

A Structured Inference Framework for Spatial Hydrological Monitoring Networks

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Abstract

Regional hydrologic and environmental inference relies on spatial monitoring networks exhibiting dependence, heterogeneity, and evolving behavior. Many regional analyses apply statistical methods in isolation, with limited structure governing when pooling, spatial modeling, or non-stationary inference is admissible. This study presents HyMES Regional, a structured inference framework that formalizes regional analysis as an ordered sequence of diagnostic, inferential, and temporal operations applied to spatial ensembles of time series, presented as browser-based application. The framework integrates network-aware spatial diagnostics, regime characterization, uncertainty-conditioned regional inference, and progression analysis under a unified analytical logic. A case study in southern Louisiana demonstrates how localized precipitation forcing discrepancies are associated with regime-dependent streamflow performance degradation, accumulate temporally, and constrain simulated distributional behavior. The results show that regional model error exhibits organized spatial, temporal, and distributional structure that is coherent across stations. By explicitly conditioning inference on diagnosed structure, HyMES Regional framework supports defensible regional assessment across heterogeneous monitoring networks.

Keywords: Regional Inference, Spatial Monitoring Networks, Uncertainty condition analysis, Web-Based Informatics

Software Availability

Name	HyMES-Regional
Developers	Carlos Erazo Ramirez
Contact Information	https://hydroinformatics.tulane.edu
Software required	Web Browser
Programming language	JavaScript, WASM, R
Platform Access	https://hydroinformatics.tulane.edu/lab/hymes-regional/
Documentation	All required usage documentation can be found within the platform.
Data	Data is retrieved by the user within the platform.

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1. Introduction

Regional inference is a central component of hydrologic and environmental analysis, supporting estimation, comparison, and interpretation across spatially distributed monitoring networks. Regional approaches are routinely applied to address data scarcity, reduce estimation variance, and characterize large-scale behavior in systems that cannot be adequately described at individual locations (Blöschl & Sivapalan, 1995; Wazneh et al., 2016; Lima et al., 2016; Yan & Moradkhani, 2015). At the same time, monitoring networks exhibit spatial dependence, heterogeneity, and evolving behavior that challenge the assumptions underlying many commonly used regional methods (Kjeldsen & Jones, 2009; Burn, 1990; Parida et al., 1998; Singh & Chavan, 2026; Pilon & Adamowski, 1992; Srinivas et al., 2008).

A persistent difficulty in regional analysis lies not in the absence of statistical tools, but in the lack of explicit structure governing their use. Spatial diagnostics, pooling strategies, uncertainty quantification, and nonstationary inference are often applied independently, with limited guidance on how results from one step condition the admissibility or interpretation of subsequent analyses (Renard, 2011; Yan & Moradkhani, 2015; Viglione et al., 2013; Verdin et al., 2019; Liu et al., 2022; Pizzaro et al., 2025). As a result, regional conclusions may implicitly rely on assumptions that are untested, violated, or inconsistent across scales and variables (Kirchner, 2006; Coon & Shuai, 2022).

This study introduces HyMES Regional, a structured inference framework designed to organize regional analysis of spatial monitoring networks as a dependent sequence of operations. The framework formalizes how spatial diagnostics, characterization of dependence and heterogeneity, uncertainty-conditioned inference, and temporal progression are linked, and clarifies where regional aggregation is supported by the data and where it is not (Beven, 2016; Beven & Binley, 1992). The framework integrates established methods within an explicit inferential logic that preserves traceability between diagnostics, assumptions, and conclusions. The resulting structure uses diagnosed spatial dependence, response similarity, and temporal behavior to determine the scope and interpretation of subsequent regional inference.

The framework treats spatially distributed time series as ensembles defined by both statistical behavior and connectivity structure. Spatial dependence is diagnosed directly, including through hydrologic network topology where appropriate, and regional inference proceeds conditionally on the identified structure. This approach is intended to support regional assessment in heterogeneous monitoring networks while maintaining consistency with data limitations and uncertainty.

The remainder of the manuscript is organized as follows. Section 2 reviews the relevant literature on statistical foundations of regional inference, spatial dependence, and nonstationary analysis relevant to monitoring networks. Section 3 presents the methodological structure of the proposed framework, detailing the sequence of diagnostic, inferential, and temporal analyses applied to spatial ensembles of time series. Section 4 applies the framework to a regional case study in southern Louisiana, examining precipitation forcing and hydrologic model performance across a connected monitoring network. Section 5 discusses the limitations of the framework, and Section 6 presents concluding remarks and directions for future development.

2. Background

2.1. Regional Hydrologic Inference

Regional hydrologic inference was developed primarily to overcome the limitations of short or incomplete records at individual monitoring locations. By pooling information across sites, regional methods reduce sampling uncertainty and enable inference at ungauged or poorly gauged locations (Weijis et al., 2010). The index-flood method formalized this concept by assuming that flood magnitudes differ only by a site-specific scale factor, allowing a common regional growth curve to be estimated from pooled data (Dalrymple, 1960; Gupta et al., 2009; Institute of Hydrology, 1999).

Subsequent developments introduced L-moment–based regional frequency analysis, which provided robust estimators of distributional shape parameters and formal diagnostics for discordancy and regional heterogeneity (Hosking, 1990; Hosking & Wallis, 1993; 1997; Hosking et al., 1985; Glass 2000, Nash & Sutcliffe, 1970). These methods remain foundational in hydrology due to their efficiency, robustness, and interpretability.

However, classical regionalization approaches typically rely on implicitly defined homogeneous regions and assume independence or weak dependence among sites. In practice, hydrologic behavior varies continuously across space, and violations of these assumptions can lead to biased estimates of regional extremes and uncertainty (Viglione et al., 2013; Castellarin et al., 2008). This motivates the explicit diagnosis of spatial dependence and heterogeneity as a prerequisite for regional pooling.

2.2. Spatial Dependence and Structure

Hydrologic and environmental variables commonly exhibit spatial dependence due to shared climatic forcing, physiographic controls, and network connectivity (Cressie, 1993; Blöschl and Sivapalan, 1995). Quantifying this dependence is essential for determining whether regional pooling assumptions are valid and for understanding how information should be transferred across sites. Global and local measures of spatial autocorrelation, such as Moran’s I and Local Indicators of Spatial Association (LISA), provide formal diagnostics for detecting clustering, dispersion, and spatial outliers in monitoring networks (Moran, 1950; Anselin, 1995). These measures have been applied in hydrology to assess spatial coherence in hydrologic extremes, trends, and model performance metrics (Douglas et al., 2000; Skøien et al., 2006; Archfield & Vogel, 2010).

Despite their utility, spatial diagnostics are often applied as exploratory tools rather than being integrated into downstream regional modeling decisions. Moreover, riverine systems are often misrepresented as hydrologic connectivity governs connectivity interaction and as a result, information about spatial structure is frequently lost when transitioning from diagnostic analysis to formal regional inference.

2.3. Regional Pooling and Uncertainty

While pooling observations across sites reduces sampling variance, it introduces additional uncertainty associated with inter-site heterogeneity and unequal record lengths. Classical regional

frequency analysis often reports uncertainty conditional on a fitted regional distribution, without explicitly accounting for between-site variability (Hosking and Wallis, 1997).

Hierarchical and Bayesian approaches address this limitation by allowing partial pooling, in which site-level estimates are shrunk toward regional means based on data support (Glaves & Waylen, 1997; Huziy et al., 2013; Yang, 2016; U.S. Water Resources Council, 1982; Griffis & Stedinger, 2007; Vogel & Fennessey, 1993; Bobée & Rasmussen, 1995; England et al., 2018; Kavetski et al., 2006; Stedinger, 1981). Such methods improve stability for short records while preserving spatial variability where sufficient information exists (Gelman et al., 2014; Renard et al., 2013; Castellarin, 2007; Castellarin et al., 2018; Saf, 2010; Bracken et al., 2016). In hydrology, hierarchical Bayesian regional models have been shown to improve extreme-value estimation and predictive performance under heterogeneous conditions (Coles and Tawn, 2005; Ribatet et al., 2012; Neykov et al., 2007; Kjeldsen et al., 2002; Kumar & Chatterjee, 2005).

However, Bayesian regional models are computationally intensive and are rarely integrated with classical regional diagnostics such as heterogeneity testing or regime classification within a single analytical workflow.

2.4. Regional Trends and Non-Stationarity

A growing body of evidence indicates that hydrologic systems are influenced by long-term climatic variability and anthropogenic change, challenging the assumption of stationarity underlying many classical hydrologic methods (Milly et al., 2008; Vogel et al., 2011). Detecting and attributing such changes requires statistical methods that distinguish coherent regional signals from isolated local variability. Nonparametric trend detection methods, including the Mann–Kendall test and Sen’s slope estimator, are widely used due to their robustness to non-normality and outliers (Mann, 1945; Kendall, 1975; Sen, 1968; Schoups & Vrugt, 2010). When applied across networks, field significance approaches control for multiple testing and spatial correlation, allowing inference about regionally coherent trends (Livezey and Chen, 1983; Yue and Wang, 2002). Beyond trends, recent work emphasizes the importance of detecting spatially evolving patterns, such as the emergence of coherent droughts or expanding model biases (Vicente-Serrano et al., 2010; Gudmundsson and Seneviratne, 2016; Sarkar et al., 2025; Demiray and Demir, 2026). Similarly, extreme-value analysis has progressed toward non-stationary formulations in which distribution parameters vary with time or covariates, providing improved representation of evolving risk (El Adlouni et al., 2007; Katz et al., 2002).

Although the statistical methods described above are well established, they are most often applied as isolated analyses and not as components of a unified regional inference system. Spatial diagnostics, pooling decisions, uncertainty quantification, and non-stationary modeling are frequently disconnected, leading to inconsistent assumptions and limited reproducibility (Montanari et al., 2013; Nearing et al., 2021; Gao et al., 2024; Hamzah et al., 2020; Hirsch, 1982; Siefken & McCarthy, 2022; Moran, 1975). Recent hydrologic applications increasingly combine heterogeneous observations, machine learning, and spatial or multi-task modeling across hydrologic processes, illustrating the growing analytical complexity of regional hydrologic

assessment (Granata et al., 2022; Demiray and Demir, 2026; Sarkar et al., 2025). The rise of large-sample hydrology and continental-scale modeling further amplifies this challenge. Regional assessments increasingly span hundreds of stations, multiple variables, and heterogeneous data sources, requiring analytical frameworks that treat spatial ensembles as first-class inferential objects (Gupta et al., 2009; Addor et al., 2017). Applications involving hydraulic observations also require careful treatment of data quality and smoothing before regional inference, further increasing the need for explicit and reproducible analytical workflows (Baydaroğlu et al., 2024).

HyMES Regional is developed to address this need by formalizing regional analysis as a sequence of statistically defined operations by defining an analytical sequence in which the result of regional characterization determines which subsequent inference operations are appropriate. Each tier performs a distinct inferential role, ensuring that assumptions about spatial dependence, homogeneity, uncertainty, and stationarity are explicitly diagnosed and propagated consistently through the analytical workflow. This regional analytical structure also supports applications in flood risk and infrastructure assessment, where spatially varying hydrologic information must be translated into consistent risk assessments across multiple locations (Duran and Demir, 2026; Islam & Demir, 2026).

3. Methodology

3.1. Framework Overview and Inferential Design

The framework is organized around three inferential roles applied to spatial ensembles of time series: regional characterization, regional inference, and optional assessment of regional progression. Regional characterization establishes spatial coherence, statistical comparability, and normalized structure prior to any pooling or spatial prediction. Regional inference produces uncertainty-aware regional and spatial estimates conditioned on this diagnosed structure. When temporal dynamics are of interest, the framework further evaluates whether regional behavior exhibits coherent progression through time. Individual analytical methods are modular and serve as operators within these inferential roles; full mathematical specifications are provided in the Supplementary Materials S1. An overview of the framework is provided in Figure 1.

Let $\mathcal{X} = \{X_i(t) : i = 1, \dots, N; t \in \mathcal{T}\}$ denote a spatial ensemble of continuous time series observed at N monitoring locations. The framework treats $\mathcal{X}$ as the primary inferential object. All analysis works on summaries, transformations, or diagnostics derived from this ensemble. Moreover, they are variable-agnostic; the same analytical operators apply to streamflow, precipitation, temperature, water quality variables, and model-derived metrics. Variable semantics (e.g., high flows versus extreme precipitation) are resolved only at the interpretation and visualization stage.

3.2. Regional Characterization

All spatial dependence diagnostics and spatial inference steps operate on a topology-aware spatial reference system derived from hydrologic network connectivity, with Euclidean distance used only when network topology is unavailable. Inter-station connectivity is defined using directed

adjacency matrices derived from NHDPlus flowlines, distinguishing upstream and downstream relationships. This representation reflects hydrologic information transfer governed by flow direction and accumulation processes. Directional global spatial autocorrelation is quantified using decomposed Moran's I statistics computed separately for downstream (I_{dn}) and upstream (I_{up}) connectivity matrices derived from the stream network $I_{dn} \propto \sum_i \sum_j w_{i,j} (x_i - \bar{x})(x_j - \bar{x})$ where x_i denotes a station-level metric and $w_{i,j}$ represents a distance-based spatial weighting. The difference between downstream and upstream dependence is summarized using an asymmetry index $I_{asym} = I_{dn} - I_{up}$, where positive values indicate cumulative downstream effects and negative values indicate dominant upstream control. Local indicators of spatial association are computed to identify localized clusters and spatial outliers. The output of this consists of global and local measures of spatial dependence and corresponding significance diagnostics and characterize the degree of spatial coherence in the network and inform the interpretation of pooled statistics and spatial modeling in subsequent steps.

