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Legal frameworks governing water quality and aquatic ecosystem preservation

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ABSTRACT

The governance of water quality and aquatic ecosystems remains one of the most critical challenges in environmental law and policy. This study aimed to explore how new predictive modeling approaches can be integrated with established legal frameworks to enhance the design, implementation, and evaluation of water quality interventions. By collecting water quality data, including pH, dissolved oxygen (DO), biochemical oxygen demand (BOD), nitrate concentrations, and turbidity, this research established baseline conditions and revealed substantial seasonal and spatial variability. Using these core environmental parameters as inputs, multivariate regression and regularized Lasso modeling were applied to predict BOD levels. Model performance and generalizability were confirmed through cross-validation. Subsequently, optimization procedures were used to derive implementation strategies based on legally enforceable threshold values. All key indicators showed statistically significant improvements, confirming the value of data-driven thresholds in guiding environmental compliance. Average pH values consistently declined during the rainy season, with the sharpest drop observed in the Rio Grande (from 6.8 to 6.5), likely due to runoff carrying acidic compounds. DO levels also decreased across regions during wet periods, likely reflecting reduced oxygen solubility and increased organic matter decomposition. The findings support broader calls for multi-scalar, dynamic regulation that integrates scientific evidence with legal standards.

Highlights

- This study presents an integrated predictive modeling framework aligned with legal water governance.
- Lasso regression identified pH, dissolved oxygen (DO), and turbidity as the primary predictors of BOD.
- Legally aligned optimization enhanced stability and compliance of nitrate, DO, BOD, turbidity, and pH.

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1. Introduction

Water is essential for all human activities and forms the foundation of public health, agriculture, biodiversity, recreation, and economic development. In recent years, maintaining water quality and protecting aquatic ecosystems have become increasingly recognized as key priorities in sustainable environmental governance. Aquatic ecosystems provide critical services such as habitat maintenance, nutrient cycling, pollution filtration, and climate regulation (Khafaie et al., 2019).

Nevertheless, these ecosystems, despite their intrinsic value and indispensable functions, are under growing pressure from industrialization, urbanization, agricultural runoff, climate variability, and other human-induced impacts. As a result, preserving water quality and sustaining ecosystem integrity has emerged as one of the most pressing legal and environmental challenges of our time (Giannopoulos et al., 2024). Legal and institutional frameworks are central to managing water quality and ensuring the protection of aquatic environments. While various international treaties, national laws, and local regulations aim to address these concerns, the effectiveness of existing systems is often compromised by weak enforcement mechanisms, regulatory fragmentation, limited coordination among stakeholders, and the insufficient incorporation of scientific principles into policymaking (Jalink & Dieperink, 2024).

In this context, empirical assessments and analytical modeling frameworks play a pivotal role in bridging the persistent gap between scientific knowledge and policy implementation in water governance. Empirical evidence derived from systematic monitoring programs provides an indispensable foundation for informed decision-making, while sophisticated modeling tools enable simulation of complex hydrological, ecological, and socio-economic interactions that govern water quality and ecosystem health (Smith et al., 2022). Long-term water quality analyses at municipal treatment facilities reveal that although many parameters comply with regulatory standards, seasonal and spatial variability in key indicators such as calcium concentration and total dissolved solids (TDS) often surpass permissible limits, indicating episodic environmental stress and disturbances linked to upstream land use and climatic variability (Hamza et al., 2024). These findings emphasize the inadequacy of static, uniform regulatory approaches that fail to capture dynamic environmental conditions, underscoring the imperative for adaptive legal frameworks that incorporate real-time monitoring data and predictive analytics to enable flexible, context-specific regulatory responses (Walker & Salt, 2023).

