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Evaluation of Biological Denitrification from Brackish Groundwater Using Different Filter Media

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Abstract

Nitrate contamination of groundwater poses significant environmental and health concerns, particularly in arid and semi-arid regions where brackish groundwater is widely exploited for non-potable uses or as feed water for desalination systems. In this study, biofilm-based nitrate removal from brackish groundwater with Electrical Conductivity ranging from 851 to 3150 µS/cm was investigated using a pilot-scale up-flow biofilter system. Seven different filter media, including Kaldnes, coarse Lightweight Expanded Clay Aggregate, fine LECA, fine sand, palm fiber, multi-media, and plastic baskets, were evaluated in parallel pilot units operated under identical conditions. The experimental program was conducted under varying influent nitrate concentrations (112.0–279.5 mg/L), flow rates (13.0–52.0 L/h), and Hydraulic Retention Times (from 1.0 h for fine sand to 7.6 h for plastic baskets) during three periods from June to November 2021. Nitrate removal performance was assessed primarily in terms of removal efficiency (%). Among the evaluated media, coarse LECA demonstrated the highest performance, achieving a nitrate removal efficiency of 82.1% followed by Kaldnes (68.1%) during Period 2. Notably, palm fiber exhibited considerable removal efficiency (61.2%), which may be attributed not only to its physical support function but also to its lignocellulosic nature. To evaluate the non-linear relationships between operational parameters, an eXtreme Gradient Boosting machine learning model was applied using independent variables including flow rate, pH, EC, temperature, and influent nitrate. The SHapley Additive exPlanations analysis revealed that the flow rate was the most critical determinant of nitrate removal efficiency, followed by pH and EC. Overall, the findings indicated that biofilm-based nitrate removal using pilot-scale up-flow biofilters can provide an effective and low-energy treatment or pre-treatment option for nitrate-contaminated brackish groundwater.

Keywords:
Biological Denitrification, Brackish Groundwater, Biofilter Media, Machine Learning, eXtreme Gradient Boosting, SHapley Additive exPlanations.

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1. Introduction

Nitrate contamination of groundwater is a widespread environmental problem resulting primarily from agricultural activities, wastewater infiltration, and improper disposal of nitrogen-rich effluents. Elevated nitrate concentrations pose significant health risks, including methemoglobinemia in infants and potential associations with gastrointestinal and thyroid cancers (Ward et al., 2018; WHO, 2011).

Consequently, nitrate control in groundwater resources remains a priority for water management authorities worldwide. In arid and semi-arid regions, groundwater resources are increasingly affected by salinity due to natural geological conditions, overexploitation, and seawater intrusion. Although saline groundwater is often unsuitable for direct potable use, it is widely utilized for non-potable applications, water blending strategies, and as feed water for desalination systems (Anning et al., 2018).

In such applications, elevated nitrate concentrations limit reuse options and complicate downstream treatment processes. Various physicochemical and biological approaches have been investigated for nitrate removal from water, including ion exchange, membrane processes, and biological denitrification (Nikaeen and Naseri, 2007; Soleymani et al., 2008; Mazarji et al., 2017; Ranjbari-Kohi et al., 2022), each with distinct advantages and limitations depending on water quality and operational conditions (Abascal et al., 2022).

Membrane-based desalination technologies such as reverse osmosis are capable of simultaneously removing salinity and nitrate; however, they are energy-intensive, costly, and sensitive to fouling when treating nitrate-rich waters (Werber et al., 2016).

Biological denitrification using biofilm-based systems has gained increasing attention as a low-energy and adaptable alternative, with several studies reporting stable nitrate removal performance under saline and hypersaline conditions (Huang et al., 2025).

The effectiveness of biofilm reactors is strongly influenced by filter media properties, which govern microbial attachment, biofilm stability, and mass transfer processes (Flemming and Wingender, 2010).

Despite previous studies on biological denitrification, predicting the complex, non-linear interactions of operational parameters in brackish water remains a significant challenge. Recent literature highlights the necessity of applying advanced predictive tools and explainable artificial intelligence in water treatment processes (Chen and Guestrin, 2016; Babaei et al., 2023; Alaei et al., 2024).

