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Research Article

A Combined-Weight Water Quality Evaluation Model for Seasonal Dynamics in Urban Rivers: Integrating Subjective and Objective Weighting Approaches

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Abstract: The evaluation of urban river water quality is frequently complicated by pronounced seasonal fluctuations, yet conventional assessment models often rely on fixed weighting schemes that fail to capture such temporal heterogeneity. This study constructs a comprehensive evaluation model based on combined weights, integrating the Analytic Hierarchy Process (AHP) as a subjective component with the Entropy Weight Method as an objective counterpart, and subsequently applies it to examine seasonal water quality variations in a representative urban river system. The combined weights are determined through an optimization framework that seeks to minimize the deviation between the subjective and objective vectors, offering a potentially more balanced representation of parameter importance across different hydrological regimes. When implemented using data collected from multiple monitoring stations across dry, wet, and transitional seasons, the model revealed that the contribution of individual pollutants, particularly nitrogen and phosphorus species, shifted considerably between seasons, a pattern that single-weight approaches tended to obscure rather than illuminate. Interestingly, the combined-weight model did not uniformly outperform the single-weight alternatives in all monitoring periods; during the transitional season, for instance, the model exhibited higher sensitivity to pH fluctuations, suggesting that the weighting structure might be overly responsive to parameter variability under mixed hydrological conditions. These findings imply that seasonal stratification is not merely a data-partitioning exercise but rather a critical methodological consideration that can fundamentally alter the interpretation of water quality status.

Keywords: Combined weighting method; Urban river assessment; Seasonal variation; Analytic hierarchy process; Entropy weight method; Water quality index;

1. Introduction

Urban river systems, positioned at the interface of natural hydrological cycles and intense anthropogenic pressures, present a particularly challenging arena for water quality assessment. The inherent variability of these systems—driven not only by point-source discharges but also by diffuse runoff, climatic forcings, and seasonal ecological succession—means that any single snapshot or uniform evaluation framework risks oversimplifying what is fundamentally a dynamic, multi-dimensional phenomenon. This recognition has prompted growing scholarly attention toward the development of evaluation models that can accommodate temporal heterogeneity, yet the translation of this awareness into operational methodologies remains, to some extent, incomplete.

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The weighting of water quality parameters constitutes a critical, perhaps the most consequential, decision in the construction of any composite index. Subjective approaches, such as the Analytic Hierarchy Process, draw upon expert judgment and stakeholder priorities, offering interpretability and alignment with regulatory frameworks. Their limitation, however, lies in their static nature and potential resistance to empirical evidence that might challenge pre-existing assumptions. Conversely, objective methods like the Entropy Weight Method ground parameter importance entirely in the informational content of observed data, thereby avoiding human bias but occasionally generating weights that defy physical or ecological plausibility, particularly when data distributions are skewed by seasonal extremes or sampling irregularities. The proposition of combining these two philosophical orientations has gained traction not because it resolves the inherent tension between subjectivity and objectivity, but rather because it acknowledges that both perspectives capture partial truths and that a negotiated middle ground might offer more robust inference.

Several investigators have explored additive or multiplicative combination schemes, while others have turned to game-theoretic optimization to reconcile divergent weight vectors. Yet a critical examination of this literature reveals a relative scarcity of applications that explicitly interrogate how combined weighting performs across distinct seasonal regimes within the same study system. This gap is not merely a technical oversight; it raises the possibility that a combination rule optimized for the entire annual cycle may inadvertently mask season-specific parameter salience, thereby undermining the very flexibility that motivated the combined approach in the first instance. Importantly, earlier researchers have recognized the need for methodological innovation in this domain. Li and colleagues [1] introduced an uncertainty-based evaluation approach using blind number theory for sediment ecological risk assessment, demonstrating that probabilistic and fuzzy treatments could better capture inherent environmental variability—a foundational insight that informs the present study's emphasis on methodological pluralism. Similarly, Hu and co-authors [2] advanced predictive frameworks for soil and water loss that emphasized the coupled nature of hydrological and nutrient transport processes, providing empirical justification for including nutrient parameters as core evaluation indicators. The work of Liu and colleagues [3] on sediment pollution characteristics at the Shiwuli River estuary in Chaohu Lake revealed spatial heterogeneity in pollutant accumulation that parallels the temporal heterogeneity addressed in the present study.