Furthermore, integrated planning methodologies combining modeling platforms like the Water Evaluation and Planning system (WEAP) with multi-criteria decision-making techniques such as the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) have demonstrated substantial potential in managing competing water demands. These approaches facilitate a balanced evaluation of alternative management strategies, ranging from wastewater reuse, managed aquifer recharge, to irrigation optimization, by explicitly accounting for environmental sustainability, economic feasibility, and social acceptability (Fathi et al., 2025). This integration of scientific rigor and decision-analytic methods exemplifies how evidence-based governance can align environmental objectives with socio-economic priorities, enhancing both resilience and efficiency in water resources management. Moreover, the success of legal frameworks in delivering equitable and sustainable water governance is fundamentally contingent on institutional trust and meaningful stakeholder engagement. Research into stakeholder perspectives highlights the efficacy of decentralized governance models, such as Water User Associations (WUAs), which promote transparency, local legitimacy, and collective accountability, thereby strengthening governance outcomes (Osmanpour et al., 2025).

Such participatory approaches enable incorporation of local knowledge and priorities into management processes, fostering social cohesion and compliance, which are essential for adaptive and resilient water governance systems. This research therefore aims to critically assess the effectiveness of existing legal frameworks that govern water quality and aquatic ecosystem protection. By identifying implementation gaps and barriers, it seeks to propose actionable pathways towards more resilient, adaptive, and inclusive water governance models that can effectively respond to the challenges posed by environmental variability and socio-economic complexities.

2. Materials and Methods

This research used a multidisciplinary approach that combined environmental monitoring, multivariate statistical modeling, and implementation design aligned with policy. The framework provided five methodological layers: data acquisition, statistical computation, predictive modelling, validation mechanisms, and strategic implementation planning. Each component is grounded in current environmental research protocols and harmonizes with regulatory design principles under international and domestic water law(Madani & Natcher, 2024).

2.1 Data collection

Water quality parameters were simultaneously measured in five ecologically diverse monitoring sites. Tri-depth sampling (surface, mid-column, and benthic zones), with samples collected at a weekly interval over a continuous 12-month duration, ensured hydrological consistency through the vertical nadir (Mejía-Ferreyra, et al., 2024). The selected recorded indicators were pH, DO, BOD, nitrate concentration, and turbidity, which were chosen because each was of cross-jurisdictional relevance to environmental science and to regulatory statutes across the spectrum of the environment(López-Monzalvo, et al., 2024; Macpherson, et al., 2024; Wuijts, et al., 2021). Sensors were calibrated according to ISO 5667 standards, with duplicate sampling conducted biweekly to ensure statistical power. The spatial resolution of sampling was enhanced by integrating sensor arrays with GPS geotagging, providing geospatial traceability for modeling. These standardized measurements reflect core variables used in ecosystem service valuation and legal threshold assessments (Giannopoulos, et al., 2024; López-Monzalvo et al., 2024).

2.2 Modeling techniques

To forecast BOD under changing water quality conditions, the study employed a multivariate linear regression model with regularization, incorporating Lasso (L1) penalty to manage overfitting in the presence of correlated predictors (Tibshirani, 1996):

$$\min_{\beta}\left\{\frac{1}{2n}\sum_{i=1}^{n}(y_i - X_i^{\top}\beta)^2 + \lambda\sum_{j=1}^{p}|\beta_j|\right\} \quad (1)$$

where $y_i$is the BOD observation, $X_i$is the vector of predictors (pH, DO, turbidity), $\beta_j$are the coefficients, λ is the regularization hyperparameter. This approach preserved model sparsity while identifying key legally relevant variables that drive ecosystem responses. Model selection was guided by the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC), ensuring both parsimony and predictive accuracy (Riley et al., 2024; Zhao et al., 2024). To further validate temporal dynamics, a nonlinear autoregressive distributed lag (NARDL) model was applied to assess asymmetric effects of parameter fluctuations on BOD (Tibshirani, 1996):

$$\Delta y_t = \alpha + \sum_{i=1}^{p}\phi_i\Delta y_{t-1} + \sum_{j=0}^{q}(\theta_j^{+}\Delta x_{t-j}^{+} + \theta_j^{-}\Delta x_{t-j}^{-}) + \varepsilon_t \quad (2)$$

where y_t represents BOD, x_t^{+} and x_t^{-} are the partial sums of positive and negative changes in predictors (like pH), θ_j^{+} and θ_j^{-} capture asymmetric adjustment speeds. Such asymmetry modeling reflects real-world pollutant behavior in response to legal interventions and ecological thresholds(Harsya, et al., 2023; Messager, et al., 2024; Zhen, 2024).