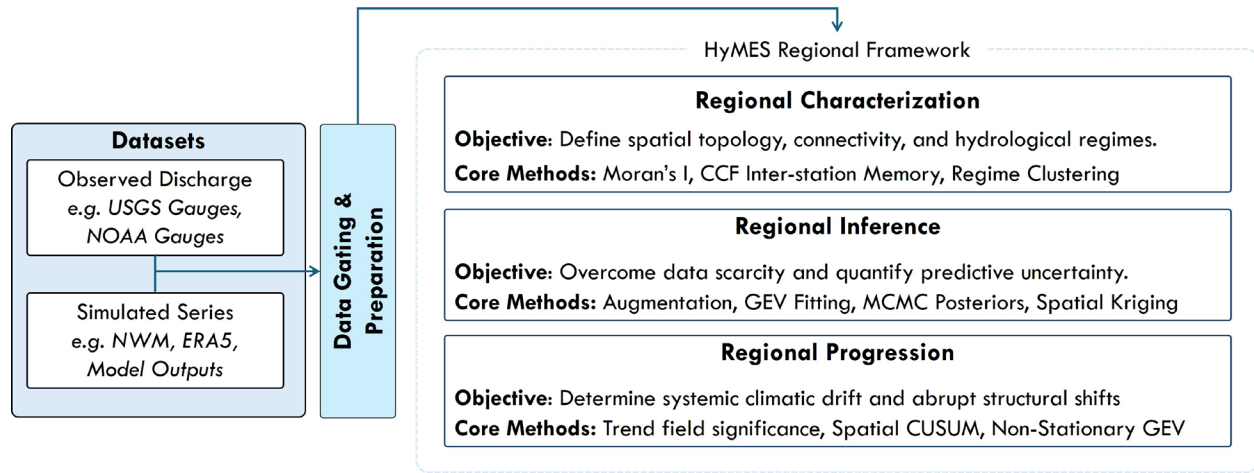


Figure 1. Overview of the HyMES Regional framework. Observed series (e.g., USGS streamflow, NOAA GHCN precipitation) and simulated series (e.g., NWM 3.0, ERA5) pass through data gating and preparation, then through three ordered inferential stages: regional characterization (spatial topology, inter-station connectivity, and regime identification), regional inference (record augmentation, regional frequency analysis, posterior uncertainty pooling, and spatial kriging), and regional progression (trend field significance, spatial CUSUM, and non-stationary GEV). The outputs of each stage condition the admissibility and interpretation of the next.

To characterize dynamic connectivity within the monitoring network, the framework computes a sparse, topology-constrained pairwise cross-correlation matrix across flow-connected stations. Pairwise correlation metrics are computed for concurrent records, allowing temporal offsets to account for routing or lagged responses. For each station pair (i, j) , the peak cross-correlation $\rho_{ij}^* = \max_{\tau} \text{Corr}(X_i(t), X_j(t + \tau))$ summarizes the strength of inter-station dependence. The resulting dependence matrix characterizes network connectivity, shared forcing, and potential

redundancy among stations. These diagnostics inform interpretation of regional trends, guide donor selection for record augmentation, and provide context for regime clustering. The outputs consist of pairwise dependence measures and corresponding lag information, interpreted as structural attributes of the monitoring network.

Station-level series are transformed into exceedance probability space and normalized by a characteristic scale (e.g., median or mean), yielding dimensionless exceedance curves that are directly comparable across locations. At each exceedance probability p , pooled summary statistics across stations define an empirical regional envelope. This representation captures variability in magnitude across the network while preserving differences in response shape. Additional scalar descriptors derived from exceedance behavior are used to characterize variability and seasonal structure. Directional asymmetry metrics derived from the hydrologic network are included explicitly in the clustering feature space, ensuring that regime identification reflects both distributional behavior and flow-directed spatial structure.

Stations are grouped into regimes using clustering applied to a low-dimensional feature representation derived from normalized distributional and temporal characteristics. Regimes correspond to internally coherent response types. The outputs include regional exceedance envelopes, station-level regime assignments, and regime-conditioned summaries. These outputs provide a probabilistic basis for pooled assessment and support stratified interpretation of model performance and extremes.

3.3. Regional Inference

Record length and temporal coverage are evaluated to determine whether sampling uncertainty compromises downstream inference. When data adequacy criteria are not met, record augmentation is applied using variance-preserving regression with a nearby donor station, expressed generically as $X_S(t) = a + b X_L(t)$, where parameters are selected to preserve the variance structure of the target series. Augmented records extend effective sample length while maintaining consistency with observed statistical behavior. The outputs consist of augmented time series, uncertainty flags, and metadata describing augmentation strength and donor relationships, reducing finite-sample variance in subsequent regional analyses.

This step evaluates whether stations exhibit sufficient similarity in distributional shape to support pooled frequency analysis. Extremes at each station are summarized using L-moments, which provide robust measures of distributional location, variability, and shape across heterogeneous sample sizes. Distributional similarity is assessed using L-moment ratios, including the L-coefficient of variation, $\tau_2 = \frac{\lambda_2}{\lambda_1}$, along with higher-order shape ratios. Station-level discordancy and regional heterogeneity diagnostics are used to identify departures from pooled distributional structure. When distributional coherence is supported, pooled L-moment ratios are used to estimate a regional frequency distribution. Site-specific quantiles are expressed using an index-based formulation that combines a regional growth curve with station-specific scaling. The results include regional distribution parameters, homogeneity diagnostics, and station compatibility indicators.

Characterization of spatial dependence is done in station-level metrics by modeling their semi-variance as a function of separation distance. Let $z(s_i)$ denote a station-level metric observed at location s_i . Spatial dependence is summarized through the empirical variogram $\gamma(h) = \frac{1}{2} \text{Var}[z(s_i) - z(s_j)]$, $\|s_i - s_j\| = h$. The empirical variogram is used to identify characteristic spatial scales of variability and to select an appropriate theoretical variogram model. Estimated spatial dependence parameters define the covariance structure required for spatial interpolation and uncertainty estimation in subsequent steps. The results include fitted variogram parameters and associated diagnostics, which condition all kriging-based inference.

Before interpolation, the isotropy assumption of the variogram is tested using directional variograms; when the ratio of maximum to minimum directional range exceeds 1.5, geometric anisotropy is corrected by rotating and rescaling coordinates along the axis of greatest continuity (see Supplementary Materials). Variogram structure is characterized in hydrologic distance where network topology is available, while continuous prediction surfaces are produced in Euclidean coordinates.

Using the spatial dependence structure previously identified, interpolation is performed to estimate continuous regional fields from discrete station observations. Let $\hat{z}(s_0)$ denote the predicted value of a metric at an unsampled location s_0 , expressed generically as a weighted linear combination of observed values, $\hat{z}(s_0) = \sum_i \lambda_i z(s_i)$. Interpolation weights are determined to ensure unbiasedness and minimum variance under the assumed covariance structure (Vogel & Stedinger, 1985; Matalas & Jacobs, 1964; Fiering, 1963; Stedinger, 1980). In addition to spatial predictions, kriging variance fields are produced to quantify location-specific estimation uncertainty. Extensions to the basic interpolation framework are applied when auxiliary spatial information is available or when probabilistic exceedance surfaces are required. These operations yield spatial fields that are explicitly uncertainty-aware and suitable for regional diagnostics, gap analysis, and decision support. Outputs include spatial prediction surfaces, kriging variance fields, and conditional probability maps.

This step addresses uncertainty associated with inter-station variability and unequal record lengths by pooling information across sites on a probabilistic basis. Station-level estimates of distributional or performance metrics are treated as noisy realizations of an underlying regional process. Regional pooling is performed using hierarchical or shrinkage-based formulations, yielding pooled estimates that balance site-specific information with network-level behavior. The resulting regional summaries are accompanied by predictive intervals that explicitly account for both within-site and between-site uncertainty. The results consist of pooled regional estimates, uncertainty envelopes, and station-level shrinkage diagnostics. These outputs support uncertainty-aware regional assessment and provide context for spatial change detection and non-stationary inference in the highest tiers.

3.4. Regional Progression

We evaluate whether monotonic temporal change exhibits coherence across the monitoring network. Trends are first estimated independently at each station using rank-based nonparametric

methods to ensure robustness to non-normality and outliers. Let β_i denote the estimated trend magnitude at station i . Regional inference is then based on the collective behavior of $\{\beta_i\}$, accounting for multiple testing across space. Field significance is assessed by comparing the observed fraction of locally significant trends to that expected under the null hypothesis of spatially independent tests. This establishes whether the detected trends represent a regionally consistent signal. The outputs include station-level trend magnitudes, significance indicators, and a regional field-significance assessment. These outputs support interpretation of coherent change and provide context for subsequent pooling and regime identification. All spatial aggregation and clustering diagnostics in the progression analysis inherit the same hydrologic connectivity structure defined during regional characterization.

We then evaluate whether temporal changes in regional metrics exhibit spatial coherence. Let $m_i(t)$ denote a station-level metric evolving over time (e.g., variability, trend magnitude, performance statistic). Regional behavior is assessed by examining the collective evolution of $\{m_i(t)\}$ across the network. Change detection is applied to spatial aggregates of station-level metrics and to their spatial dependence structure. Sequential statistics, such as cumulative sums computed over time, $\mathcal{C}(t) = \sum_{\tau \leq t} (\bar{m}(\tau) - \mu_0)$, are used to identify persistent departures from a reference state. Complementary diagnostics track the evolution of spatial autocorrelation within moving temporal windows to assess whether changes become increasingly clustered or diffuse over time. Outputs include temporal trajectories of regional change statistics and indicators of spatial coherence. These outputs identify periods during which regional behavior departs structurally from baseline conditions.

We evaluate whether the statistical properties of extremes evolve over time. This extends classical extreme-value and distributional analysis by allowing selected parameters to vary with temporal covariates. Non-stationary formulations are expressed generically by allowing a distributional parameter θ to vary as a function of time, $\theta(t) = \theta_0 + \theta_1 t$, with stationary and non-stationary models compared using information criteria. Time-varying quantiles derived from the selected model provide estimates of evolving regional risk. As a complementary approach, distributional properties are also evaluated using moving-window statistics to detect gradual changes in variability and asymmetry without reliance on parametric assumptions. These analyses provide robust evidence of non-stationary behavior when sample sizes are limited or distributional assumptions are uncertain. The outputs include model selection diagnostics, estimates of temporal change in distributional parameters, and time-varying extreme quantiles. These results characterize whether observed changes reflect transient variability or sustained regional evolution.

3.5. Computational Implementation and Execution

3.5.1. Browser-Based Execution

HyMES Regional is implemented as a browser-based analytical framework in which all statistical computation is executed locally utilizing WebR (WebR, 2025), HydroLang (Erazo Ramirez et al., 2022; 2023), and HydroCompute (Erazo Ramirez et al., 2024a). This design demonstrates the full regional inference workflow described in this manuscript to be run interactively and reproducibly

without reliance on server-side infrastructure or proprietary software environments (Figure 2). Advanced analytical processing pipelines have been extensively implemented leveraging the current browser technologies that enable on the fly execution of heavy processing and storage (Sermet & Demir, 2018, 2023; Pierleoni et al., 2024; Franke & Haehn, 2020; Erazo Ramirez et al., 2024b; Goltzsche et al., 2018; Souffront Alcantara et al., 2019, Sit et al., 2021).

All analyses are executed using the same statistical procedures regardless of deployment context. The browser runtime performs the complete set of regional diagnostics and inferential operations, including distributional analysis, spatial dependence modeling, regional pooling, and non-stationary inference, without approximation or simplification (Franke & Haehn, 2020). As a result, the inferential logic described in the Methods and Supplementary Materials is identical to that executed in practice. Browser-native execution supports integrated exploration across diagnostic, regional, spatial, and temporal views within a single analytical environment. This interoperability is essential for regional inference, where interpretation depends on the consistent propagation of spatial dependence, heterogeneity, and uncertainty across analytical stages.

The framework is not geographically bound and operates on generic spatial ensembles of time series. While applications in this study focus on large monitoring networks in the conterminous United States, the analytical structure applies without modification in other regions, subject to data availability. Deterministic execution ensures that results are reproducible across platforms given identical inputs and configuration.

3.5.2. AI-Assisted Workflow Navigation and Interpretation

AI-assisted workflows are increasingly being applied to scientific code generation, data analysis, education, and the execution of multi-step computational workflows, extending AI support from individual tasks to broader research and learning processes (Erazo Ramirez & Demir, 2025; Pursnani et al., 2026a; 2026b). The framework includes an optional assisted orchestration layer that supports workflow configuration, navigation, and result interpretation. This layer operates strictly at the level of orchestration and explanation, it does not perform statistical estimation, modify analytical outputs, or replace the inferential procedures defined in methodology section. All analytical results are generated deterministically by the same statistical routines, regardless of whether assisted guidance is enabled.

Assisted guidance maps analytical objectives to appropriate components of the framework, provides contextual explanations of results relative to upstream diagnostics and assumptions, and preserves traceability by explicitly linking each output to the diagnostics and inferential steps on which it depends. Recommendations are constrained by the framework's dependency structure and are conditioned on the satisfaction of required diagnostic criteria; assisted workflows therefore remain statistically consistent with the formal inferential design. To support different analytical perspectives, the framework allows alternative organizations of results and explanatory emphasis (e.g., diagnostic-focused exploration, model evaluation, or inference-driven analysis). These perspectives affect interaction and interpretation only and do not alter the underlying analytical methods, assumptions, or results.