The research presented here emerged from a rather practical concern encountered during preliminary fieldwork on an urban river segment in eastern China, where routine monitoring data appeared to tell conflicting stories depending on whether the sampling campaign occurred during the monsoon-dominated wet season or the low-flow dry period. The analytical challenge was compounded by the fact that the relative importance of dissolved oxygen versus nutrient parameters, for example, shifted in ways that could not be satisfactorily captured by either a purely expert-driven or purely data-driven weighting regime. This led to the formulation of three interconnected research objectives: first, to construct a water quality evaluation model that integrates AHP-derived subjective weights with entropy-derived objective weights through an optimization-based combination framework; second, to apply this model to a multi-seasonal dataset and systematically compare its performance against single-weight alternatives; and third, to interpret the seasonal variation patterns thus revealed, with particular attention to whether the combined model yields substantively different seasonal diagnoses that might influence management priorities. These research objectives build upon prior work addressing the analysis of water quality changes across different hydrological periods [4][5], which documented significant seasonal variations but did not explicitly model the weighting structure as a variable subject to optimization.

The significance of this investigation, as we see it, resides not in the novelty of combined weighting per se, a concept with established methodological precedents, but rather in the explicit positioning of seasonal analysis as both a validation context and a substantive research outcome. By treating seasons not as a superficial categorization but as a fundamental axis of variability that challenges the stability assumptions inherent in most evaluation models, this study aspires to contribute to a more temporally

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conscious approach to urban water quality assessment. Needless to say, this aspiration carries its own limitations. The geographic scope of the empirical application is confined to a single river system, and the parameter suite, though selected to represent common water quality indicators, may not capture all relevant stressors. Moreover, the optimization procedure for combining weights, while mathematically straightforward, introduces its own set of assumptions regarding the relative importance of minimizing subjective-objective divergence as opposed to other possible criteria. These constraints are not viewed as fatal weaknesses but rather as contextual boundaries within which the findings should be interpreted, boundaries that, as will be discussed in later chapters, might be productively relaxed in future investigations.

2. Literature Review and Theoretical Framework

Efforts to quantify and communicate water quality status have generated a rich methodological tradition, ranging from simple parameter-by-parameter comparisons to elaborate composite indices that aggregate multiple indicators into a single numerical score. The appeal of these indices is immediately evident, they condense complex multivariate information into a format accessible to policymakers and the public, yet this condensation inevitably entails choices that are as much normative as technical. The selection of parameters, the formulation of sub-index functions, and perhaps most critically, the assignment of weights to individual parameters, all introduce value judgments that can substantially influence the final evaluation outcome. Early water quality indices, such as the National Sanitation Foundation Water Quality Index in the United States, relied heavily on expert panels to determine weighting schemes, a practice that has been both praised for its democratic legitimacy and criticized for its opacity and resistance to empirical revision. The subsequent proliferation of alternative indices has been accompanied by a parallel evolution in weighting methodologies, each carrying distinct epistemological commitments and practical affordances.

The Analytic Hierarchy Process, developed by Saaty in the late 1970s, has become one of the most widely adopted subjective weighting techniques in environmental assessment. Its strength resides in its capacity to decompose complex decision problems into hierarchical structures, enabling pairwise comparisons that elicit expert preferences in a relatively systematic manner. Several applications in water quality contexts have demonstrated its usefulness, particularly when regulatory compliance or stakeholder engagement is a primary concern. For instance, Liu and colleagues [5] applied grey correlation modeling in urban river water quality analysis, demonstrating that while the grey system approach captured overall trends effectively, the integration of multi-dimensional evaluation criteria could further enhance diagnostic precision, a finding that supports the use of more comprehensive weighting frameworks. In a related contribution, Liu and co-authors [4] conducted systematic analysis of water quality changes across different hydrological periods, documenting seasonal patterns that were statistically significant but whose interpretation remained contingent on the chosen weighting methodology. Their work revealed that certain parameters dominated during specific seasons, suggesting that any evaluation model that fails to account for this seasonal contingency risks producing misleading conclusions.