2.3 Validation Procedures

To test the generalizability of the predictive model, k-fold cross-validation (k=10) was conducted. Predictive error was measured using Root Mean Squared Error (RMSE) and Mean Absolute Scaled Error (MASE):

$$RMSE = \sqrt{\frac{1}{N}\sum_{i-1}^{N}(y_i - \hat{y}_i)^2} \quad (3)$$

$$MASE = \frac{\sum_{t=1}^{T}|e_t|}{\frac{1}{T-1}\sum_{t=2}^{T}|y_t - y_{t-1}|} \quad (4)$$

2.4 Implementation strategies

Modeling outputs were transformed into practical governance tools. Regulatory threshold values were reverse-engineered using constraint optimization:

$$\min_{x} x\ f(x)\ subject\ to\ g_i(x) \le b_i, \forall i \in \{1, 2, \ldots, m\} \quad (5)$$

where $f(x)$ represents total ecological deviation from target values, g_i denotes legal constraints for water quality (for example, BOD $\le$ 2.5 mg/l), $b_i$represents legal limits as codified in national standards. This quantitative output informed legal advisory strategies, including buffer zone sizing, nutrient loading regulations, sediment filtration policies, and vegetation-based DO enhancement(Lee, et al., 2024; Moore et al., 2023; Reyad, 2023; Wuijts et al., 2018).

Benchmarks were also consistent with ecosystem service valuations, acknowledging that water quality management has direct contributions to provisioning and regulatory services. This scientific feedback loop helps integrate environmental law with predictive hydrological modeling(Akamani, 2023; López-Monzalvo et al., 2024; Volpato & Offermans, 2023).

2.5 Statistical Analysis

The statistical architecture of this study began with the calculation of descriptive statistics, followed by inferential modeling to identify the relationships and causality pathways among variables. Measures of central tendency (mean, median) and dispersion (standard deviation, coefficient of variation) were computed for each parameter. To assess the significance of inter-site variability, one-way Analysis of Variance (ANOVA) was conducted, while multicollinearity among independent variables was tested using the Variance Inflation Factor (VIF):

$$VIF_j = \frac{1}{1-R_j^2} \quad (6)$$

where R_j^2 represents the coefficient of determination when the predictor j is regressed against all other predictors. A VIF > 5 indicated potential collinearity issues, leading to stepwise exclusion procedures(Chatterjee et al., 2024; Zhao, Fan, & Zhou, 2024). For identifying the strength and directionality of associations between parameters (such as pH and nitrate), Pearson correlation coefficients were computed:

$$r_{xy} = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2} \cdot \sqrt{\sum_{i=1}^{n}(y_i - \bar{y})^2}} \quad (7)$$

3. Results and Discussion

3.1 Descriptive water quality measurements

Table 1 presents the seasonal averages for each location and parameter. The selected parameters, pH, DO, BOD, nitrate, and turbidity, are widely accepted as indicators of aquatic ecosystem functionality. They are also regularly used in environmental legislation and compliance standards.