4. Results and Discussions

4.1. Case study: Spatial Error Propagation into Hydrological Model Performance Over Southern Louisiana

This case study evaluates how spatially structured precipitation forcing errors propagate into hydrologic model performance across southern Louisiana. Precipitation observations from the NOAA Global Historical Climatology Network (GHCN) were compared against ERA5 reanalysis outputs to characterize spatial forcing discrepancies. Streamflow simulations from the National Water Model (NWM 3.0) were evaluated against observed discharge from USGS stations to quantify downstream hydrologic response errors (Johnson et al., 2019). The analysis spans the period 2010–2023. Although AORC forcing data is used as forcings for NWM, ERA5 provides an independent reanalysis reference suitable for diagnosing precipitation bias structure (Kim & Villarini, 2022; Chowdhury et al., 2025; Hughes et al., 2024). All datasets used in this study are accessible through the application interface, which includes dedicated modules for precipitation and streamflow diagnostics.

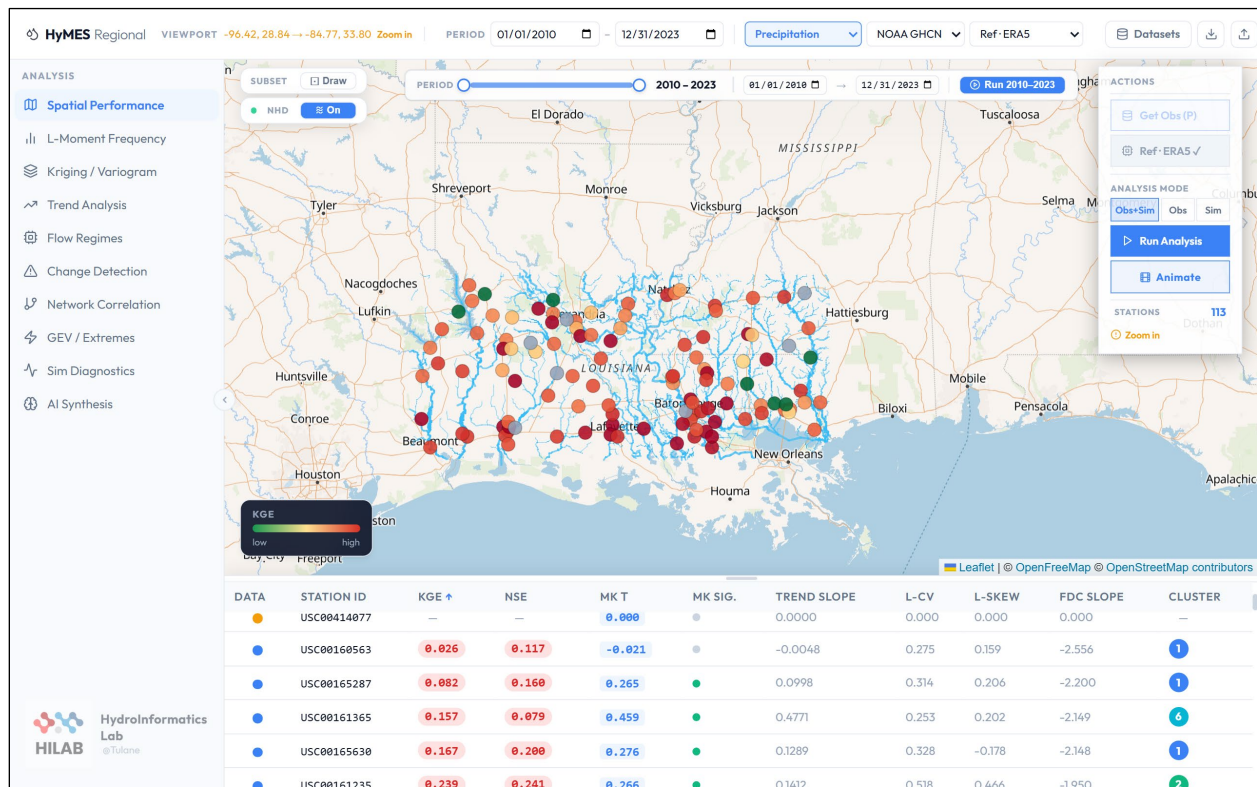


Figure 2. The HyMES Regional interface during the precipitation analysis of the case study (NOAA GHCN observations against ERA5, 2010–2023). Left: analysis modules. middle: station map colored by the active metric (here KGE). right: controls for period, observation and reference sources, and analysis mode. Bottom: per-station table of performance (KGE, NSE), trend (Mann–Kendall τ , significance, and Sen slope), distributional (L-CV, L-skewness, FDC slope), and regime metrics. All computation runs locally in the browser through WebR/WebAssembly, without server-side processing.

4.1.1. Spatial Structure of Forcing

The spatial distribution of mean precipitation bias between ERA5 and GHCN reveals coherent regional patterns across the study domain (Fig. 3). Bias values are predominantly negative, ranging approximately from -100% to 0% , indicating underestimation of observed precipitation by the reanalysis product. Spatially contiguous areas of enhanced bias are evident around Lake Charles, Alexandria, and Baton Rouge, suggesting geographically organized forcing discrepancies. Global spatial autocorrelation of the precipitation bias field, quantified using Moran's I , is weak and not statistically significant at the domain scale ($I = 0.0350$, $Z = 0.70$, $p = 0.4830$), indicating limited domain-wide coherence. Directional Moran's I computed along the stream network similarly shows weak and non-significant dependence in both upstream-to-downstream ($I_{up} = 0.0259$, $p = 0.773$) and downstream-to-upstream ($I_{dn} = -0.0915$, $p = 0.583$) directions, with a positive but non-significant asymmetry index ($I_{asym} = 0.1174$, $p = 0.224$).

Despite the absence of statistically significant global or directional autocorrelation, LISA identify sub-regional low–low clustering and isolated spatial outliers within the network (Fig. 3b). These localized structures indicate that precipitation errors organize at sub-regional scales along connected portions of the network, forming coherent bias patterns that are not captured by domain-averaged metrics. Such localized organization represents a plausible source of systematic forcing error capable of propagating into downstream hydrologic simulations, particularly in areas with limited station density or strong precipitation control. The presence of these local structures motivates regime-conditioned characterization of forcing behavior and limits the interpretation of domain-wide aggregation. Subsequent regional inference is consequently evaluated within the spatial and response structures identified during characterization.

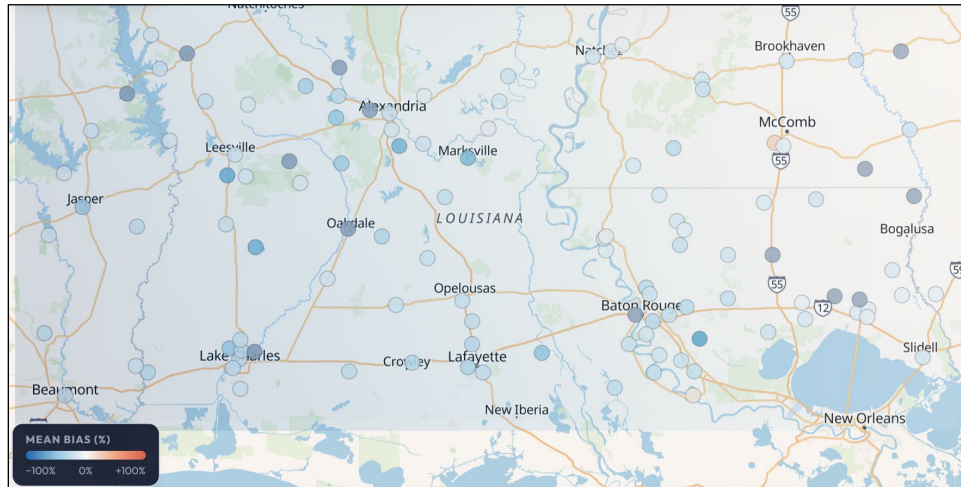
4.1.2. Regime Dependent Behavior

Six distinct regimes were identified across the 113 stations included in the analysis ($k=6$, selected in 10 of 11 seeded runs with mean silhouette width of 0.310 indicating weak but non-random structure, see Kaufman & Rousseeuw, 1990). These regimes represent groups of stations sharing similar exceedance behavior and distributional structure, reflecting common hydrologic response characteristics under comparable forcing conditions. At the domain scale, the spatial distribution of regimes is sparse, with stations belonging to the same regime occurring non-contiguously across the study area reflecting similarity in hydrologic response characteristics instead of strict geographic proximity. This organization indicates that geographic proximity alone does not provide a sufficient basis for defining regional response groups in the study network. Figure 4a and c illustrate the spatial distribution of regime assignments and corresponding regional exceedance probability accounting for all stations. For the upper tail, normalized exceedance at the 1 % level exhibits an interquartile range of 3.32–4.94, a median of 3.93, and a P5–P95 envelope of 2.57–9.96. At the 5 % exceedance level, values narrow to an interquartile range of 2.46–2.97, a median of 2.70, and a P5–P95 envelope of 2.25–5.22. Exceedance values continue to taper toward lower percentiles, reflecting reduced variability away from the extreme tail.

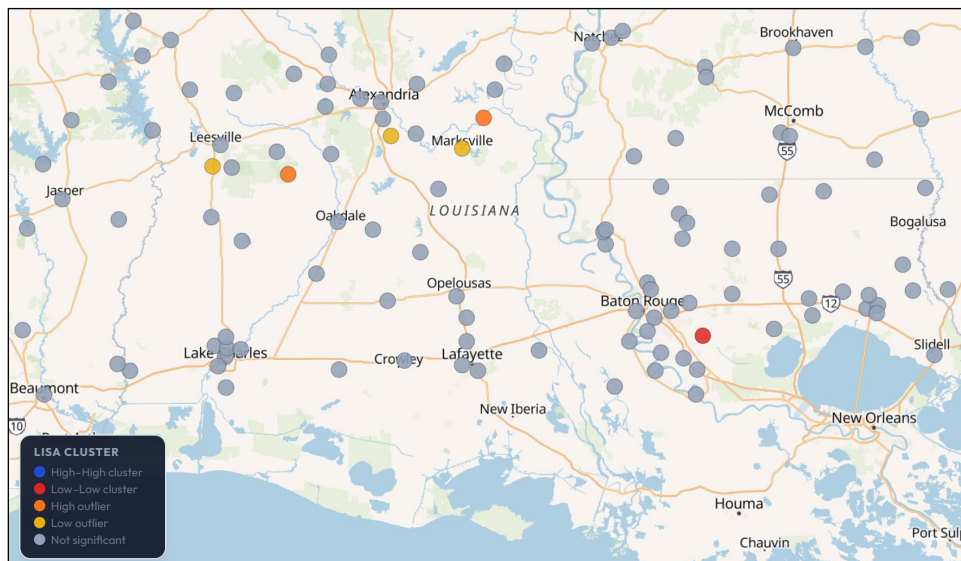
Among the identified regimes, Clusters 2 and 4 represent typical network behavior and are selected as representative cases for subsequent analysis. Cluster 4 comprises 30 stations and exhibits moderate model skill (mean KGE = 0.40), higher variability (L-CV = 0.24), and moderately right-skewed distributions (L-skewness = 0.32). Cluster 2 includes 27 stations with comparable model performance (mean KGE = 0.414) but lower variability (L-CV = 0.20) and reduced skewness (L-skewness = 0.15), indicating more subdued flow responses. These clusters span the central tendency of regime behavior in terms of skill, variability, and distributional shape.

Table 1. Summary averages of KGE, L-Skewness, and L-CV for the most representative clusters in the precipitation stations.

Cluster	# Stations	KGE	L-Skewness	L-CV
4	30	0.400	0.325	0.245
2	27	0.414	0.148	0.199



(a)



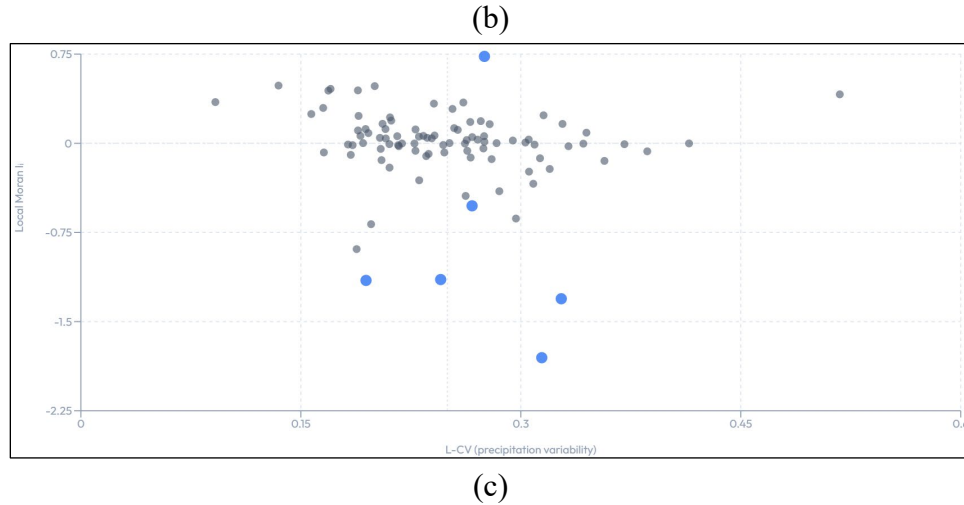


Figure 3. Spatial structure of precipitation forcing error in the precipitation network (central and northern Louisiana and adjacent areas), 2010–2023. (a) Mean relative bias (%) of ERA5 against NOAA GHCN at each gauge; negative values indicate underestimation by ERA5. (b) LISA classification of the bias field into high–high and low–low clusters, high–low and low–high outliers, and non-significant stations (permutation test, $\alpha = 0.05$). (c) Local Moran's I_i plotted against station L-CV; highlighted points are locally significant ($p < 0.05$). Global Moran's $I = 0.035$ ($p = 0.48$).