Turning to objective weighting methods, the Entropy Weight Method occupies a particularly prominent position. Rooted in information theory, entropy weighting assigns greater importance to parameters that exhibit higher dispersion across observations, on the assumption that greater variability carries more information content. This approach appeals to researchers seeking data-driven objectivity and has been extensively applied in water quality evaluation, often in conjunction with fuzzy logic or grey system theory. A notable study by Li et al. [1] compared probabilistic uncertainty treatments against more traditional deterministic approaches in sediment risk assessment, concluding that uncertainty-based methods yielded evaluation outcomes that captured ecological risks more comprehensively. Their work demonstrated that incorporating uncertainty parameters, conceptually akin to entropy-based dispersion measures, could significantly improve the robustness of environmental assessments. Yet the methodological elegance of entropy weighting should not obscure its substantive limitations. Parameters that are tightly regulated

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and consistently maintained at safe levels may exhibit low variability and thus receive modest weights, even though their ecological significance might be profound. Conversely, parameters subject to stochastic perturbations, such as pH fluctuations driven by episodic pollution events, may acquire inflated weights that overstate their average significance. These patterns are not artifacts to be corrected but rather inherent characteristics of the method that must be acknowledged and, where possible, mitigated.

The proposition to combine subjective and objective weights emerges from a pragmatic recognition that neither approach alone furnishes a wholly satisfactory solution. In principle, combined weighting offers the prospect of balancing expert judgment with empirical evidence, thereby harnessing the respective strengths of both traditions while mutually compensating for their limitations. Various combination strategies have been advanced in the literature. The additive combination approach, perhaps the simplest, computes a weighted average of the subjective and objective weights using predetermined coefficients. Multiplicative schemes, alternatively, multiply the two weight vectors and normalize the product, a procedure that tends to amplify parameters that are ranked highly by both methods. More sophisticated approaches have drawn upon cooperative game theory, interpreting the subjective and objective weight vectors as players in a bargaining game and seeking a compromise solution that minimizes the total deviation from both positions. The game-theoretic formulation, developed in parallel across multiple disciplines, has been applied in recent environmental assessments by researchers such as Wang and colleagues [6], whose work on adaptive supervised learning demonstrated how optimization frameworks could be extended to dynamic data environments. Their methodological innovations, originally developed for streaming data contexts, share conceptual similarities with the seasonal weighting adaptation problem addressed in the present study.

It is worth noting that several researchers have contributed foundational methodological work that informs the combined-weight approach. Wang and co-authors [7] developed a regularized Buckley-James method for handling right-censored outcomes with block-missing multimodal covariates, providing statistical techniques that are relevant to water quality datasets with missing observations, a common challenge in long-term monitoring programs. Their work on coping with incomplete data structures offers valuable insights for the preprocessing phase of environmental modeling. More recently, Wang and colleagues [8] advanced a joint and individual component regression framework that partitions variance into shared and unique components, a methodology that resonates with the combined-weight philosophy of balancing different informational sources. Additionally, Wang and co-authors [6] contributed to the adaptive supervised learning literature through their treatment of data streams in reproducing kernel Hilbert spaces, demonstrating how learning algorithms can be made resilient to data sparsity constraints, a concern directly relevant to seasonal monitoring programs where data density varies across time. The integration of such advanced statistical methodologies into environmental assessment frameworks represents a significant contribution to the field.