Therefore, to bridge this research gap, the present study aims to evaluate the performance of seven distinct biofilter media for nitrate removal from brackish groundwater. Furthermore, as a novel approach in this domain, an explainable machine learning model based on eXtreme Gradient Boosting[1] (Chen and Guestrin, 2016) coupled with SHapley Additive exPlanations[2] (Lundberg and Lee, 2017) was employed to deeply interpret the complex effects of independent operational factors (e.g., flow rate, pH, and Electrical Conductivity[3]) on the biological treatment system.

2. Materials and methods

2.1. Experimental setup and pilot configuration

A pilot-scale biofiltration system consisting of fourteen cylindrical Polyvinyl Chloride[4] columns (120 cm height × 10 cm internal diameter) were operated from June 22 to November 24, 2021, under ambient temperatures (Fig. 1). Seven filter media (Kaldnes, coarse Lightweight Expanded Clay Aggregate[5], fine LECA, fine sand, palm fiber, multi-media, and plastic baskets) were tested in duplicate. The influent water was collected from a decommissioned drinking-water well containing natural brackish groundwater. When necessary, the raw groundwater was appropriately diluted with tap water to obtain the desired nitrate concentrations. Subsequently, sodium chloride was added, when required, to adjust the EC to the target experimental levels, resulting in influent EC values ranging from 851 and 3150 µS/cm. This preparation procedure enabled controlled adjustment of salinity while maintaining groundwater as the primary source water. Dilution with tap water also helped minimize potential chloride interference during nitrate measurements. Influent nitrate concentrations ranged from 112 to 279.5 mg/L as NO_3^-–N, and pH varied between 7.1 and 8.5.

Each column was packed with a single medium (total bed depth: 120 cm), except the multi-media column, which was layered: 15 cm fine sand (bottom), 15 cm Granular Activated Carbon[6], 10 cm fine LECA, 15 cm fine sand (middle), 50 cm coarse LECA, and 15 cm fine sand (top). Fine sand layers (15 cm) at the top and bottom of all columns ensured uniform flow distribution and minimized media loss. All experimental columns contained a 15-cm layer of standard GAC, commonly used in water treatment applications, placed between the bottom supporting layer and the main filter medium. The GAC layer was identical in all columns and was therefore considered a fixed component of the experimental configuration rather than an experimental variable.

[1] eXtreme Gradient Boosting (XGBoost)
[2] SHapley Additive exPlanations (SHAP)
[3] Electrical Conductivity (EC)
[4] Polyvinyl Chloride (PVC)
[5] Lightweight Expanded Clay Aggregate (LECA)
[6] Granular Activated Carbon (GAC)



Fig. 1. The biofiltration pilot used in the current study with fourteen cylindrical PVC columns

No external soluble carbon source, such as methanol, ethanol, or acetate, was added to the system. Among the main filter media, palm fiber was identified as the only lignocellulosic organic medium, by which a biodegradable solid carbon source is probably provided, in addition to being utilized as a support for biofilm development. Operational conditions were categorized into three sequential periods based on the influent nitrate concentrations. Period 1 (June–August) corresponded to a concentration range of 112–154 mg/L, representing system start-up and biofilm maturation. In Period 2 (September–October), the influent nitrate concentration remained highly stable at a constant value of 167.5 mg/L. Finally, Period 3 (November) included a range of 182–279.5 mg/L, reflecting naturally increased loading conditions from the groundwater source. This grouping allowed a comparative evaluation of the filter media under different loading scenarios.