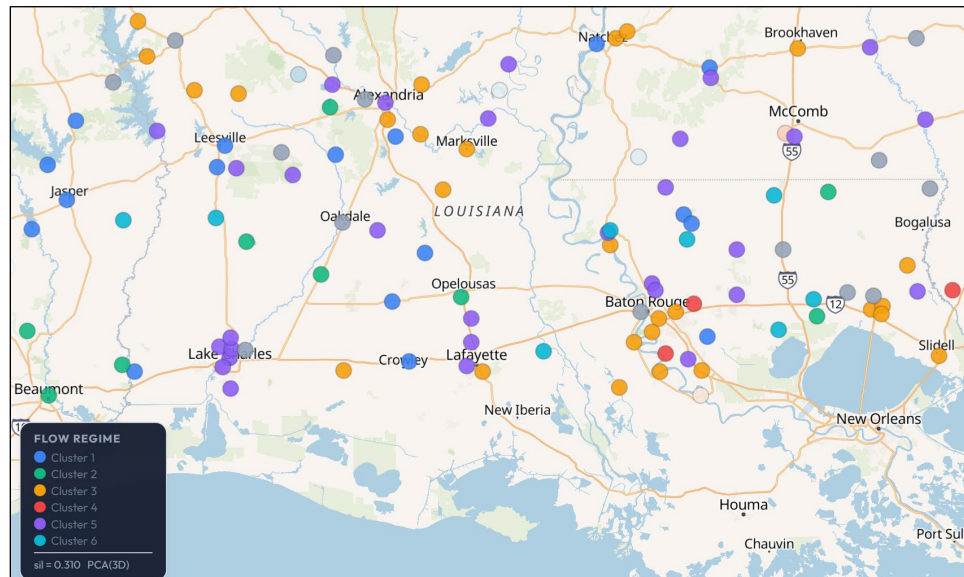
4.1.3. Spatial Structure of Streamflow Error

Streamflow simulations from the National Water Model exhibit spatially heterogeneous agreement with observations across the study domain. Mean bias patterns show increasing positive bias toward the delta region, with pronounced discrepancies downstream of Baton Rouge (Fig. 5). Network connectivity analysis identifies a dominant correlation hub near Baton Rouge, with a mean absolute inter-station correlation of $|r| = 0.71$, indicating strong shared signal structure in streamflow errors within this portion of the network. Global spatial autocorrelation of the bias field is positive but does not reach conventional significance thresholds (Moran's $I = 0.1252$, $Z = 1.66$, $p = 0.0976$), indicating limited domain-wide coherence. Directional Moran's I evaluated along the stream network shows weak but consistently positive dependence in both upstream-to-downstream ($I_{up} = 0.1635$, $p = 0.090$) and downstream-to-upstream ($I_{dn} = 0.1734$, $p = 0.088$) directions, with a near-zero asymmetry index ($I_{asym} = -0.0099$, $p = 0.833$), suggesting balanced directional structure. LISA further identify localized low–low clustering near Baton Rouge alongside several spatial outliers (Fig. 5b). These results indicate that streamflow model errors are not uniformly distributed across space, but organize into localized coherent structures aligned with network connectivity.

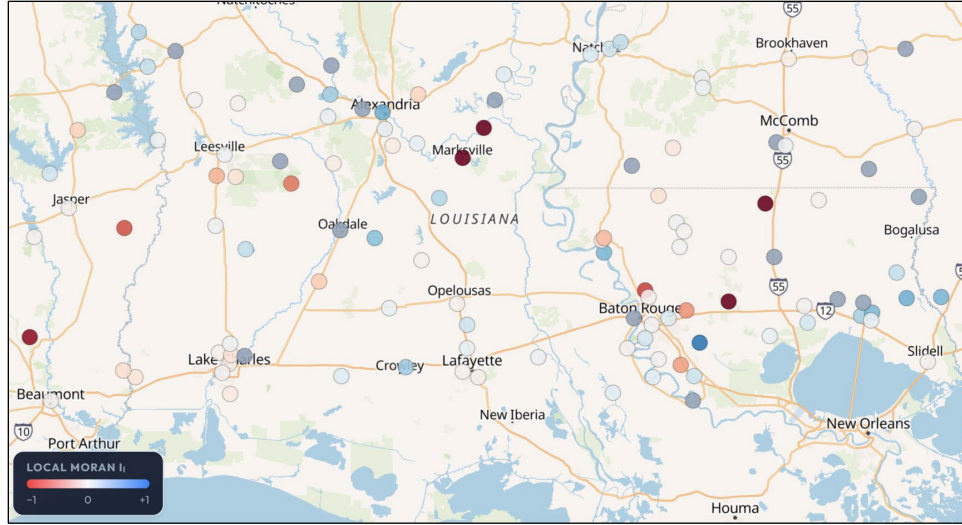
The spatial alignment between localized precipitation bias structures and downstream streamflow error clustering suggests that forcing discrepancies contribute to organized hydrologic performance degradation, although the relationship is modulated by basin connectivity and hydrologic routing processes.

4.1.4. Regime-Conditioned Model Behavior and Forcing Linkage

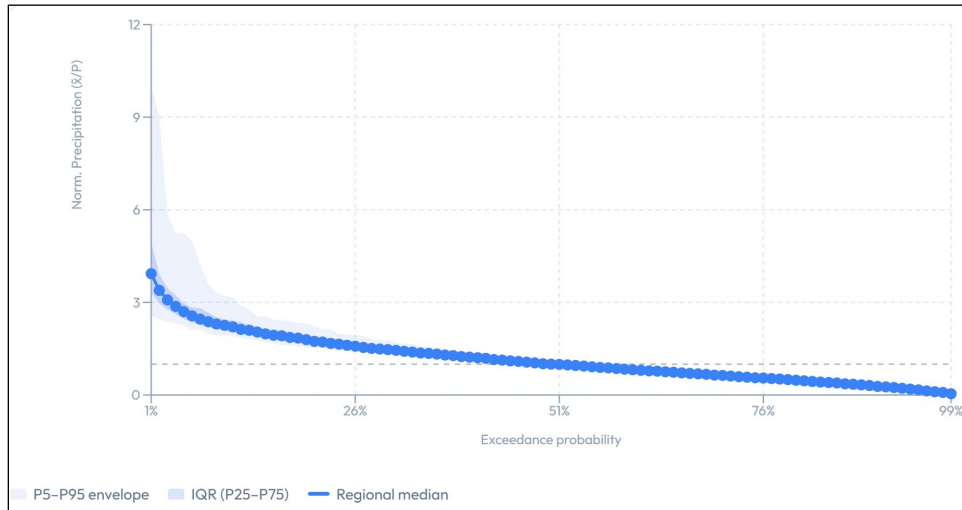
Two distinct flow regimes emerge from the exceedance-based clustering for the streamflow analysis, with clear differences in both hydrologic behavior and model performance (Table 2). Cluster C1, comprising 21 sites, represents a stable and hydrologically homogeneous regime characterized by infrequent but pronounced high-flow events, smoothly transitioning mid-range flows, and tightly convergent low-flow behavior indicative of strong baseflow control. This structure is reflected in high distributional asymmetry and variability (mean L-skewness = 0.56, mean L-CV = 0.33). Correspondingly, model performance in this regime is degraded, with mean KGE = -0.21 and mean NSE = -1.01. In contrast, Cluster C2 includes 22 sites and exhibits a broader dynamic range with weaker distributional skewness and lower variability (mean L-skewness = 0.08, mean L-CV = 0.22). Exceedance behavior transitions more gradually from moderate to low-magnitude flows, indicating comparatively subdued hydrologic responses. Despite this reduced variability, model performance is substantially worse in this regime, with mean KGE = -0.99 and mean NSE = -9.26, highlighting that lower apparent hydrologic variability does not correspond to improved simulation skill. This mismatch between subdued hydrologic variability and degraded skill is reflected in the structural variability of KGE across the identified flow regimes (Figures 6 and 7).



(a)

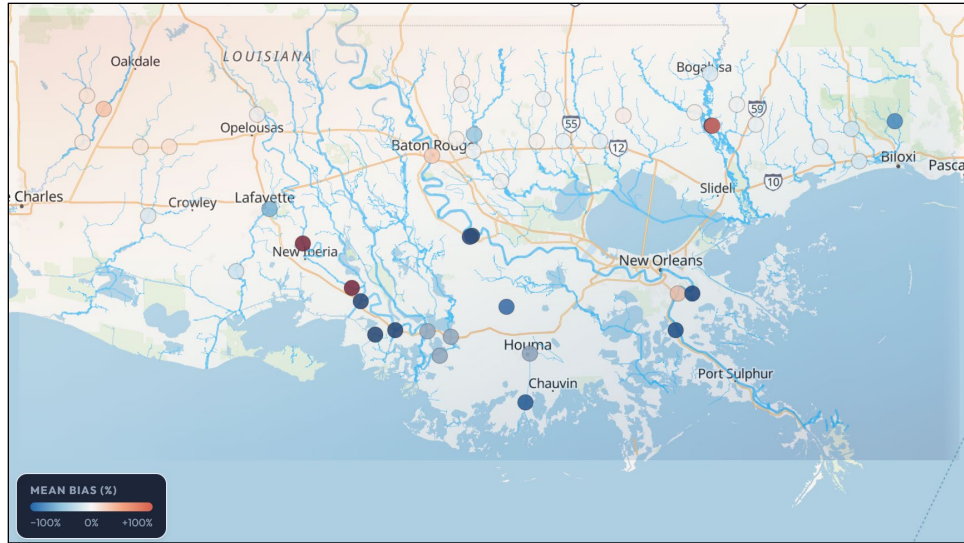


(b)

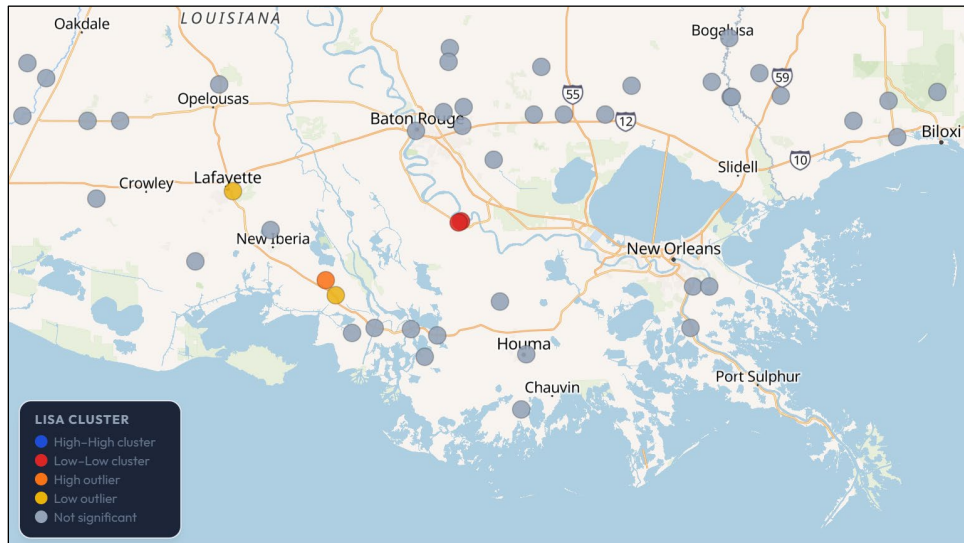


(c)

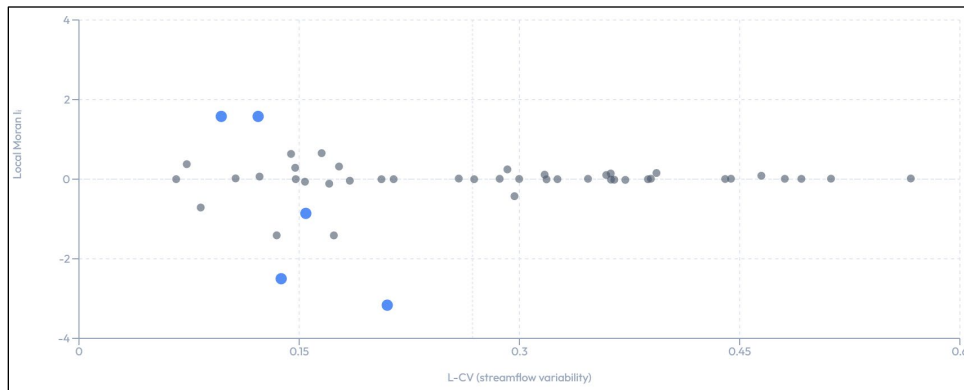
Figure 4. Regime structure of the precipitation network (113 stations). (a) Regime assignments from k-means clustering on principal components of normalized distributional features, with $k = 6$ selected by the silhouette criterion. (b) Local Moran's I_i of precipitation bias on a diverging scale from -1 (spatial outlier) to $+1$ (local cluster). (c) Regional normalized exceedance curve for all stations: the regional median of $P/\tilde{P}$ (each station normalized by its own median) against exceedance probability, with the interquartile ($P25-P75$) and $P5-P95$ inter-station envelopes.