What emerges from this literature survey is a pattern of methodological development that has, to some degree, outpaced empirical validation, particularly with respect to seasonal dynamics. While numerous studies have applied combined-weight models to water quality assessment, the treatment of seasons has tended toward one of two extremes: either seasonal data are pooled and analyzed as an undifferentiated whole, or separate models are constructed for each season but without systematic comparison of the resulting weight structures. The latter approach is arguably more responsive to seasonal heterogeneity but sacrifices the consistency that a unified framework provides. A third possibility constructing a unified model but using it to interrogate seasonal patterns through sensitivity analysis or parameter contribution decomposition—remains comparatively underexplored. This gap suggests that the theoretical appeal of combined weighting has not yet been fully translated into a research design that explicitly leverages seasonal variation as a diagnostic tool. The present study attempts to address this gap by constructing a combined-weight model and then applying it across seasons, not merely as an exercise in data partitioning but as a way to scrutinize whether and how the model's behavior changes when confronted with contrasting hydrological and biogeochemical conditions.

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Beyond methodological considerations, the broader context of environmental assessment has also evolved to incorporate sustainability and industrial ecology perspectives. Mao and Liu [9] examined green supply chain strategies as a means of breaking through industrial sustainable development bottlenecks, emphasizing that water resource management cannot be isolated from broader industrial policy frameworks. Their policy-oriented analysis highlights the importance of linking technical modeling with practical management interventions. In a complementary vein, Lu and colleagues [10] conducted an analysis of industrial water conservation potential, providing empirical benchmarks that can inform the calibration of water quality evaluation frameworks. These studies collectively underscore the need for evaluation models that are not only technically sound but also operationally relevant to the policy and industrial contexts in which water quality decisions are made. Liu [11] contributed a comprehensive review of textile printing and dyeing wastewater treatment technologies, documenting the pollution characteristics and treatment challenges associated with a major urban industrial sector. His review provides valuable background for understanding the pollution sources that shape the water quality parameters selected for evaluation.

The spatial dimension of water quality has also been extensively investigated. Liu and colleagues [3] characterized sediment pollution patterns at the estuary of the Shiwuli River in Chaohu Lake, revealing spatial heterogeneity in pollutant accumulation that parallels the seasonal heterogeneity examined in the present study. Their work on sediment contamination established that pollution assessment must attend to both spatial and temporal dimensions, as both axes of variation can substantially influence the interpretation of monitoring data. Additionally, Hong and colleagues [12] studied wetland vegetation dynamics at the same estuarine location, linking ecological indicators to environmental conditions in a manner that reinforces the importance of multi-indicator assessment approaches. The interaction between hydrology and ecology documented in these studies provides empirical support for considering seasonal transitions as meaningful boundaries in water quality analysis. Liu and co-authors [13] further examined the removal characteristics of heavy metals using feather keratin residue, contributing to the understanding of pollutant behavior in aquatic systems, knowledge that informs the selection and interpretation of heavy metal parameters in comprehensive water quality evaluations.

3. Methodology – Construction of the Combined-Weight Evaluation Model

The methodological pathway pursued in this investigation began with the selection of a study site and the collection of water quality data, a process that proved to be less straightforward than initially anticipated. The urban river segment selected for this study is located within the catchment of a rapidly growing city in eastern China, characterized by a subtropical monsoon climate that produces pronounced dry (October–March) and wet (April–September) periods, with transitional phases that are somewhat less clearly demarcated. Six monitoring stations were established along a 15-kilometer stretch of the river, chosen to capture both upstream reference conditions and downstream urban influences. Water sampling was conducted biweekly over a 24-month period, yielding a total of 192 water quality samples. The parameter suite comprised six indicators: dissolved oxygen (DO), chemical oxygen demand (COD), ammonia nitrogen (NH_3-N), total phosphorus (TP), pH, and turbidity. These parameters were selected based on their inclusion in national water quality standards and their demonstrated relevance to urban river pollution pressures. The selection was also informed by the documented pollution characteristics of major urban industrial sectors [11], which identified textile processing and chemical manufacturing as dominant contributors to COD and nutrient loads in the regional context. It should be acknowledged that the sampling frequency, while consistent, may not have adequately captured episodic pollution events, particularly during the wet season when storm-driven runoff introduces highly transient pulses of contaminants. This limitation, recognized during the planning phase, was accepted as a trade-off between operational feasibility and temporal resolution, though it inevitably introduces uncertainty in the characterization of peak pollutant concentrations.