2.2. Hydraulic conditions and flow control

The total influent flow rate supplied to the pilot-scale system, consisting of 14 parallel columns, ranged from 13 to 52 L/h. The flow was maintained using an intermediate flow-control tank supplied from a 1 m³ main reservoir. A constant water level in the intermediate tank provided a stable hydraulic head. Assuming uniform flow distribution among the columns, the flow rate per column was calculated by dividing the total system flow rate by the number of columns yielding approximately 0.93–3.71 L/h per column. The Hydraulic Loading Rate[1] was calculated for each column using the column cross-sectional area and the corresponding flow rate, according to Eq. 1:

$$HLR = \frac{Q}{\pi r^2} \quad (1)$$

Where

Q is the flow rate through an individual column (m³/day) and r is the column internal radius (m). For a column with an internal radius of 0.05 m, the resulting HLR ranged from approximately 2.8 to 11.4 m³/m²·day. The theoretical Hydraulic Retention Time[2] was calculated based on the effective pore volume of the packed bed, as expressed in Eq. 2:

$$HRT = \frac{\varepsilon * V_{bed}}{Q} \quad (2)$$

Where

V_{bed} is the total packed-bed volume (m³), and ε is the bed porosity expressed as a dimensionless fraction. This calculation assumed saturated flow and uniform flow distribution. Because the filter media differed in porosity and packing characteristics, the actual theoretical HRT could differ among columns operated at the same flow rate. Water samples were collected from sampling ports installed at 35 cm intervals after stable saturated flow had been established. The calculated HRTs, based on the average porosity values reported in Table 1, ranged from 1.8-7.2, 1.3-5.3, 1.2-4.8, 1.0-4.0, 1.8-7.2, 1.9-7.6 and 1.2-4.7 h for Kaldnes, fine LECA, coarse LECA, fine sand, palm fiber, plastic baskets and multi-media bed, respectively, across the two flow rates (0.00093 and 0.00371 m³/h).

2.3. Characteristics of biofilter media

Filter media were selected based on prior use in biofiltration applications, availability, and potential for biofilm support. Although porosity and specific surface area were not measured directly, manufacturer specifications and literature sources were used to qualitatively classify media for comparative interpretation (Loh et al., 2021). Various filter media

[1] Hydraulic Loading Rate (HLR)

[2] Hydraulic Retention Time (HRT)

Table 1. Physical characteristics of the individual filter media considered in this study

Row	Filter media	Porosity (%, mean)	Specific surface area (m^2/m^3)	Reference
1	Kaldnes (K3/K1)	85-95 (90)	500-800	(Rusten et al., 2006)
2	Fine LECA	- (60)	2200	(Nikiema and Heitz, 2010; Taheriyoun et al., 2026)
3	Coarse LECA	51-55 (53)	470-550	(Nkansah et al., 2012)
4	Fine sand	35-45 (40)	>1000	(Edzwald, 2011)
5	Palm fiber	85-98 (91)	113-2013	(El-Dessouky and Al Marshad, 2016)
6	Plastic baskets	>95 (96)	98-223	(Tchobanoglous et al., 2014)
7	GAC	35-40 (37)	800-1000*	(Worch, 2021)

* The unit is m^2/g.

were used in this study. The Kaldnes K3 moving bed media was supplied by Kavian Co. (Iran) with standard geometric specifications. The physical characteristics (porosity and specific surface area) of all applied media, based on manufacturer details and reliable scientific literature, are summarized in Table 1.

2.4. Experimental periods and operational strategy

Operational conditions were categorized into three sequential periods based on influent nitrate levels. Period 1 (June-August) corresponded to 112-154 mg/L and represented system start-up and biofilm maturation. Period 2 (September-October) featured stable nitrate concentrations (~167.5 mg/L) and served as the primary basis for comparing media performance. Period 3 (November) involved elevated nitrate loads (182-279.5 mg/L) and focused on coarse LECA and palm fiber media due to their superior performance in earlier periods. Period 2 was characterized by stable nitrate levels, in contrast to Periods 1 and 3, during which concentrations varied.

2.5. Water quality analysis

Water quality parameters were measured according to Standard Methods for the Examination of Water and Wastewater (Rice et al., 2017). Nitrate (NO_3^-–N) was analyzed using the cadmium reduction method, with special calibration to minimize chloride interference due to salinity. Ammonium (NH_4^+–N) was measured using the phenate method, and ammonia (NH_3) concentrations were estimated based on pH and temperature relationships. Since the detected concentrations of Ammonium (NH_4^+) were strictly negligible and did not impact the overall denitrification process, further monitoring was discontinued and the data were excluded from the final analyses. pH, EC and temperature were determined with calibrated probes and instruments.