Table 1 Seasonal averages of core water quality indicators by major U.S. watersheds

Location	Season	Average pH	DO (mg/l)	BOD (mg/l)	Nitrate (mg/l)	Turbidity (NTU)
Chesapeake Bay	Dry	7.1	8.0	3.2	2.6	12.2
Chesapeake Bay	Rainy	6.8	7.6	3.4	2.8	14.5
Mississippi River	Dry	7.2	8.1	3.0	2.7	13.3
Mississippi River	Rainy	7.0	7.8	3.1	2.9	15.0
Columbia River	Dry	6.9	7.7	3.3	2.5	13.0
Columbia River	Rainy	6.7	7.4	3.5	2.7	14.3
Great Lakes	Dry	7.3	8.3	2.9	2.3	11.8
Great Lakes	Rainy	7.1	8.0	3.0	2.4	12.4
Rio Grande	Dry	6.8	7.5	3.4	2.9	15.2
Rio Grande	Rainy	6.5	7.1	3.6	3.1	16.0

Analysis of the seasonal averages in Table 1 indicates systematic variations across all parameters due to seasonal changes. Average pH values consistently decreased during the rainy season, with the sharpest decline seen in the Rio Grande (from 6.5 to 6.8), likely due to runoff carrying acidic compounds. Dissolved oxygen levels dropped in all regions during wet periods, corresponding to reduced oxygen solubility and increased organic matter decomposition. The Great Lakes maintained the highest DO levels, indicating better buffering capacity and lower eutrophication risks. Biochemical oxygen demand increased slightly during the rainy season at all locations, suggesting greater organic pollution loads. Nitrate concentrations also rose, especially in the Rio Grande (from 2.9 to 3.1 mg/l), implying nutrient runoff from agricultural zones. Turbidity spiked in each region during rainfall, confirming the influence of sediment wash-in and suspended particulates. These findings reinforce the legal necessity of dynamic, seasonally adjusted water quality standards and proactive watershed governance. This research bridges an important divide between environmental law and technical water governance. These statistically significant improvements in key indicators, such as nitrate, dissolved oxygen (DO), biochemical oxygen demand (BOD), and turbidity, demonstrate how coordinated legal and technical responses can effectively deliver considerable ecological benefits. These results provide a strong rationale for the inclusion of predictive analytics and scenario-based legal compliance strategies as formal components of comprehensive environmental governance.

Table 1 shows the correlation matrix, highlighting the interactions among every pair of water quality factors. In statistical analysis, this matrix is a useful instrument since it helps one understand the interactions among several parameters. Regarding water quality, it improves knowledge of interdependence among several indicators.

3.2 Correlations and variance analysis

To uncover significant interrelationships between water quality parameters and support robust modeling efforts, Pearson correlation analysis was conducted across the entire dataset. This statistical technique enables identification of linear dependencies that are crucial for both environmental interpretation and regulatory design. The parameters analyzed, pH, DO, BOD, nitrate concentration, and turbidity, serve as both biological and chemical indicators in most regional and federal water quality legislation. The correlation coefficients presented in Table 2 highlight the strength and direction of these relationships, offering quantitative insight into how fluctuations in one parameter may drive or predict changes in another.

The data in Table 2 reveals several strong and statistically meaningful relationships between core water quality parameters. The most prominent is the negative correlation between pH and nitrate levels (R = -0.72), suggesting that more acidic conditions are associated with elevated nitrate concentrations. This aligns with known biochemical pathways, where lower pH environments enhance nitrogen solubility and mobility. A similar negative correlation is observed between DO and BOD (R = -0.65), indicating that higher oxygen levels are typically accompanied by reduced organic pollution. Turbidity shows a moderate positive correlation with BOD (R = 0.58), likely due to suspended solids increasing microbial decomposition demand.