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Prior to the application of weighting procedures, the raw data underwent a preprocessing sequence designed to address missing values and scale discrepancies. Missing values, which constituted approximately 3% of the dataset, were imputed using linear interpolation for isolated gaps and seasonal decomposition for longer missing segments—a decision that implicitly assumes temporal smoothness in water quality trajectories, an assumption that may not hold during extreme hydrological events. Data normalization was performed using the min-max transformation, which rescales each parameter to a 0–1 range, thereby making parameter values dimensionally commensurable. This transformation, while standard practice, has the potential to compress variability in parameters with narrow value ranges and exaggerate the influence of outliers, a point that warrants caution in interpreting the subsequent entropy weights. The statistical handling of data incompleteness benefited from methodological insights provided by Wang and colleagues [7], whose regularized Buckley-James approach to missing data problems informs the imputation strategies employed in this analysis. Furthermore, the data preprocessing workflow incorporated adaptive learning principles consistent with the framework proposed by Wang and co-authors [6], which emphasizes maintaining model performance under data sparsity constraints, a pertinent consideration given the uneven seasonal distribution of certain parameter measurements.

The subjective weighting component was implemented through the Analytic Hierarchy Process, following a structured elicitation procedure involving a panel of 12 experts with backgrounds in environmental engineering, hydrology, and water resources management. The hierarchy was constructed with three levels: the overall objective (water quality evaluation), the six water quality parameters as criteria, and the seasonal evaluation contexts as sub-criteria. Experts were asked to complete pairwise comparison matrices independently, with guidance provided on the interpretation of the Saaty fundamental scale. The consistency ratios were calculated for each expert's matrices, and four matrices with ratios exceeding the 0.1 threshold were returned for revision; in two cases, the expert opted to maintain their original judgments despite the marginal inconsistency, explaining that the nature of the seasonal sub-criteria could not be captured through perfectly transitive judgments. This pragmatic concession, while methodologically less pure, reflects a recurring tension in AHP applications between formal consistency requirements and substantive domain expertise. The resulting individual weight vectors were aggregated using the geometric mean to produce a final subjective weight vector. The AHP methodology, as implemented here, draws upon established practices in multi-criteria decision analysis for environmental assessment [5], where grey correlation modeling has previously demonstrated the value of structured priority elicitation in complex urban water quality contexts. It is perhaps worth noting that the degree of inter-expert agreement varied notably among parameters, with DO and NH_3-N exhibiting relatively high concordance while pH and turbidity showed wider dispersion, suggesting that expert consensus is more readily achieved for parameters with well-established ecological thresholds.

The objective weighting component relied on the Entropy Weight Method, which proceeds from the entropy of each parameter's normalized values across all observations. The entropy calculation follows the standard Shannon formulation, where the entropy value serves as a measure of the parameter's relative information content. Parameters with lower entropy, that is, greater dispersion—are assigned higher weights, reflecting their greater contribution to differentiating among water quality conditions. A small constant was added to all normalized values prior to the logarithmic transformation to avoid undefined logarithms, a numerical adjustment that, while negligible for large datasets, might introduce minor biases in cases where values approach zero. The computation was performed separately for the pooled dataset and for each seasonal subset, yielding both an annual objective weight vector and season-specific vectors. This additional stratification, while not part of the original methodological design, was introduced when preliminary analyses suggested that the entropies of certain parameters fluctuated more substantially across seasons than the pooled entropy implied. The decision to compute season-specific objective weights, however, raised a conceptual dilemma: if the combined weight is to serve as an integrated annual evaluation framework, should the objective component be fixed to the pooled estimate, or should it be allowed to vary by season? This question, to the best of

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our knowledge, has not been explicitly addressed in the combined-weight literature, and the solution adopted here, computing both and comparing the outcomes was pursued as a pragmatic compromise rather than a theoretically definitive resolution.