2.6. Data processing and statistical analysis

Nitrate removal efficiency (%) was calculated based on influent and effluent concentrations. Outlier screening was conducted using the interquartile range method. Analysis of Variance[1], followed by Tukey's Honestly Significant Difference[2] test, was applied to assess statistically significant differences among filter media. Pearson correlation analysis was used to evaluate linear relationships between flow rate and nitrate removal efficiency.

Machine learning analysis was performed using XGBoost regression to model nitrate removal efficiency as a function of operational parameters, including flow rate, pH, EC, temperature, influent nitrate concentration, and filter media type, following recent environmental applications of machine learning approaches (Liu et al., 2025).

A total of 88 data records collected under steady-state conditions were used to develop the predictive model. XGBoost was selected due to its high performance with tabular data, computational efficiency, and robustness against overfitting. The preprocessed dataset, comprising inflow rate, pH, EC, temperature, influent nitrate concentration, and one-hot-encoded media types, was randomly split into an 80% training set and a 20% independent test set at the independent batch level to prevent data leakage. During training, 5-fold cross-validation was applied exclusively within the training subset for hyperparameter tuning, while the independent test set was reserved for final model evaluation. The optimized XGBoost hyperparameters were as follows: n_estimators=300, max_depth=6, learning_rate=0.05, subsample=0.8, and colsample_bytree=0.9. Model performance was evaluated using coefficient of determination (R^2), Root Mean Squared Error[3] and Mean Absolute Error[4].

[1] Analysis of Variance (ANOVA)
[2] Honestly Significant Difference (HSD)
[3] Root Mean Squared Error (RMSE)
[4] Mean Absolute Error (MAE)

Categorical variables, such as filter media type, were processed using one-hot encoding to avoid introducing unintended ordinal bias and allow the model to independently assess the contribution of each material. Model interpretability and feature importance were assessed using SHAP, based on established methodologies (Chen and Guestrin, 2016; Lundberg and Lee, 2017). SHAP values were used instead of traditional β coefficients to quantify the contributions of individual features in the nonlinear, tree-based XGBoost model. The TreeSHAP method, implemented using the TreeExplainer class in Python's SHAP library, was employed to calculate SHAP values efficiently and accurately for the tree ensemble. TreeSHAP estimates the marginal contribution of each feature to model predictions, and each prediction is expressed as the sum of a baseline value and the SHAP values of the individual features, enabling consistent interpretation of feature contributions.

3. Results and discussion

3.1. Comparison of nitrate removal efficiency among filter media

The nitrate removal efficiency during Period 2 was shown in Fig. 2. Significant differences were observed among media, emphasizing the importance of media characteristics for effective biofilm development and denitrification (Song et al., 2025). Coarse LECA showed the highest efficiency (82.1±4.8%), followed by Kaldnes (68.1±9.0%) and palm fiber (61.2±14.9%) (Table 2). Fine sand showed moderate efficiency (46.3±6.1%), while multi-media and plastic baskets were ineffective. The superior performance of coarse LECA is consistent with recent pilot-scale evaluations of porous mineral media, which emphasize enhanced biofilm stability and mass transfer (Albuquerque et al., 2009; Song et al., 2025).

The comparative analysis of nitrate removal efficiencies (Tables 2 and 3) reveals a strong relationship between the physical characteristics of the filter media—specifically porosity and specific surface area—and their biological performance. Coarse LECA exhibited the highest removal efficiency (82.1% in Period 2 and 65.9% in Period 3). This superior performance can be attributed to an optimal balance between its specific surface area (200_ 400 m^2/m^3) and adequate porosity (40-50%), combined with a rough surface texture that promotes robust biofilm attachment while maintaining sufficient hydraulic pathways to prevent clogging.