Table 2 Pearson correlation coefficients between key water quality parameters

Parameter 1	Parameter 2	Correlation Coefficient
pH	Nitrate	-0.72
DO	BOD	-0.65
Turbidity	BOD	0.58
DO	Nitrate	0.33
pH	DO	-0.45

The weaker yet notable correlation between DO and nitrate (r = 0.33) implies a partial coupling of nutrient loads and oxygen dynamics. The negative relationship between pH and DO (R = -0.45) further reinforces the link between acidification and reduced oxygen availability. These findings underscore the interconnected nature of water quality indicators and support their inclusion in multivariate regulatory thresholds. Compared to previous studies, our results reaffirm and extend scholarly understanding of the relationship between legal frameworks and water quality outcomes. For instance, Kokke's (2023) analysis of Brazil's fragmented water regulation system illustrates how inconsistencies in national legal structures can undermine policy effectiveness. In contrast, our findings demonstrate that legally harmonized, site-specific interventions, especially when guided by model-optimized thresholds, can overcome such fragmentation by translating scientific outputs into enforceable targets. This integration of predictive analytics with legal standards supports Zhen's (2024) argument on the value of quantitative assessments in evaluating policy efficacy and sustainability.

3.3 Predictive modeling outcomes

To forecast biochemical oxygen demand (BOD) using key environmental predictors, a Lasso regression model was applied. The predictors selected included pH, dissolved oxygen (DO), and turbidity, which were retained after penalization. The Lasso model supports the identification of the most influential environmental variables affecting BOD, providing a statistically grounded basis for regulatory prioritization. Table 3 presents the coefficients, standard errors, and statistical significance of each parameter within the fitted model, highlighting their predictive roles.

Analysis of the Lasso regression results in Table 3 indicates that all three independent variables, pH, DO, and turbidity, are statistically significant predictors of BOD, at the 1% confidence level. The negative coefficient for pH (-0.18) suggests that as pH decreases (becomes more acidic), BOD tends to rise, likely due to increased microbial activity in acidic environments. The positive coefficient for DO (0.22), although seemingly counterintuitive, reflects the consumption of oxygen in areas with high organic matter, illustrating the dynamic balance of oxygen-requiring decomposition processes. Turbidity exerts the strongest influence on BOD, with the highest relative t-value (6.4), likely due to suspended solids transporting decomposable organic material. The intercept value of 3.05 approximates baseline BOD levels without significant variation in predictors. Collectively, the model explains over 84% of BOD variance, highlighting its utility for forecasting organic pollution from easily measurable field parameters.

As Reyad (2023) notes, a lack of harmonization between national and international environmental laws often leads to insufficient mechanisms for managing transboundary and climate-sensitive ecosystems. While this study does not aim to address transboundary governance or international legal convergence, it recognizes the critical need for greater international engagement, as local optimizations may be difficult to generalize. Furthermore, although our optimization framework successfully derived implementation targets within environmental and legislative constraints, it inadequately addresses stakeholder trade-offs. This contrasts with the interdisciplinary and participatory legal reform processes advocated by Volpato and Offermans (2023), who emphasize the importance of incorporating societal values and sector priorities.

3.4 Model validation and residual analysis

To evaluate the predictive robustness and generalizability of the BOD forecast model, a ten-fold cross-validation procedure was implemented. Error metrics used for validation include Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Mean Absolute Scaled Error (MASE). These indicators quantify both average deviation and the relative improvement over naïve prediction. Table 3 summarizes the validation outcomes across all ten folds. The validation results in Table 3 show consistent predictive performance across all folds. MAE ranged from 0.11 to 0.14 mg/l, and RMSE from 0.13 to 0.16 mg/l, indicating stable accuracy with minimal deviation.

Table 3 Ten-fold cross-validation metrics for BOD prediction model

Fold	MAE	RMSE	MASE
1	0.12	0.14	0.38
2	0.13	0.15	0.40
3	0.11	0.13	0.35
4	0.12	0.14	0.37
5	0.14	0.16	0.41
6	0.12	0.14	0.38
7	0.11	0.13	0.36
8	0.13	0.15	0.39
9	0.12	0.14	0.37
10	0.12	0.14	0.38

MASE scores remained below 0.41, confirming the model's efficiency over naïve forecasts. Fold 3 had the lowest errors, likely due to favorable predictor distribution. Overall, the model demonstrated strong reliability and precision, supporting its use in BOD forecasting for regulatory applications. The findings support the shift toward ecosystem-based, scale-sensitive legal frameworks. As Macpherson et al. (2024) highlight, laws must operate across ecological and temporal scales, especially at marine–freshwater interfaces.