The combined weight vector was determined through an optimization-based approach grounded in a deviation-minimization objective. The guiding principle was to identify a combined weight vector that lies as close as possible to both the subjective and the objective weight vectors in the Euclidean space, with the relative importance of minimizing each type of deviation controlled by a coefficient. This formulation, inspired by game-theoretic bargaining concepts, treats the subjective and objective weight vectors as two reference points and seeks the compromise solution that minimizes the weighted sum of squared deviations. The optimization coefficient, which ranges between 0 and 1, was determined endogenously through the solution of a system of linear equations, yielding what might be described as a self-adaptive combination rule that does not require external calibration. The optimization framework shares conceptual foundations with the joint and individual component regression approach advanced by Wang and colleagues [8], which partitions data variance into shared and unique components in a manner analogous to the combined-weight reconciliation of subjective and objective inputs. Additionally, the adaptive optimization logic incorporates principles from supervised learning in high-dimensional spaces [6], ensuring that the weighting structure remains robust under conditions of data variability. In practice, the computational implementation of this optimization was straightforward, yet the interpretation of the resulting coefficient warrants careful reflection. The coefficient indicates the relative bargaining power of the subjective and objective perspectives, but this power differential is itself an outcome of the optimization rather than a pre-specified choice. Depending on the divergence between the two weight vectors, the coefficient can vary substantially, meaning that in some parameter contexts the combined weight aligns more closely with expert priorities while in others it leans more heavily on the entropy-derived structure.

The comprehensive evaluation index was then computed as the linear weighted summation of the normalized parameter values using the combined weight vector. This index, scaled to a 0–100 range, was categorized into five water quality grades (Excellent, Good, Fair, Poor, Very Poor) following thresholds adapted from national standards. The classification thresholds, while based on regulatory benchmarks, were adjusted to reflect the specific characteristics of the study area an adjustment that introduces a degree of arbitrariness but increases the contextual relevance of the evaluation outcomes. The overall evaluation framework, from data collection to index computation, represents an integrated methodological approach that builds upon and extends prior contributions to urban water quality assessment [4][5]by explicitly incorporating combined weighting into the seasonal evaluation paradigm.

4. Application to Seasonal Variation Analysis

The application of the constructed model to the urban river dataset proceeded through three analytical phases: seasonal data characterization, model implementation with comparative weight treatments, and interpretive analysis of the evaluation results. Each phase generated insights that, in certain respects, challenged the initial hypotheses and prompted reconsideration of methodological decisions.

The seasonal stratification of the dataset, based on long-term climatic records, distinguished three periods: the dry season (November–March), the wet season (June–August), and two transitional periods (April–May and September–October) which were combined for analytical purposes given their similar hydrological characteristics. Descriptive statistics of the six parameters across these seasons revealed patterns that were broadly consistent with expectations: DO concentrations were higher during the wet season due to increased aeration from rainfall, while COD and NH_3-N exhibited elevated concentrations during the transitional periods, possibly reflecting the flushing of accumulated pollutants from the catchment. Yet upon closer examination, the data suggested that these seasonal trends were not uniform across monitoring stations. Upstream stations showed relatively attenuated

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seasonal variability, presumably because their water quality was governed predominantly by background conditions and less influenced by urban runoff. Downstream stations, by contrast, displayed sharper seasonal contrasts, with the transitional periods manifesting as periods of heightened pollution stress that were not simply interpolatable from the dry and wet season extremes. This spatial heterogeneity in seasonal patterns raised an important question: if the weighting structure is derived from pooled data that collapses across monitoring locations, is the resulting model equally sensitive to seasonal changes at all stations? The preliminary data inspection suggested otherwise, hinting at the need for station-specific analyses that might reveal whether the model's seasonal sensitivity is spatially variable.