(a)



(b)



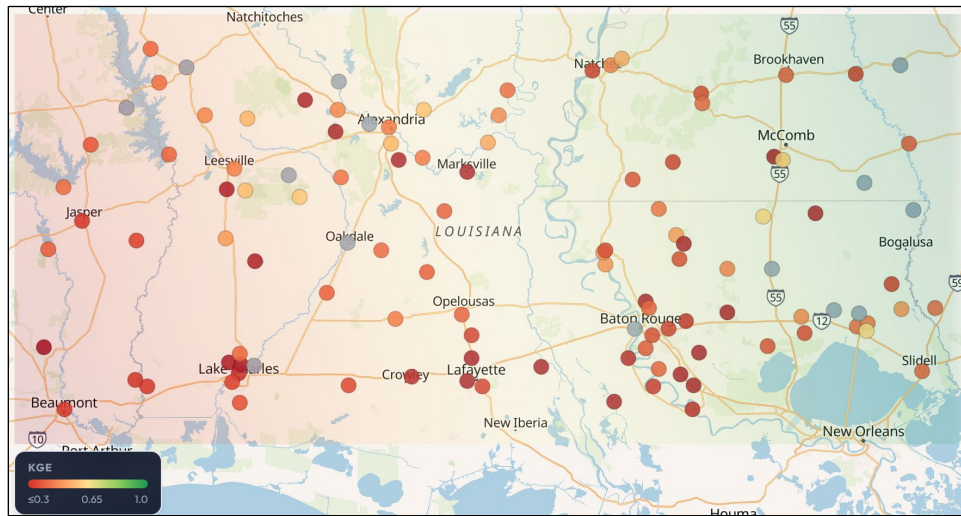
(c)

Figure 5. Spatial structure of streamflow simulation error at the 43 USGS gauges in southern Louisiana, 2010–2023. (a) Mean relative bias (%) of NWM 3.0 simulated streamflow against

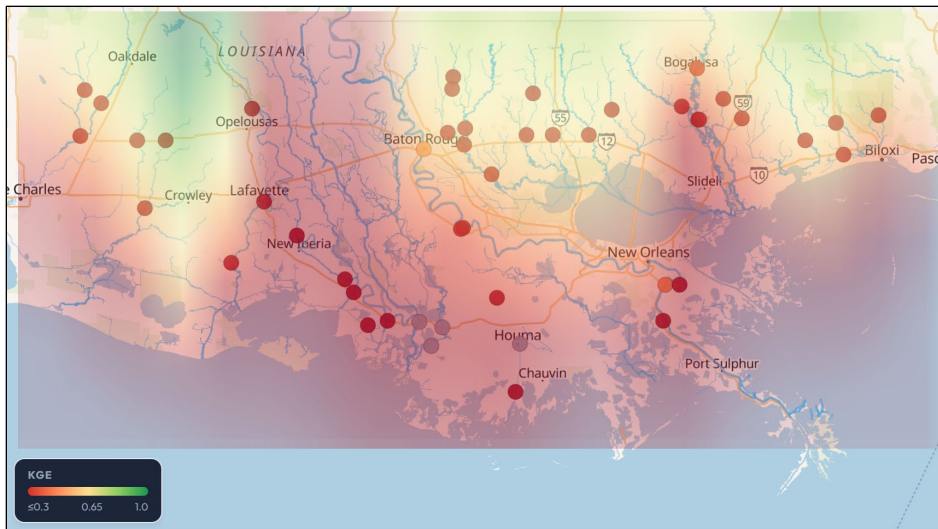
observations; positive values indicate overestimation. (b) LISA classification of the bias field (categories as in Fig. 3b). (c) Local Moran's I_i plotted against station L-CV; highlighted points are locally significant ($p < 0.05$). Global Moran's $I = 0.125$ ($p = 0.098$).

Table 2. Hydrologic performance of each of the identified clusters with overlapping observed and simulated values across the region. The metrics represent mean values per cluster.

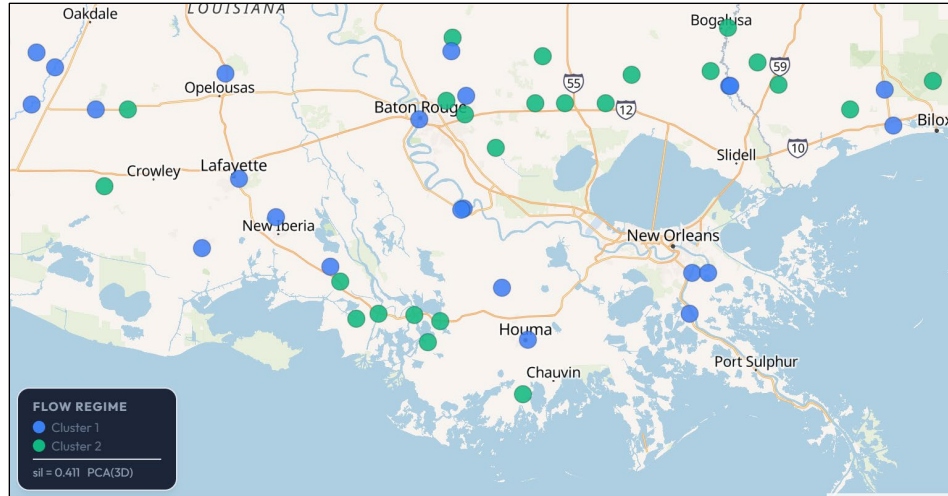
Cluster	# Sites	KGE	NSE	L-Skewness	L-CV
1	22	-0.751	-9.26	0.082	0.220
2	21	-0.083	-0.96	0.73	0.333



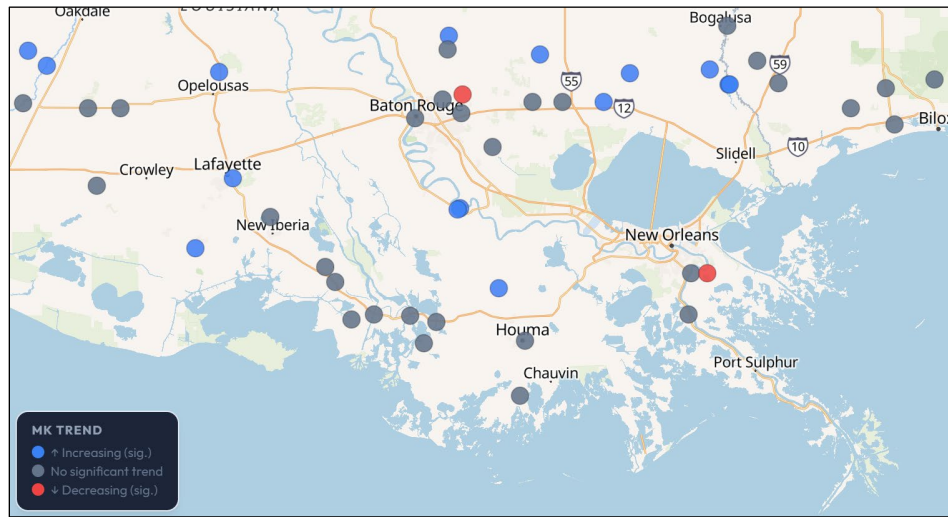
(a)



(b)



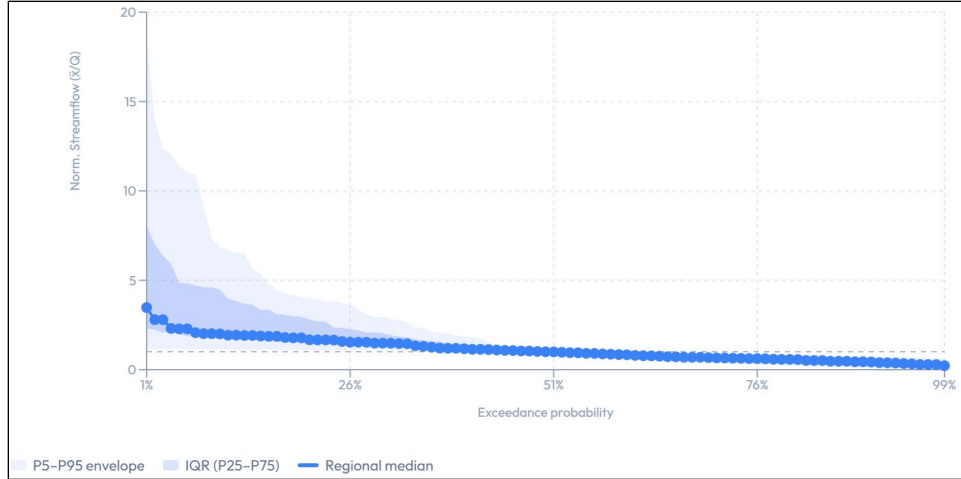
(c)



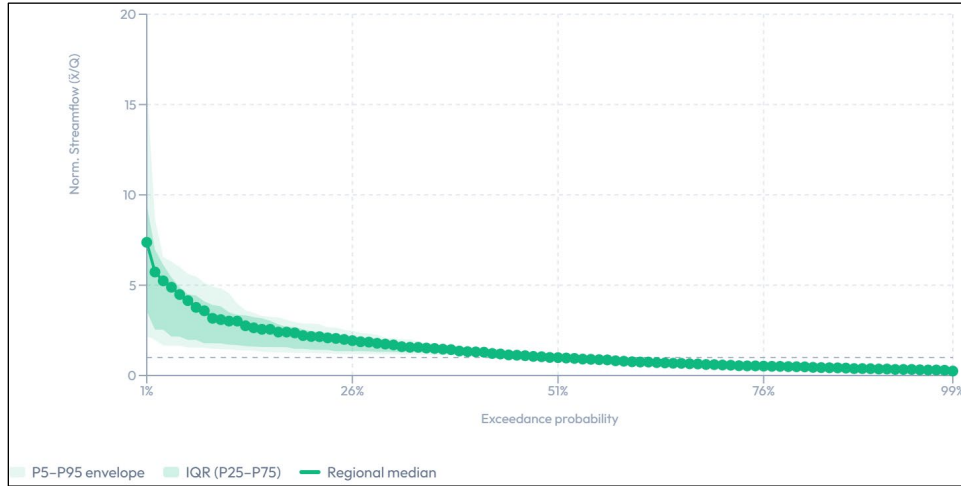
(d)

Figure 6. Model skill, regimes, and trends across the case-study networks. (a) KGE of ERA5 against NOAA GHCN precipitation at each gauge (points), over the kriged KGE surface (kriging with external drift). (b) As in (a), for NWM streamflow against USGS observations. (c) Flow-regime assignment of the 47 streamflow stations (C1, $n = 23$; C2, $n = 24$); 43 of these have NWM 3.0 simulations. (d) Mann–Kendall trend test on monthly observed streamflow: significant increasing, significant decreasing, or no significant trend ($\alpha = 0.05$).

The contrasting performance behavior between regimes indicates that hydrologic response variability alone does not control model skill. Regime-specific forcing characteristics and basin response dynamics jointly determine simulation reliability. This finding supports the hypothesis that structured precipitation error contributes to regime-dependent performance degradation not following a uniform model failure across the network.



(a)



(b)

Figure 7. Regional normalized flow-duration envelopes for the two streamflow regimes: (a) C1 ($n = 23$) and (b) C2 ($n = 24$). Lines show the regional median of $Q/\tilde{Q}$ (each station normalized by its own median flow); bands show the interquartile (P25–P75) and P5–P95 inter-station envelopes against exceedance probability (Vogel & Fennessey, 1994). The regime in (a) has a lower median upper tail but a much wider inter-station spread between roughly 1% and 25% exceedance, indicating heterogeneous high-flow response; the regime in (b) has a pronounced upper tail with a comparatively narrow envelope.

4.1.5. Temporal Evolution, Extremes, and Regional Uncertainty

Temporal and distributional diagnostics reveal asymmetry in streamflow model performance across the study domain, particularly under extreme flow conditions (Figure 8). Representative station-level statistics summarized in Table 3 illustrate the magnitude and directional variability of errors in both upper and lower distribution tails. The largest upper-tail (Q90) errors occur at distributary and canal gauges. Simulated high flows are near zero at Wax Lake Outlet (07381590), the Gulf Intracoastal Waterway (07381670), and Wilson Slough (02492111), corresponding to

biases approaching -100% , whereas the East Pearl River (02492110), which shares the bifurcation at Walkiah Bluff with Wilson Slough, overestimates Q_{90} by more than $+250\%$. Opposing errors at the two branches of the same bifurcation are consistent with the dendritic channel network of the NWM, which does not partition flow at channel splits. Distributaries and canals receive little or no routed flow, while the main branch carries the full upstream discharge. These errors therefore reflect a structural limitation of the routing network in the deltaic portion of the domain and are unlikely to be resolved by forcing corrections alone.

Lower-tail diagnostics (Q_{10}) similarly indicate asymmetric model response, with multiple stations exhibiting either suppressed low-flow representation or inflated baseflow magnitudes relative to observations. For example, the canal gauges 07381670 (Gulf Intracoastal Waterway) and 07385790 (Charenton Drainage Canal) exhibit near-zero simulated low flows despite non-zero observed discharge, consistent with the routing limitation described above, whereas the Mississippi River main-stem stations 07374000 (Baton Rouge) and 07374525 display systematic overestimation of low-flow magnitudes. These distributional distortions are reflected in degraded overall model performance metrics, with several stations exhibiting strongly negative KGE values (e.g., $KGE = -2.39$ at Station 02492110), indicating divergence between simulated and observed hydrograph structure.

Temporal diagnostics further indicate that these performance deficiencies evolve systematically through time. The cumulative sum (CUSUM) of regional mean residuals, summarized in Table 4, exceeds the statistical detection threshold of $64,635.72 \text{ ft}^3/\text{s}$ (set at 5σ of the historical variance), confirming statistically significant deviation from stationary model behavior. A breakpoint detected at window index 106 marks the onset of sustained regional drift, indicating that model bias accumulates progressively across the 2010–2023 analysis period. This temporal drift reflects cumulative propagation of forcing and structural inconsistencies, resulting in sustained performance degradation under evolving hydrologic conditions.