3.5 Implementation Outcomes Based on Legally-Aligned Optimization Targets

Table 4 presents the quantitative outcomes for each primary water quality indicator, including nitrate, DO, biochemical oxygen demand BOD, turbidity, and pH stability.

Table 4 Implementation outcomes based on legally-aligned optimization targets

Parameter	Baseline Value	Post-Implementation Value	Improvement (%)	Implementation Action
Nitrate (mg/l)	2.6	2.2	15.0	Nutrient runoff reduction
DO (mg/l)	7.8	8.6	10.0	Riparian vegetation restoration
BOD (mg/l)	3.1	2.8	9.70	Aeration system enhancement
Turbidity (NTU)	12.8	11.2	12.5	Sediment capture systems
pH Stability (±)	0.2	0.1	50.0	Buffer zone maintenance

Post-implementation results (Table 4) show significant improvements in all key water quality indicators. Nitrate levels dropped by 15%, DO increased by 10% (from 7.8 to 8.6 mg/l), and BOD decreased by 9.7%, reflecting the success of targeted interventions like nutrient runoff control, riparian restoration, and aeration systems. Turbidity fell by 12.5%, and pH variability was halved due to buffer zone maintenance. These outcomes highlight the effectiveness of data-driven, legally supported interventions. The results also support the need for localized governance within broader regulatory frameworks. As Wuijts et al. (2018) suggest, effective water governance depends on coordination across scales. Our site-specific strategies underscore the importance of flexible legal models responsive to local monitoring data yet aligned with national goals.

4. Conclusion

This study demonstrates the effectiveness of integrating environmental predictive modelling with regulatory strategy design to improve water quality and protect aquatic ecosystems. By combining field data with legal standards, it examines the complex interplay between ecological variability and legal enforceability in water governance. The results confirm:

1. Integrating predictive modeling with legal frameworks resulted in measurable improvements in key water quality

indicators, including nitrate, BOD, DO, turbidity, and pH stability.

2. Translating scientific data into enforceable legal thresholds enabled more adaptive, data-driven, and effective environmental regulation.

3. Spatially and temporally informed interventions tailored to local conditions enhanced the flexibility and impact of water governance systems.

The study relies on historical data, which may not accurately reflect future conditions shaped by climate change, land-use shifts, or extreme hydrological events. Socio-economic factors and stakeholder perspectives were not incorporated into the current modeling framework. Additionally, the approach treats legal thresholds as fixed constraints, whereas in practice, they should be flexible and responsive to evolving environmental and social conditions. Transboundary water issues and the broader impacts of climate change were also not directly addressed. Future studies should aim to integrate socio-economic dimensions and actively involve stakeholders in both model development and policy design. Applying multi-criteria decision analysis (MCDA) can help incorporate diverse values, including environmental justice, into legal and regulatory frameworks. Legal thresholds should be treated as dynamic, adapting over time through negotiation among scientists, policymakers, and affected communities. Further work is needed to improve the alignment between predictive modeling and legal systems, particularly in decentralized water governance and ecosystem service evaluation. Strengthening interdisciplinary collaboration will be essential to translate this integrated approach into practical tools for managing complex water quality challenges.

Statements and Declarations

Data availability

The data used in this research are provided in the text of the article.

Conflicts of interest

The author of this paper declared no conflict of interest regarding the authorship or publication of this paper.

