advanced economies where it is clear which grades of recycled water are for what applications. ML acts as a bridge and an accelerant for the transition towards a future where critical raw materials are recovered for both sustainability and security purposes, however not many if at all, any regulations give focus on using ML to manage waste recovery. The framework paper is unique by providing ML insights into nutrient CE within the context of WWTPs, and serves as a foundation for ML-integrated CE for waste-derived fertilisers in a world where environmental, social and governance regulations serve to secure future generations with critical materials.

It is proposed that future studies should explore performance evaluation criteria and protocols towards implementing correct ML models based on influent load data with the most promising nutrient recovery technologies weighed against market prices of fertilisers and GHG emissions. Given that each country will have unique environmental problems and therefore, solutions to achieve those goals — different nutrient technologies will be prioritised. Different actors throughout this framework such as governments, societies, households, consumers, farmers, non-governmental organisations and WWTP operators and their influence on the successful outcomes of CE using ML should also be studied. This will help identify the strongest and weakest links between various WWTP stakeholders and nutrient CE WWTP operators that can help prioritise relationships. By understanding the impacts of ML across CE WWTPs would a true economy of scale in recovered nutrients for fertiliser production be achieved.

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. Ho Kyong Shon serves as a co-Executive Editor for the DWT journal, while the editorial handling and review of this manuscript were overseen by a different co-Executive Editor.

Data availability

No data was used for the research described in the article.

Acknowledgements

This project is supported by the Australian Research Council (ARC) through the ARC Research Hub for Nutrients in a Circular Economy (NiCE) (IH210100001).

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