Spatial diagnostics evaluated concurrently with temporal evolution demonstrate that performance degradation is not uniformly distributed across the domain. Global Moran's I computed for cross-sectional KGE values remains near zero ($I = -0.025$), indicating the absence of synchronized domain-wide failure. However, localized performance degradation is evident in station-level diagnostics summarized in Table 5, where persistently negative KGE values coincide with small but non-zero local Moran statistics. Stations such as 02492111 and 07381328 exhibit sustained negative model skill ($KGE < -0.5$) alongside localized clustering tendencies, indicating that model failure manifests initially as isolated regional anomalies before contributing to broader performance drift through cumulative propagation.

The combined temporal and spatial diagnostics demonstrate that streamflow model uncertainty evolves through interacting mechanisms involving distributional distortion, localized spatial degradation, and progressive temporal drift. These processes collectively produce non-stationary model behavior that disproportionately affects extreme-flow representation (Mann, 1945; Ekeu-Wei et al., 2020; Hussain & Pasha, 2009; Jin & Stedinger, 1989). The magnitude of upper- and lower-tail asymmetry observed across representative stations highlights the limitations of

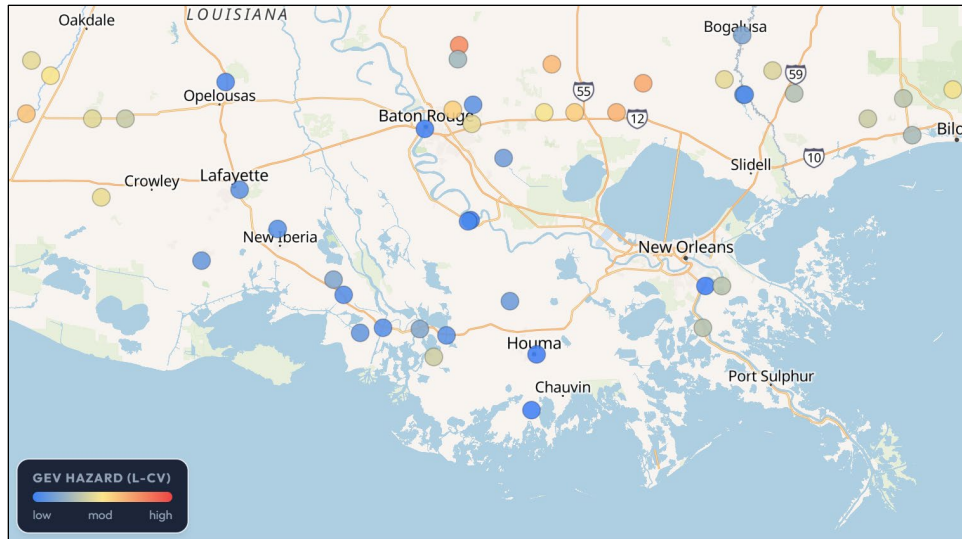
stationary performance assumptions and underscores the importance of regime-aware and uncertainty-conditioned regional diagnostics.

4.1.6. Synthesis of Spatial Error Propagation and AI Interpretation

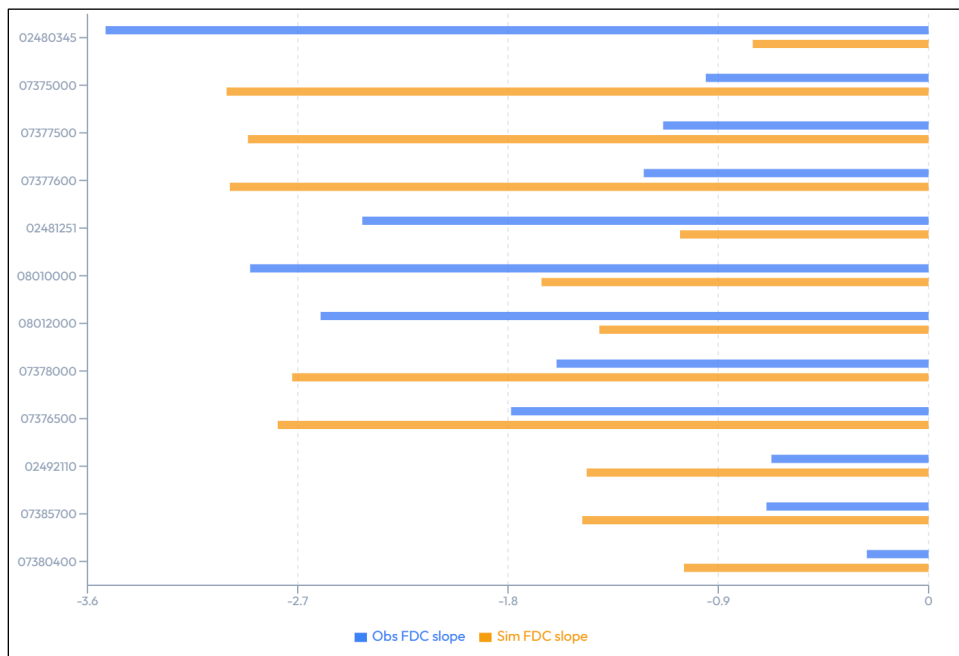
Across southern Louisiana, precipitation forcing discrepancies exhibit localized spatial organization that propagates into hydrologic simulation performance through regime-dependent mechanisms. While global spatial autocorrelation remains weak, localized clusters of precipitation bias coincide with structured streamflow performance degradation, particularly near major hydrologic junctions such as Baton Rouge. Temporal diagnostics further demonstrate that these localized errors accumulate over time, producing non-stationary drift in regional model bias. Distributional diagnostics provide complementary evidence of structural organization, with simulated precipitation and streamflow constrained to a narrow region of ratio space while observed records span a broader range of distributional behavior. The combined spatial, temporal, and distributional evidence indicates that hydrologic model performance degradation emerges from structured forcing uncertainty interacting with basin connectivity, routing dynamics, and systematic regularization of higher-order behavior.

Table 3. Observed and simulated high-flow (Q90) and low-flow (Q10) quantiles (ft³/s), Q90 bias, and KGE for selected streamflow stations. Stations 07381590 (Wax Lake Outlet), 07381670 (Gulf Intracoastal Waterway), 07385790 (Charenton Drainage Canal), and 02492111 (Wilson Slough) are distributary or canal gauges.

Station	Obs Q90	Sim Q90	Bias %	Obs Q10	Sim Q10	KGE
07374000	1030000.0	1152580.1	+11.9%	235900.0	394145.8	0.499
07374525	994000.0	1235930.4	+24.3%	233000.0	373268.6	0.457
07381590	173000.0	2.1	-100.0%	41100.0	0.0	-0.770
02489500	29500.0	20639.2	-30.0%	1940.0	1653.7	0.366
07381670	14700.0	21.1	-99.9%	2751.0	2.1	-0.727
07385790	8425.0	40.6	-99.5%	498.5	5.7	-0.670
07377300	8117.0	3573.2	-56.0%	447.3	138.4	-0.068
07381328	6761.0	1023.0	-84.9%	1160.0	144.1	-0.519
08012150	6750.0	6202.5	-8.1%	182.0	480.2	0.124
02492110	6180.0	21673.2	+250.7%	1790.0	1463.1	-2.393
07380120	5630.0	5983.7	+6.3%	380.0	389.3	0.173
02492111	5340.0	0.0	-100.0%	1540.0	0.0	-0.734
07378500	4600.0	4122.6	-10.4%	392.0	113.7	0.110
02492000	3720.0	4089.1	+9.9%	668.0	594.5	0.098
08015500	3708.0	6605.4	+78.1%	181.0	311.5	-0.213



(a)



(b)

Figure 8. Extremes and flow-regime distortion at the streamflow stations. (a) At-site L-CV of annual maximum streamflow, classed as low, medium, or high hazard; higher L-CV indicates more variable extremes. (b) Observed (blue) and simulated (orange) flow-duration-curve slopes, $(\log_{10} Q_{10} - \log_{10} Q_{90})/0.8$, at 12 selected stations; more negative values indicate a steeper, flashier flow regime.

Table 4. Global diagnostics evaluated for the simulation and observations. The metrics evaluated were regional mean residual for accumulated bias over time and cross sectional KGE for clustered performance degradation.

Diagnostic	Value	Interpretation
Change detected	Yes	Significant deviation from stationary behavior
Breakpoint (window index)	106	Onset of systematic regional drift
CUSUM threshold	64,635.72 ft ³ /s	Exceeded by cumulative residual process
Metric evaluated	Regional mean residual	Indicates accumulating bias over time
Global Moran's I	-0.025	No domain-wide synchronized failure
Spatial radius	3.0°	Neighborhood used for spatial weighting

To clarify how these interacting mechanisms manifest in the diagnostic space, the consolidated regional metrics were examined through the AI assisted interpretive synthesis. The synthesis highlights timing misrepresentation as a dominant contributor to degraded performance, with low correlation values indicating systematic errors in storm response and routing behavior across the network. The synthesis also identifies a negative bias in flow-duration-curve slopes, which under the slope convention used here indicates simulated flow regimes that are steeper (flashier) than observed, consistent with Figure 8b, where simulated slopes are steeper at 8 of the 12 stations, alongside a positive bias in L-CV that signals distortion of variability. These features organize spatially within specific regimes, consistent with the regime-conditioned structure identified earlier, and concentrate among stations exhibiting persistently low KGE values. The resulting interpretation identifies storm dynamics and routing processes as plausible contributors to the observed performance degradation, while remaining contingent on the diagnostic abstraction and the possibility of unresolved forcing intermittency or scale mismatch within the modeling system. The complete response from the AI assisted layer's through different persona lenses can be found in the Supplementary materials, with an overview in Figure 9.

Table 5. KGE and Local Moran's I for selected stations.

Station ID	KGE	Local Moran's I
02492111	-0.73	+0.004
295124089542100	-0.72	+0.004
08013500	0.21	+0.002
07381328	-0.52	0.000
07381000	-0.25	0.000
07386880	-0.27	0.000
07377300	-0.07	-0.001
07377500	-0.04	-0.001

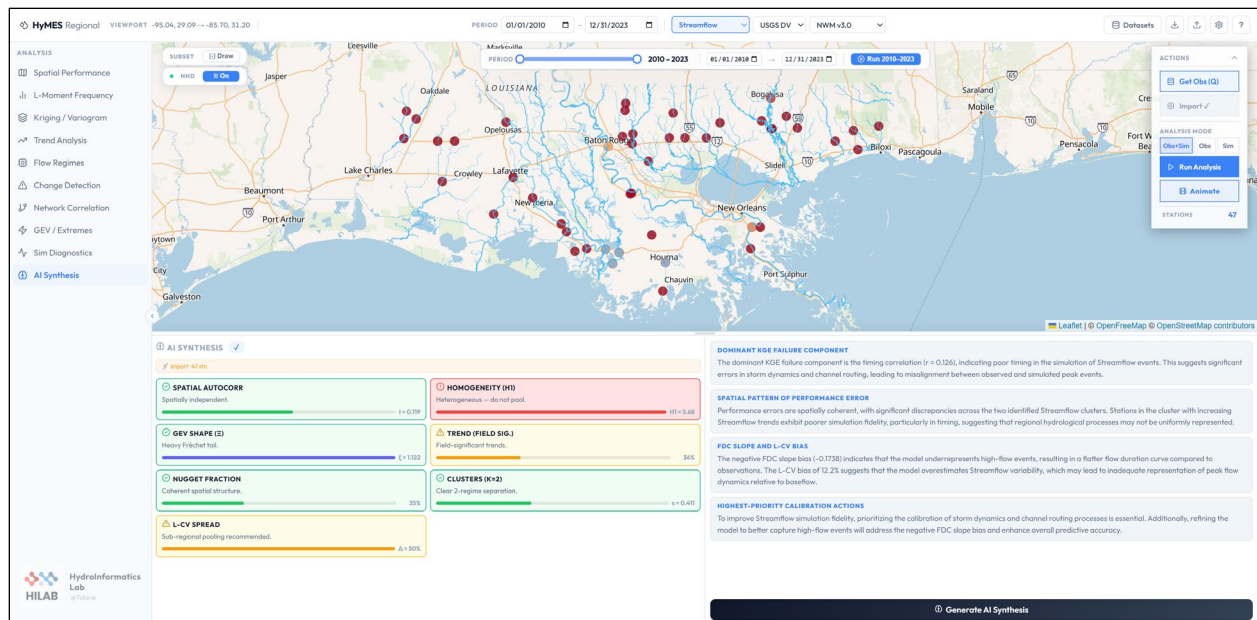


Figure 9. AI-assisted synthesis panel for the streamflow analysis (hydrologist-evaluator persona). Left: diagnostic summaries of upstream results (spatial autocorrelation, homogeneity H1, GEV shape, trend field significance, regime count, nugget fraction, and L-CV spread), each flagged by status. Right: the generated interpretation. The model receives only the diagnostics computed by the HyMES Regional routines and does not modify any analytical output

4.2. Discussions

This case study demonstrates how regional characterization determines the structure within which subsequent inference and progression are interpreted. The southern Louisiana network does not exhibit a single domain-wide spatial response. Global spatial dependence is weak, localized clusters are present, and stations with similar response characteristics occur across non-contiguous portions of the network. These results provide a data-based basis for separating regional behavior into distinct response structures before evaluating distributional, uncertainty, and temporal properties.