Author contribution

Y. A. Ahmed: Methodology, Investigation, Conceptualization, Writing Original Draft; K. Kadhim: Investigation, Conceptualization, Revising the Draft; A. M. H. Mezian: Methodology, Investigation, Conceptualization, Writing Original Draft; A. O. Hussan: Investigation, Conceptualization, Revising the Draft; A. Sabahr: Supervision, Review-Editing, S. Kazemi: Conceptualization, Writing – Review & Editing.

AI Use Declaration

This study did not incorporate artificial intelligence techniques; instead, all analyses and optimizations were conducted using conventional and widely accepted analytical methods.

References

Akamani, K. (2023). The roles of adaptive water governance in enhancing the transition towards ecosystem-based adaptation. *Water, 15*(13). https://doi.org/10.3390/w15132341

Chatterjee, T., Gogoi, U. R., Samanta, A., Chatterjee, A., Singh, M. K., & Pasupuleti, S. (2024). Identifying the Most Discriminative Parameter for Water Quality Prediction Using Machine Learning Algorithms. *Water, 16*(3). https://doi.org/10.3390/w16030481

Fathi, S., Bahrami, J., Momeni, S., Seyedrezaei, M., & Javidi Sabbaghian, R. (2025). A multi-criteria framework for water resource management: Combining WEAP and TOPSIS for optimal solutions. *Advances in Civil Engineering and Environmental Science*, *2*(1), 10–22. https://doi.org/10.22034/acees.2025.484672.1011

Chen, S., & Ding, Y. (2023). Tackling Heavy Metal Pollution: Evaluating Governance Models and Frameworks. *Sustainability, 15*(22). https://doi.org/10.3390/su152215863

Giannopoulos, M., Tsagkatakis, G., & Tsakalides, P. (2024). Higher-Order Convolutional Neural Networks for Essential Climate Variables Forecasting. *Remote Sensing, 16*(11). https://doi.org/10.3390/rs16112020

Harsya, R. M. K., Bhaskoro, A., Sinaga, H., Koynja, J. J., & Judijanto, L. (2023). Environmental Justice and Sustainable Development: Assessing Legal Frameworks for a Balanced Future. *Global International Journal of Innovative Research*.

Hamza, A., Hama, B., Karim, M., & Ahmed, K. (2024). *Water quality assessment for Qaladze Water Treatment Plant*. *Advances in Civil Engineering and Environmental Science*, 1(1), 15–24. https://doi.org/10.22034/acees.2024.464631.1004

Jalink, H., & Dieperink, C. (2024). Towards Design Principles for Good Multi-Level Drought Risk Governance: Some Lessons from the Rhine Basin. *Water, 16*(6). https://doi.org/10.3390/w16060879

Kokke, M. (2023). Brazilian's Legal Framework and Water Regulation. *Macro Management & Public Policies, 5*(4), 36-40. https://doi.org/10.30564/mmpp.v5i4.5819

Lee, J., Park, M., Choi, B., Kim, J., & Na, E. H. (2024). Analyzing Priority Management for Water Quality Improvement Strategies with Regional Characteristics. *Water, 16*(10). https://doi.org/10.3390/w16101333

López-Monzalvo, M. L., Batllori-Sampedro, E., Ayala-Godoy, J. A., Guerrero-Ruiz, E., & Hernández-Terrones, L. M. (2024). Connecting Water Quality and Ecosystem Services for Valuation and Assessment of a Groundwater Reserve Area in South-East Mexico. *Water, 16*(10). https://doi.org/10.3390/w16101358

Macpherson, E., Mortiaux, R., & Jorgensen, E. (2024). Scale-sensitive marine law and policy design: Towards ecosystem-based management across spatial and temporal scales. *WIREs Energy and Environment, 13*(5), e537. https://doi.org/10.1002/wene.537

Madani, Z., & Natcher, D. (2024). Water, Energy and Food (WEF) Nexus in the Changing Arctic: An International Law Review and Analysis. *Water, 16*(6). https://doi.org/10.3390/w16060835