In contrast, Fine sand, despite possessing the highest specific surface area (>1000 m^2/m^3), demonstrated a significantly lower efficiency (46.3±6.1%). This indicates that excessive surface area is counterproductive if not accompanied by sufficient porosity. The lower porosity of fine sand likely led to rapid bed clogging and flow channeling, thereby reducing the effective HRT and the contact between the biofilm and the influent nitrate. Furthermore, highly porous media such as Kaldnes (68.1%) and Palm fiber (61.2%) showed satisfactory performances. Their high porosity (>80%) facilitated smooth water flow and minimized clogging risks. However, media with high porosity but insufficient surface area and smooth textures, such as Plastic baskets (~0% removal), failed to develop a stable denitrifying biofilm, highlighting that both a minimum specific surface area and favorable surface roughness are essential prerequisites for successful biological denitrification.

Table 2. Nitrate removal efficiency (%, Period 2)

Media	Nitrate removal efficiency* (%)
Coarse LECA	82.1 ± 4.8
Kaldnes	68.1 ± 9.0
Palm fiber	61.2 ± 14.9
Fine LECA	48.1 ± 1.1
Fine sand	46.3 ± 6.1
Multi-media	7.8 ± 4.8
Plastic baskets	~0

*Removal efficiency (%) = ((Cin − Cout) / Cin) × 100

Table 3. Removal efficiency under high nitrate loading (Period 3)

Media	Removal efficiency (%)
Coarse LECA	65.0-67.0
Palm fiber	49.8-52.2

Influent nitrate concentration ranged from 182 to 279.5 mg/L.

Although no external soluble carbon source was added, all experimental columns contained an identical GAC layer as a fixed component of the bed configuration. GAC was not considered a readily biodegradable carbon source or a direct electron donor in the present study; however, its high specific surface area may have supported biofilm development and may have influenced the microbial microenvironment through the adsorption and concentration of naturally occurring organic matter from the influent groundwater. Furthermore, because natural groundwater rather than synthetic water was used, the possible contribution of naturally occurring organic matter or other native electron donors cannot be excluded. Palm fiber, due to its lignocellulosic nature, may have provided a slowly biodegradable solid carbon source. However, due to the lack of direct characterization of dissolved organic carbon, chemical oxygen demand, other potential electron donors, and the microbial community, the specific electron-donor pathway remained unclear. Consequently, the contribution of individual microbial groups to the overall process could not be conclusively established.

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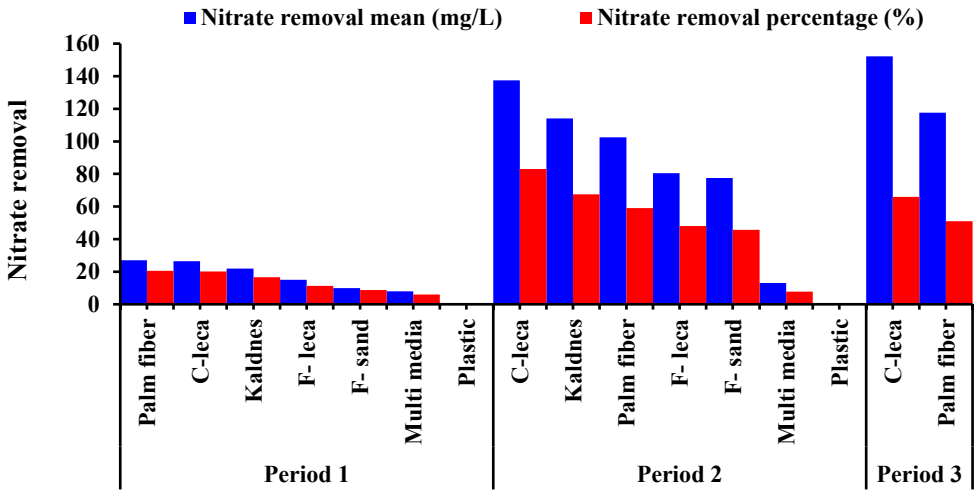

Fig. 2. Mean and percentage removals of nitrate through different medias with inlet nitrate concentrations of 133, 167.5 and 230.7 during Periods 1, 2 and 3, respectively. F: Fine; C: Coarse