Regional characterization establishes the statistical context for analysis by diagnosing spatial dependence, network connectivity, and probabilistic structure across the monitoring network. In southern Louisiana, these diagnostics show limited domain-wide coherence alongside pronounced sub-regional organization. Normalized exceedance behavior and regime identification reveal that stations sharing similar hydrologic response characteristics are not spatially contiguous, indicating that geographic proximity alone does not define comparable behavior. These results constrain the admissible space for aggregation and pooling by distinguishing structurally similar responses from coincidental alignment.

Regional inference operates within this constrained space by conditioning pooling, spatial modeling, and uncertainty estimation on the diagnosed structure. Distributional coherence diagnostics guide regional frequency analysis, while dependence modeling informs spatial prediction and uncertainty propagation. In the case study, weak global spatial autocorrelation combined with localized clustering supports inference at regime-conditioned and sub-regional

scales. Regional inference operates within the structures identified during characterization by conditioning pooling, spatial modeling, and uncertainty estimation on the diagnosed dependence and response behavior. Distributional coherence diagnostics guide regional frequency analysis, while dependence modelling informs spatial prediction and uncertainty propagation. In the case study, weak global spatial autocorrelation combined with localized clustering and non-contiguous response regimes supports inference at regime-conditioned and sub-regional scales. This structure preserves the distinctions among station responses identified during characterization when regional estimates and uncertainty are evaluated.

Regional progression evaluates whether the spatially structured behavior identified during characterization and inference evolves coherently through time. Trend diagnostics, spatial change detection, and non-stationary analyses show that localized performance degradation accumulates into regional drift without synchronized domain-wide failure. Temporal evolution differs across regimes and connectivity contexts, linking progression directly to the spatial structure diagnosed earlier. Interpretation of these changes depends on the prior identification of dependence structure and response regimes, since identical temporal signals carry different implications across hydrologic contexts. This temporal analysis extends the regional structure identified earlier by testing whether diagnosed spatial and response patterns remain stable through time.

Spatial diagnostics delimit admissible inference, conditioned inference structures uncertainty, and progression analysis evaluates the stability of inferred behavior through time. The compounding effect produces regional conclusions that remain consistent with observed spatial organization, distributional structure, and temporal evolution, supporting defensible regional assessment without reliance on assumption-blind aggregation.

5. Limitations

Several limitations reflect the scope and design choices of the proposed framework and should be acknowledged. The framework depends on the availability of spatially and temporally sufficient monitoring data. Record augmentation and multi-site pooling reduce sampling variance and stabilize regional estimates, yet they do not substitute for missing physical information. In regions with sparse monitoring networks, short records, or highly intermittent observations, diagnostic evaluation may indicate that regional inference is weakly supported, constraining the interpretability of pooled estimates, spatial fields, and temporal assessments.

Spatial inference within the framework assumes second-order or intrinsic stationarity over the domain of analysis. While spatial dependence is explicitly diagnosed using network-aware and Euclidean representations as appropriate, these assumptions may still be violated in regions characterized by abrupt physiographic transitions, strong externally driven nonstationarity, or connectivity patterns that are not adequately represented by the adopted covariance structures. In such settings, spatial diagnostics may reveal organization that cannot be fully captured by the fitted models, limiting the reliability of interpolation and associated uncertainty estimates.

Regime identification is data-driven and reflects similarity in observed statistical behavior, not necessarily explicit physical or administrative boundaries. The resulting groupings are

internally coherent within the diagnostic space, yet they are not guaranteed to align with basin delineations, physiographic regions, or management units. Interpretation therefore requires domain knowledge, and regime assignments should be treated as analytical constructs rather than deterministic classifications.

Nonstationary behavior is represented using linear time-varying GEV parametrizations, selected through information-criterion-based model comparison, together with rank-based trend tests and moving-window L-moment diagnostics. These representations emphasize parsimony and interpretability and are designed to limit overfitting in short records. As a result, detected nonstationarity should be interpreted as statistical evidence of evolving behavior, while attribution of underlying physical drivers requires complementary process-based analysis.

Finally, the framework prioritizes statistical consistency and reproducibility over computational efficiency. Several components, including hierarchical uncertainty pooling and nonstationary distributional analysis, introduce substantial computational cost. Because the current implementation executes locally within a browser environment, performance is constrained by client-side memory, processor availability, and execution time limits. These constraints may limit applicability for very large networks, high-frequency data, or extensive resampling without additional optimization or alternative execution pathways.

6. Conclusions

This study presents HyMES Regional, a structured inference framework for regional analysis of spatial monitoring networks. The framework formalizes regional analysis as an ordered set of diagnostics, inferential, and temporal operations applied to spatial ensembles of time series, with explicit dependencies that govern when and how regional inference is admissible. The contribution lies in organizing established statistical methods into a coherent analytical structure that preserves consistency, traceability, and reproducibility across spatial scales and variables.

The framework was demonstrated through a regional case study in southern Louisiana, examining how spatially structured precipitation forcing discrepancies to propagate into hydrologic model performance. The analysis shows that regional behavior is characterized by limited domain-wide coherence, pronounced sub-regional organization, and regime-dependent response patterns. Spatial diagnostics, normalized exceedance behavior, and dependence analysis constrain admissible aggregation, while regional inference produces uncertainty-aware spatial and pooled estimates consistent with the diagnosed structure.

Temporal diagnostics further show that localized performance degradation accumulates into regional drift without synchronized domain-wide failure. Across the case study, the results illustrate how spatial structure, distributional behavior, uncertainty, and temporal evolution interact within a single analytical framework. By treating spatial ensembles as first-class inferential objects and conditioning inference on diagnosed structure, HyMES Regional supports defensible regional assessment in heterogeneous monitoring networks without reliance on assumption-blind pooling or isolated station-level analysis.

6.1. Future Work

Several extensions of the framework follow naturally from the structure and behavior observed in the case study. With hydrologic network topology embedded as the spatial reference for diagnostics and inference, a primary direction is further refinement of connectivity representations. Alternative stream-network distance formulations, flow-directed covariance models, and spatial stream network variants would enable more flexible treatment of information transfer in complex river systems while preserving the existing analytical logic.

A second direction concerns covariate-informed nonstationary inference. Allowing distributional parameters to vary as functions of climatic indices or land-use metrics would strengthen interpretation of detected change and support attribution. Such extensions require constrained formulations to manage identifiability, collinearity, and degrees-of-freedom accounting, particularly where covariate availability varies spatially, while remaining compatible with regional pooling and uncertainty estimation.

Further methodological development is warranted for pooling strategies that respond continuously to diagnosed spatial coherence and data adequacy. The current framework supports regime-conditioned shrinkage within statistically coherent groups. Extending this formulation to allow pooling strength to vary smoothly across the network would improve flexibility in heterogeneous domains while retaining explicit uncertainty control.

From an implementation perspective, ongoing work focuses on expanding interoperability and scalability. Support for additional data formats and metadata standards is under development to broaden applicability across monitoring systems. Execution pathways using Node-based or server-side computation are also being explored for analyses that exceed browser-side resource limits, with explicit consideration of tradeoffs related to accessibility, privacy, and reproducibility.

Finally, future work will focus on tighter integration of uncertainty across the analytical workflow. While uncertainty is quantified at individual stages, closer coupling between distributional estimation, spatial prediction, and pooling would clarify how uncertainty evolves as information is conditioned across analyses. Continued application across regions, variables, and hydroclimatic settings will further inform calibration of diagnostic thresholds and interpretation of regionally coherent signals.

Declaration of AI-Assisted Technologies

During the preparation of this work, the authors used ChatGPT to improve the flow of the text, correct any potential grammatical errors, and improve the writing. After using this tool, the authors reviewed and edited the content as needed and took full responsibility for the content of the publication.

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Supplementary Materials

1. Regional Characterization

The framework establishes the baseline spatial topology, defining inter-station connectivity, and partitioning the study area into different behavioral regimes before any predictive modeling occurs. To validate the statistical viability of spatial association, the framework quantifies the directional spatial structure using a decomposed Moran's I. Instead of assuming isotropic Euclidean influence, connectivity is defined by a row-standardized binary connectivity matrix W_{up} (downstream neighbors) and W_{dn} (upstream neighbors) derived from NHDPlus flowlines. Domain-wide spatial clustering is assessed via I_{dn} and I_{up} to differentiate between broad atmospheric signals and cumulative watershed effects:

$$I_{dn} = \frac{N}{\sum w_{ij}} \frac{\sum_i \sum_j W_{dn,ij} (z_i - \bar{z})(z_j - \bar{z})}{\sum_i (z_i - \bar{z})^2}$$

The significance of the directional flux is evaluated via the Asymmetry Index ($I_{asym} = I_{dn} - I_{up}$), where large positive values imply point-source or structural accumulative effects. To identify localized anomalies, the framework employs a topological version of Local Moran's I (LISA), flagging stations with significant local spatial association within the stream network determined by permutation testing ($n_{perm} = 499$). The framework sets to map hydrologic connectivity and the temporal coherence of storm-forcing across the region by computing a sparse pairwise cross-correlation matrix. To ensure computational scaling for large networks, pairwise comparisons are pruned using a configurable maximum separation distance, with the default value informed by reported empirical hydrologic decorrelation scales. For concurrent monthly series Q_i and Q_j , the correlation across varying lags is evaluated as $\rho_{ij}(\tau) = \text{Corr}(Q_i(t), Q_j(t + \tau))$. Each computed pair is rigorously tested for significance using the Fisher Z-transform. Network influence is quantified using both mean absolute correlation magnitude and degree centrality, capturing signal coherence as well as the underlying connectivity structure of the sensor network.

In an attempt to remove harden structural responses, the framework normalizes observations to compare basins across vastly different scales. Absolute time series are transformed into normalized exceedance curves by ranking values and dividing by their median, $\tilde{Q}$, generating cross-station P5 to P95 envelopes. The slope of the resulting Flow Duration Curve (FDC) serves as a robust variability index. Median normalization is applied strictly to stabilize inter-station comparability and does not control tail behavior. Variability is quantified from the log-space FDC slope, which is robust to normalization-induced distortions and extreme outliers. These characteristics are synthesized using K-means clustering to partition the network into hydro-meteorological regimes, grouping stations based on a multivariate feature vector $u = [\tau_2, \tau_3, \text{FDC slope}, F_s, I_{asym}]$ that integrates L-CV, L-skewness, flashiness, and the seasonal strength F_s and directional asymmetry index extracted via STL residual decomposition. K-means clustering (20 random starts) is applied in PCA-reduced feature space. The number of clusters $k \in [2, 8]$ is selected by consensus across 11 independently seeded runs, in each run, the k with the highest mean silhouette width is recorded, and the most frequently selected k is adopted, with the partition taken from the highest-silhouette solution for that k . Clusters are numbered in order of increasing mean L-CV, so that labels are reproducible across runs.

2. Regional Inference

Prior to uncertainty quantification, a topological alignment protocol snaps each coordinate-based gauge to the nearest NHDPlus segment. A hard distance limit is enforced: $\min_{\text{segment}} D_{\text{snap}} \leq 5 \text{ km}$.

Stations exceeding this threshold are flagged as unsnapped and are excluded from the SSN covariance structures, reverting to Euclidean distance metrics to ensure analytical continuity in coastal or unmapped regions. Once the regional topology and behavioral regimes are characterized, the framework addresses data scarcity and prediction confidence through rigorous station-level uncertainty quantification, robust regional estimation techniques, and the complex spatial interpolation of continuous fields.

2.1 Station-Level Uncertainty Quantification (UQ)

Before any regional aggregation occurs, individual station uncertainty is explicitly quantified to isolate systemic bias from noise misspecification. The framework utilizes a Random-Walk Metropolis Markov Chain Monte Carlo (MCMC) sampler to infer the noise scale (σ_r) and bias multiplier (b). Depending on the error distribution, the algorithm evaluates either a Gaussian likelihood:

$$l(b, \sigma_r) = -\frac{1}{2} \sum_i \left[\frac{(o_i - b \cdot q_i)^2}{\sigma_r^2} + \ln(2\pi\sigma_r^2) \right]$$

or a Laplace likelihood:

$$l(b, \sigma_r) = -\sum_i \frac{|o_i - b \cdot q_i|}{\sigma_r} - n \ln(2\sigma_r)$$

Chain convergence is strictly monitored via the Effective Sample Size (ESS), the Geweke Z-score (testing stationarity between the first 10% and last 50% of the chain), and the Gelman-Rubin $\hat{R}$ potential scale reduction factor.

This Bayesian approach is complemented by a Generalized Likelihood Uncertainty Estimation (GLUE) routine, which applies a behavioral filter to Monte Carlo samples over the (b, σ_r) space. Models failing to meet a baseline NSE = 0.4 are rejected with this value serving as a pragmatic filter, and uncertainty bounds are derived from the NSE-weighted quantiles of the behavioral ensemble. To understand the primary drivers of this uncertainty, a first-order Sobol sensitivity analysis decomposes the model output variance. For instance, the sensitivity to the noise scale is evaluated as $S_{\sigma_r} = \frac{V[E(Y|\sigma_r)]}{V_{\text{total}}}$. The framework tests for non-stationary structural breaks in model performance using the non-parametric Pettitt Change-Point Test on the residual series:

$$K_t = \sum_{i \leq t} \sum_{j > t} \text{sign}(x_j - x_i)$$

The significance of the peak test statistic K^* is approximated asymptotically as $p = 2 \exp(-6K^{*2}/(n^3 + n^2))$. If a significant break is detected ($p < 0.05$), a Stratified Signature Analysis evaluates the pre- and post-break segments independently. If the Composite Skill Score (CSS)—an aggregate of KGE, r^2 , and FDC slope ratio—degrades such that the upper bound of the bootstrap 95% confidence interval ($n = 499$) falls below -5 CSS points, the model is flagged as failing to represent the physically altered system.