Mejía-Ferreyra, L. D., García-Romero, L., Sánchez-Quispe, S. T., Apolinar-Cortés, J., & Orantes-Avalos, J. C. (2024). Automatic Rainwater Quality Monitoring System Using Low-Cost Technology. *Water, 16*(12). https://doi.org/10.3390/w16121735

Messager, M. L., Pella, H., & Datry, T. (2024). Inconsistent Regulatory Mapping Quietly Threatens Rivers and Streams. *Environmental Science & Technology, 58*(39), 17201-17214. https://doi.org/10.1021/acs.est.4c01859

Moore, C. C., Corona, J., Griffiths, C., Heberling, M. T., Hewitt, J. A., Keiser, D. A., . . . Wheeler, W. (2023). Measuring the social benefits of water quality improvements to support regulatory objectives: Progress and future directions. *Proceedings of the National Academy of Sciences, 120*(18), e2120247120. https://doi.org/10.1073/pnas.2120247120

Osmanpour, M., Eskandari, F., Abdul Nariman, N., & Qarani Aziz, S. (2025). *Stakeholder perspectives on the formation of Water User Associations in Iran*. *Advances in Civil Engineering and Environmental Science*, 2(1), 23–32. https://doi.org/10.22034/acees.2025.498505.1016

Reyad, S. (2023). Relationship between international and national law and issues of their harmonization. . *Uzhhorod National University Herald. Series: Law, 2*(78). https://doi.org/10.24144/2307-3322.2023.78.2.63.

Riley, R. D., Archer, L., Snell, K. I. E., Ensor, J., Dhiman, P., Martin, G. P., . . . Collins, G. S. (2024). Evaluation of clinical prediction models (part 2): how to undertake an external validation study. *BMJ, 384*, e074820. https://doi.org/10.1136/bmj-2023-074820

Singh, A., & Roy, S. . (2024). A Study the concept and legal principles of Water Management. *Journal of Advances and Scholarly Researches in Allied Education, 21*(2), 62-71. https://doi.org/10.29070/mgn02g48

Tibshirani, R. (1996). Regression shrinkage and selection via the lasso. *Journal of the Royal Statistical Society: Series B (Methodological)*, *58*(1), 267–288. https://doi.org/10.1111/j.2517-6161.1996.tb02080.x

Volpato, A., & Offermans, A. (2023). Lessons for Participation from an Interdisciplinary Law and Sustainability Science Approach: The Reform of the Sustainable Use of Pesticides Directive. *European Journal of Risk Regulation, 14*(2), 253-270. https://doi.org/10.1017/err.2023.9

Walsh, C., Clouting, H., Kühl-Stenzel, A., & Schwemmer, H. (2024). Ecosystem-based maritime spatial planning in practice? On the limitations of a legalistic planning tradition. *Town Planning Review, 95*(6), 643-664. https://doi.org/10.3828/tpr.2024.29

Wuijts, S., Driessen, P. P. J., & Rijswick, H. F. M. W. v. (2018). Towards More Effective Water Quality Governance: A Review of Social-Economic, Legal and Ecological Perspectives and Their Interactions. *Sustainability, 10*, 914.

Wuijts, S., Rijswick, H. F. M. W. v., & Driessen, P. P. J. (2021). Achieving European Water Quality Ambitions: Governance Conditions for More Effective Approaches at the Local-Regional Scale. *Sustainability*.

Zhao, Z., Fan, B., & Zhou, Y. (2024). An Efficient Water Quality Prediction and Assessment Method Based on the Improved Deep Belief Network—Long Short-Term Memory Model. *Water, 16*(10). https://doi.org/10.3390/w16101362

Zhen, R. (2024). Advancing Environmental Sustainability: A Quantitative Assessment of Legal Frameworks and Policy Efficacy. . *Communications in Humanities Research, 32*, 221-226. https://doi.org/10.54254/2753-7064/32/20240076