3.2. Effect of hydraulic conditions on nitrate removal efficiency

Negative correlations were observed between flow rate and nitrate removal efficiency across all media, with coarse LECA exhibiting the strongest statisitically significant inverse relationship (r=-0.65, p=0.030), followed by palm fiber (r=-0.62, p=0.040). Although Kaldnes (r=-0.49 p=0.081) and fine sand (r=-0.38, p=0.117) also exhibited negative correlations (Table 4), their p-values exceeded the 0.05 significance threshold, indicating non-significant trends. These findings confirm that increasing flow rates reduce HRT, thereby limiting the contact time between nitrate and the biofilm surface, which ultimately decreases removal efficiency. The stronger negative correlations observed in coarse LECA and palm fiber can be attributed to their higher specific surface areas and more favorable biofilm attachment properties, making them more sensitive to hydraulic fluctuations. These results are consistent with previous studies in biofilm-based systems (Tchobanoglous et al., 2014), reinforcing the critical role of HRT in optimizing nitrate removal performance.

3.3. Statistical validation of media performance

Tukey's HSD test (Table 5) confirmed that coarse LECA significantly outperformed fine sand, multi-media, and plastic media (p<0.001), highlighting the critical role of media structure, porosity, and surface roughness in biofilm-based nitrate removal. Palm fiber also exhibited significantly higher removal efficiency than fine sand (p=0.031), although with greater variability, likely associated with progressive degradation of its organic matrix and dynamic biofilm development. These findings are consistent with previous studies emphasizing the importance of media physical characteristics in fixed-film denitrification systems (Flemming and Wingender, 2010; Tchobanoglous et al., 2014).

Table 4. Pearson correlation analysis

Media	r	p-value
Coarse LECA	-0.65	0.030
Palm fiber	-0.62	0.040
Kaldnes	-0.49	0.081
Fine sand	-0.38	0.117

Negative r indicates decreasing removal efficiency with increasing flow rate.

Table 5. Tukey HSD pairwise comparison (Period 2)

Comparison	Mean difference (%)	p-value
Coarse LECA – Fine sand	+35.8	0.001
Coarse LECA – Palm fiber	+20.9	0.004
Coarse LECA – Plastic	+82.1	0.001
Palm fiber – Fine sand	+14.9	0.031

Tukey HSD test following one-way ANOVA; significance at $p < 0.05$.

3.4. Performance under high nitrate loading conditions

During Period 3, coarse LECA maintained high nitrate removal efficiencies ranging from 65.0 to 67.0 % when subjected to fluctuating conditions (Table 3). Palm fiber sustained moderate removal efficiencies (49.8–52.2%) under similar stress. This indicates continued denitrification activity despite increased influent concentrations. The observed robustness of coarse LECA under high-load conditions is consistent with earlier reports on the stability of porous mineral media in

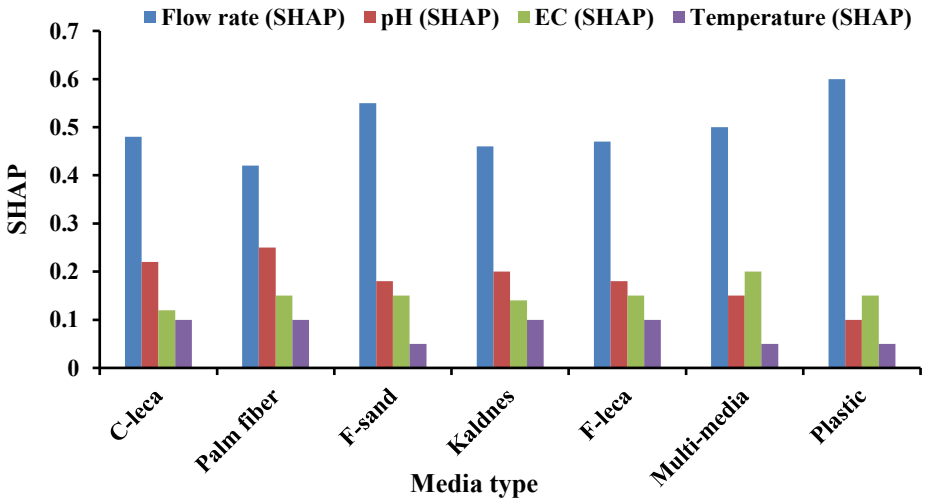

Fig. 3. Mean absolute SHAP values for factors influencing nitrate removal during Period 2 over different medias