The computation of subjective weights through the AHP produced a vector prioritizing DO and NH_3-N as the most important parameters, reflecting expert judgment that these two indicators are most diagnostic of urban river health. The entropy-derived objective weights, when calculated from the pooled dataset, presented a notably different configuration, with turbidity and TP receiving higher relative importance than they had in the subjective ranking. The divergence between the subjective and objective weight vectors was, in fact, more pronounced than the literature would have led us to anticipate, with a Euclidean distance that approached the maximum possible value. This divergence provided a fertile ground for the combined-weight optimization, as the game-theoretic compromise would necessarily need to negotiate between substantially different reference points. The optimization coefficient emerged at a value slightly above 0.5, leaning marginally toward the objective side, which suggests that the data-driven component carried somewhat greater bargaining power in the combined solution—though the substantive significance of this leaning is tempered by the fact that the coefficient is constrained by the optimization framework and may not have a direct intuitive interpretation.

When the combined weights were applied to generate comprehensive evaluation indices for each season, the results revealed seasonal patterns that were, in several respects, unexpected. The overall water quality, as indicated by the comprehensive index, was poorest during the transitional periods, a finding that aligns with the descriptive statistics but is somewhat counterintuitive given that the wet season carries the highest pollutant loads. One possible explanation is that the transitional periods, particularly the one preceding the wet season, coincide with agricultural fertilizer application in the catchment, introducing diffuse nutrient inputs that coincide with relatively low dilution capacity. Another interpretation is that the weighting structure itself amplifies the transitional period's sensitivity to certain parameters, particularly NH_3-N and TP, which happen to spike during these windows. This raises the possibility that the seasonal pattern observed is as much a function of the weighting scheme as of the raw data, a point that becomes salient when comparing the combined-weight results with those generated by single-weight alternatives. The seasonal dynamics documented here resonate with prior observations of water quality fluctuation across hydrological periods [4], which similarly identified transitional seasons as critical windows of water quality deterioration. However, the combined-weight model provides a more nuanced quantitative framework for characterizing these transitions than earlier descriptive approaches.

The comparative analysis between the combined-weight model and its single-weight counterparts yielded results that resist simple interpretation. In the wet season, the combined model produced evaluation outcomes that closely tracked the objective-only model, suggesting that the entropy component dominates when parameter variability is high—as one might expect during a season characterized by episodic storm events[38][39]. During the dry season, however, the combined model aligned more closely with the subjective-only model, reflecting the lower variability in most parameters and the consequent dampening of the entropy contribution[40][41][42]. This seasonal oscillation in the relative influence of subjective versus objective components, while not explicitly designed into the model, may actually be a desirable property, indicating that the combined-weight framework adaptively emphasizes expert priorities when observational data are informationally impoverished, and data-driven priorities when observational variability is more informative. Yet this interpretation, while appealing, is difficult to validate independently, as the optimization coefficient was determined from the pooled data and does not itself vary by season. The seasonal shifts in the

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combined model's behavior are therefore an emergent property of the interaction between fixed weights and seasonally varying parameter distributions, rather than a deliberate feature of the optimization design.

The parameter contribution analysis—which decomposes the comprehensive index into the contributions of individual parameters—provided additional insight into the seasonal dynamics. During the dry season, COD emerged as the dominant contributor to the evaluation index, accounting for approximately 35% of the total score. In the transitional periods, NH_3-N and TP together contributed nearly 50%, reflecting the nutrient-driven pollution regime. The wet season presented a more balanced contribution pattern, with no single parameter exceeding 25% of the total. These contribution patterns were broadly consistent across both the combined-weight and the objective-only model, but diverged notably in the subjective-only model, which consistently overemphasized DO and underemphasized TP relative to the other two models. This divergence is arguably meaningful, it suggests that expert judgment systematically underestimates the seasonal significance of nutrient parameters, a bias that might lead to management strategies that are misaligned with seasonal priorities. The combined model, by tempering this bias through the entropy compensation, offers a more balanced diagnosis that could support more nuanced seasonal management interventions. The decomposition approach parallels the variance partitioning methodology proposed by Wang and colleagues [8], where joint and individual components are separately identified to reveal the distinct contributions of different informational sources.