biological nitrate removal systems (Nurk et al., 2009). These results suggest that media capable of supporting stable and well-developed biofilms are better suited for treatment scenarios involving fluctuating or high nitrate loads.

3.5. Machine learning interpretation of controlling factors

SHAP analysis (Table 6 and Fig. 3) identified flow rate as the most influential factor, followed by influent pH and EC. The SHAP summary plot (Fig. 3) presents the global absolute feature importance (mean absolute SHAP values) across all predictors, including the binary one-hot-encoded media variables. The XGBoost regression model on the test dataset yielded an R^2 of 0.84, RMSE of 8.78% relative error, and MAE of 4.51% relative error. Due to the non-linear structure of gradient boosted decision trees, traditional linear regression metrics such as β coefficients and p-values are methodologically inappropriate. Therefore, feature importance and the relative influence of operational parameters on nitrate removal efficiency were interpreted using mean absolute SHAP values (Table 6).

Table 6. Mean absolute SHAP values of operational parameters in the XGBoost model

Parameter	SHAP value
Flow rate	0.48
Influent pH	0.22
Influent EC	0.15
Temperature	0.09
Influent nitrate concentration	0.06

SHAP values indicate relative importance of predictors in the XGBoost model.

3.6. Implications for brackish groundwater treatment

Although brackish groundwater is generally unsuitable for direct potable use, effective nitrate removal remains essential for blending strategies, environmental protection, and pre-treatment prior to desalination processes. Previous studies have shown that high nitrate concentrations in saline groundwater can exacerbate downstream treatment challenges, including membrane fouling and increased operational costs in desalination systems (Tchobanoglous et al., 2014).

The results of this study demonstrated that biofilm-based nitrate removal can substantially reduce nitrate loads upstream of advanced treatment units, thereby improving the overall sustainability and efficiency of integrated groundwater treatment schemes. Similar benefits of biological pre-treatment for saline and brackish waters have been reported in arid and semi-arid regions, where groundwater quality constraints require multi-stage treatment approaches (González-Costa et al., 2026).

Furthermore, the strong dependence of nitrate removal efficiency on hydraulic conditions highlights the importance of optimizing flow rate and HRT, particularly for decentralized and small-scale systems. As emphasized in established water treatment design frameworks, proper hydraulic control is a key factor in enhancing the performance and reliability of fixed-film biological reactors (Tchobanoglous et al., 2014). Accordingly, biofilm-based nitrate removal systems can be effectively integrated as a robust and adaptable pre-treatment step for brackish groundwater management.

4. Conclusion

The proposed up-flow biological system demonstrated significant sustainability for groundwater treatment. This

sustainability is achieved through the utilization of low-cost, naturally available media (LECA and palm fiber), low energy requirements compared to conventional systems, and the ability to directly treat brackish groundwater without energy-intensive pre-treatment. The results further revealed that coarse LECA was the most efficient media, achieving nitrate removal efficiencies of 82.1% under steady-state conditions (Period 2). The coarse LECA primarily functioned as physical support for biofilm development. The different removal function was also observed by palm fiber, through which its lignocellulosic composition potentially provided supplementary electron donors for denitrification. These media also exhibited high resilience, maintaining satisfactory performance even under fluctuating flow rates and varying brackish conditions. The application of the XGBoost machine learning model, coupled with SHAP value analysis, provided deep insights into the process dynamics. It revealed that flow rate, followed by influent pH and EC, were the most influential operational parameters on the system's efficiency. Overall, the integration of natural filter media with advanced predictive modeling offers a sustainable, robust, and scalable framework for managing nitrate contamination in brackish water resources.

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