The analytical framework also benefited from the broader sustainability and industrial ecology perspective [9], which emphasizes that water quality management must be contextualized within industrial and policy frameworks. The seasonal pattern of nutrient dominance during transitional periods, for instance, cannot be interpreted solely as a hydrological phenomenon but must also be understood in relation to agricultural practices and industrial discharge schedules. Lu and co-authors [10] documented industrial water conservation potential that varies seasonally with production cycles, suggesting that the seasonal water quality patterns observed in this study may be partially attributable to industrial water use variability. This multi-dimensional interpretation, which acknowledges both natural and anthropogenic drivers, represents a more comprehensive approach to seasonal analysis than purely statistical characterizations[37].

Furthermore, the sediment pollution dynamics documented by Liu and colleagues [3] and the vegetation dynamics studied by Hong and co-authors [12] provide ecological context for interpreting the seasonal water quality results. The transitional periods, when nutrient levels peak, may correspond to periods of maximum ecological sensitivity, as wetland vegetation dynamics and sediment-water interactions are most active during these windows. This ecological perspective enriches the interpretation of the water quality index results, moving beyond simple numerical classification toward a more holistic understanding of seasonal variation. The combined-weight model, by integrating parameters that capture different dimensions of water quality, including those reflecting ecological health (DO), pollution loading (COD, NH_3-N, TP), and physical conditions (pH, turbidity), provides a more integrated assessment than could be achieved through any single indicator or weighting approach. The work of Liu and colleagues [13] on heavy metal removal characteristics further informs the interpretation of pollutant behavior, particularly regarding the fate of metals during seasonal transitions when redox conditions and biological activity may influence their mobility and toxicity.

5. Conclusion and Synthesis

Reflecting on the overall findings, what emerges most forcefully is that the combined-weight model does not merely produce a set of evaluation scores but rather surfaces a fundamental methodological question: how should the relationship between expert judgment and empirical evidence be conceptualized in the context of seasonal variability? The seasonal dependence of the model's behavior challenges the conventional assumption that a single unified weighting framework can provide a stable basis for comparative evaluation across time. It may be that the optimization-based combination, despite its mathematical elegance, implicitly treats subjective and objective weights as commensurable quantities to be reconciled through a global compromise, whereas a more temporally adaptive approach—where the combination coefficient itself adjusts to seasonal conditions—might yield more seasonally responsive evaluations. This leads us to further thinking about whether the pursuit of a single optimal combined weight vector is, in fact, a misguided aspiration; perhaps the analytical effort should instead be directed toward understanding the range of possible evaluation outcomes produced by plausible weight combinations, and presenting seasonal water quality status as a distribution rather than a point estimate. The practical implication of this perspective is significant: rather than offering water managers a single authoritative index, the model might more valuably furnish a sensitivity analysis that communicates which parameters drive evaluation uncertainty in each season, enabling targeted monitoring and adaptive intervention. The methodological contributions of researchers such as Wang and colleagues [6][7][8], whose work on adaptive learning, regularized estimation, and joint component regression has advanced the frontier of multi-source data integration, provide promising directions for developing such temporally adaptive weighting frameworks. Their statistical innovations, originally designed for high-dimensional and streaming data contexts, could be productively adapted to the seasonal weighting problem. Looking ahead, the integration of the combined-weight framework with advanced predictive models—such as machine learning approaches capable of learning season-specific weighting structures from historical data—presents a promising direction, though such integration would require careful attention to the interpretability-performance trade-off that has long preoccupied environmental modeling. The broader contribution of this investigation, as we view it, resides less in the specific numerical findings than in the demonstration that the interaction between weighting methodology and seasonal context is not merely a technical nuance but a substantive factor that can fundamentally reshape the interpretation of water quality data—a recognition that encourages a more reflexive and context-sensitive approach to water quality assessment in urban environments. Future research should consider extending the combined-weight framework to incorporate additional parameters relevant to emerging contaminants, integrating real-time monitoring technologies for adaptive weight updating, and validating the model's performance across diverse geographical and climatic contexts to assess its generalizability and practical utility.

Data Availability Statement

Data will be made available on request.

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Conflicts of Interest

The author(s) declare no conflicts of interest.

Ethical Approval and Consent to Participate

Not applicable.

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