2.2 Record Augmentation (MOVE.1)

Because short-record stations introduce unacceptably high estimation variance into regional frequency models, the framework applies the Maintenance of Variance Extension (MOVE.1) algorithm. A short-record target site S is correlated with a concurrent long-record donor L, selected via a k-d tree spatial search requiring ≥ 10 years of concurrent overlap. The augmented record is generated using:

$$\ln \widehat{Q}_S(t) = \bar{a} + \bar{b} \ln Q_L(t)$$

MOVE.1 enforces a variance-preserving slope defined by the ratio of standard deviations, $\bar{b} = s_S/s_L$, with the intercept scaled accordingly, $\bar{a} = \bar{x}_S - \bar{b}\bar{x}_L$.

2.3 L-Moment Frequency Analysis

Extreme value behavior is characterized using L-moment frequency analysis. For an ordered sample $x_{(1)} \leq \dots \leq x_{(n)}$, probability-weighted moments (PWMs) are derived as:

$$\begin{aligned} b_0 &= n^{-1} \sum_j x_{(j)} \\ b_1 &= n^{-1} \sum_j \frac{j-1}{n-1} x_{(j)} \\ b_2 &= n^{-1} \sum_j \frac{(j-1)(j-2)}{(n-1)(n-2)} x_{(j)} \end{aligned}$$

These yield the foundational L-moments: the L-mean ($\lambda_1 = b_0$), L-scale ($\lambda_2 = 2b_1 - b_0$), and the dimensionless L-CV ($\tau_2 = \lambda_2/\lambda_1$) and L-skewness ($\tau_3 = (6b_2 - 6b_1 + b_0)/\lambda_2$). Anomalous sites are excluded via a Discordancy test, measuring the distance of a site's feature vector $u_i = [\tau_{2,i}, \tau_{3,i}, \tau_{4,i}]^T$ from the regional centroid $\bar{u}$:

$$D_i = \frac{N}{3} (u_i - \bar{u})^T A^{-1} (u_i - \bar{u})$$

Sites exceeding $D_i > 3$ are flagged. Regional homogeneity is then enforced by calculating the observed weighted L-CV dispersion, $V_1 = \sum_i n_i (\tau_{2,i} - \bar{\tau}_2)^2 / \sum_i n_i$, and standardizing it against a simulated Kappa-distribution space to derive the H_1 statistic.

For the regional distribution fit (e.g., GEV), the shape parameter ξ is derived from τ_3 via Newton's method, yielding the scale (σ) and location (μ) parameters:

$$\sigma = \frac{\lambda_2 \kappa}{\Gamma(1 + \kappa)(1 - 2^{-\kappa})}, \quad \mu = \lambda_1 - \sigma \frac{1 - \Gamma(1 + \kappa)}{\kappa}$$

Distributional selection is guided by plotting station scatter against theoretical polynomial recurrences on an L-Moment Ratio Diagram. Return levels are scaled using the index-flood approach: $Q_T(i) = \lambda_{1,i} \cdot q_T$.

2.4 Multi-Site Uncertainty Pooling and MCMC

To bound parameter uncertainty at ungauged locations, a Random-Walk Metropolis MCMC algorithm evaluates the full GEV log-likelihood across the network:

$$l(\mu, \sigma, \xi) = -n \ln \sigma - \left(1 + \frac{1}{\xi}\right) \sum_i \ln \left[1 + \xi \frac{x_i - \mu}{\sigma}\right] - \sum_i \left[1 + \xi \frac{x_i - \mu}{\sigma}\right]^{-1/\xi}$$

To stabilize these regional estimates, posteriors are regularized using cluster-based Empirical Bayes (James-Stein) shrinkage, where pooling occurs only within hydrologically homogeneous regimes. Highly variable posteriors from short records are pulled toward the precision-weighted regional mean μ . The required shrinkage factor utilizes the between-station variance $\widehat{\sigma}_\theta^2 = \max(0, V_{\text{between}} - V_{\text{within}}/n)$:

$$B_i = \frac{\widehat{\sigma}_\theta^2}{\widehat{\sigma}_\theta^2 + \widehat{\sigma}_i^2/n_i}$$

The resulting pooled mean, $\widehat{\mu}_i^{\text{pool}} = (1 - B_i)\widehat{\mu}_i + B_i\mu_0$, ensures data anomalies do not skew the network-level 90% predictive interval, defined as $\text{PI}_{90} = [\widehat{\mu}_\theta - 1.645\widehat{\sigma}_{\text{total}}, \widehat{\mu}_\theta + 1.645\widehat{\sigma}_{\text{total}}]$.

2.5 Geostatistics

Spatial dependence of a station-level metric z is characterized using the method-of-moments experimental variogram

$$\hat{\gamma}(h) = \frac{1}{(2|N(h)|)} \cdot \sum_{(i,j) \in N(h)} [z(s_i) - z(s_j)]^2$$

evaluated over 15 lag classes extending to half the maximum inter-station separation. Spherical, exponential, and Gaussian models are fitted by weighted least squares, with weights proportional to $\sqrt{|N(h)|}$. The model with the lowest leave-one-out cross-validation error is retained, and its nugget, partial sill, and range define the covariance used by the kriging systems.

When stations are successfully snapped to the NHDPlus network, dependence is additionally characterized in hydrologic distance $H(i,j)$. For flow-connected sites, $H(i,j)$ is the difference in NHD path lengths; for flow-unconnected sites, it is the sum of distances to the lowest common junction. The network covariance is modeled as

$$C(s_i, s_j) = \theta_{TU} C_{TU}(s_i, s_j) + \theta_{TD} C_{TD}(s_i, s_j) + \theta_0 \delta_{ij}$$

where the tail-up component C_{TU} uses flow-proportional weights (Ω), so covariance does not cross junctions between unconnected branches, and the tail-down component C_{TD} allows dependence among flow-unconnected sites. The network variogram describes dependence along flow paths. Continuous prediction surfaces, however, are produced on a regular longitude–latitude grid whose nodes do not lie on the stream network, so spatial prediction is performed in Euclidean coordinates.

Because the omnidirectional variogram pools station pairs across all directions, it assumes that dependence decays at the same rate in every direction. This assumption is tested before interpolation. Directional experimental variograms are computed along four azimuths (0° , 45° , 90° , and 135° , counter-clockwise from east) with an angular tolerance of $\pm 22.5^\circ$, and an exponential model is fitted in each direction to estimate a direction-specific practical range $a(\theta)$. The anisotropy ratio $\lambda = \max a(\theta) / \min a(\theta)$ measures the strength of directional dependence, and $\theta^* = \operatorname{argmax} a(\theta)$ identifies the axis of greatest spatial continuity. When $\lambda > 1.5$, geometric anisotropy is adopted, and inter-point distances are evaluated in a rotated and rescaled frame:

$$d_{aniso(i,j)} = \sqrt{\left[\left(\frac{\Delta x \cos \theta^* + \Delta y \sin \theta^*}{\lambda} \right)^2 + (-\Delta x \sin \theta^* + \Delta y \cos \theta^*)^2 \right]}$$

This shrinks separations along the major axis so that covariance is evaluated in an equivalent isotropic space (Isaaks & Srivastava, 1989; Goovaerts, 1997). When $\lambda \leq 1.5$, the isotropic model is retained. As a complementary diagnostic, a variogram map $\hat{\gamma}(h, \theta)$ is built by binning station pairs jointly by separation distance and azimuth; cells supported by fewer than three pairs are masked.

Prediction surfaces are produced by: (i) kriging with External Drift (KED), using a linear trend in the coordinates as the drift; (ii) indicator kriging of $I(z \leq z_c)$, with the indicator variogram refitted by the same cross-validation procedure and $z_c = 0.5$ for KGE and the regional mean otherwise; (iii) co-kriging under a linear model of coregionalization with a common range, constraining the cross-sill as $|b_{12}| \leq \sqrt{b_{11} b_{22}}$ to guarantee positive definiteness (Goulard & Voltz, 1992). L-skewness is the secondary variable (L-CV when L-skewness is the primary).

The geometric anisotropy transformation is applied to the KED and indicator-kriging systems. All three methods report the kriging variance at each grid node.

3. Regional Progression

Under the pressures of anthropogenic climate change and landscape alteration, the foundational assumption of stationarity is increasingly invalid. To address this, the framework explicitly tracks spatial and temporal non-stationarity, separating continuous climatic drift from abrupt structural shifts across the sensor network.

3.1 Regional Trend Analysis and Field Significance

Temporal drift is initially assessed at the station level using the non-parametric Mann-Kendall test. The test evaluates monotonic trends by computing the test statistic S :

$$S = \sum_{i < j} \text{sign}(x_j - x_i)$$

The variance of S , which accounts for tied values within the series, is calculated as:

$$\text{Var}[S] = \frac{n(n-1)(2n+5) - \sum_s t_s(t_s-1)(2t_s+5)}{18}$$

This allows for the derivation of the standard normal deviate $Z_{MK} = (S - \text{sign}(S))/\sqrt{\text{Var}[S]}$. A trend is flagged as locally significant if $|Z_{MK}| > 1.96$ ($\alpha = 0.05$), with the magnitude of the drift quantified by the Sen slope, $\beta = \text{median}[(x_j - x_i)/(j - i)]$.

However, evaluating trends independently across a dense, spatially correlated sensor network introduces a severe risk of Type I errors (false discovery). To rigorously validate whether a cluster of local trends represents a genuine regional signal, the framework applies the Livezey-Chen binomial test for Field Significance. For a network of N stations with an expected chance fraction of $\alpha = 0.05$, the probability of observing n^* significant local trends strictly by random chance is:

$$P(X \geq n^*) = \sum_{k=n^*}^N \binom{N}{k} 0.05^k 0.95^{N-k}$$

A regional trend signal is only accepted as field-significant if this probability falls below 0.05, ensuring the observed network drift cannot be explained by multiple-testing artifacts alone.

3.2 Spatial Change Detection

While monotonic trends capture gradual climatic drift, structural or abrupt shifts in regional performance require distinct diagnostics. To capture these shifts, a cross-sectional Spatial Cumulative Sum (CUSUM) algorithm aggregates spatial means over time, tracking shifting performance regimes. The one-sided upper CUSUM statistic evaluates the spatial mean $\bar{x}_t$ at each timestep:

$$C_t = \max(0, C_{t-1} + (\bar{x}_t - \mu_0 - k))$$

Where μ_0 represents the in-control mean established during the first third of the record, and the allowance factor $k = \sigma/2$ filters out expected natural variability. The framework issues a structural shift alert when the trajectory exceeds the threshold $h = 5\sigma$, which corresponds to a standard Average Run Length (ARL) of 370 under a true null hypothesis. These parameter choices follow standard statistical process control practice and are selected to ensure known false-alarm characteristics. To distinguish between isolated localized anomalies and phenomena that are actively expanding to dominate the region, the framework tracks a Moving Moran's I . This statistic is evaluated iteratively across a rolling W -year temporal window the NHD-based connectivity matrix. A rising trajectory in t isolates periods when localized events transition into spatially coherent, downstream-propagating regional processes. A rising trajectory in the resulting $I(t)$ series indicates an increasing spatial clustering of the evaluated metric, successfully isolating periods when highly localized events—such as an intensifying drought or an expanding systemic model bias—transition into spatially coherent regional processes.

3.3 Non-Stationary Frequency Analysis

To fully relax the stationary assumption within extreme value modeling, the framework implements a Non-Stationary Generalized Extreme Value (NS-GEV) distribution. This parametric architecture requires a minimum of 8 annual maxima and allows the location parameter to shift as a linear function of time:

$$\mu(t) = \mu_0 + \mu_1 t$$

The parameters are inferred by maximizing the time-dependent log-likelihood function via the Nelder-Mead algorithm:

$$l(\mu_0, \mu_1, \sigma, \xi) = -n \ln \sigma - \left(1 + \frac{1}{\xi}\right) \sum_i \ln \left[1 + \xi \frac{x_i - \mu(t_i)}{\sigma}\right] - \sum_i \left[1 + \xi \frac{x_i - \mu(t_i)}{\sigma}\right]^{-1/\xi}$$

The framework evaluates stationary, non-stationary location (NS- μ), and non-stationary location-scale (NS- $\mu\sigma$) GEV formulations. Model selection is governed by Akaike Information Criterion (AIC), and increased complexity is adopted only when statistically justified. The framework formally adopts the non-stationary variant only if the evidence justifies the complexity, requiring a $\Delta AIC = AIC_{NS} - AIC_S \leq -2$. If selected, the resulting time-varying return level explicitly models continuous climatic evolution:

$$Q_T(\text{year}) = \mu(\text{year}) - \frac{\sigma}{\xi} \{1 - [-\ln(1 - 1/T)]^{-\xi}\}$$

As a robust, distribution-free alternative, the framework concurrently executes Non-Stationary L-Moments. This methodology computes L-moments on overlapping temporal windows (e.g., 15-year widths progressing in 5-year steps). The Theil-Sen regression trend is then extracted across the window midpoints for both L-CV (τ_2) and L-skewness (τ_3). This sliding-window approach allows the framework to detect if the fundamental variability (more extreme events relative to the mean) or asymmetry of the regional hydrology is shifting over time, completely free from the constraints of parametric distributional assumptions. Estimates derived from samples with $n < 20$ are explicitly flagged as high-uncertainty, consistent with commonly recommended minimum thresholds (≈ 15 – 20) for stable extreme value inference.

4. Artificial Intelligence Integration for Diagnostic Synthesis

HyMES-Regional includes an AI-assisted diagnostic synthesis layer for interpreting outputs generated across multiple analytical modules. The statistical backend performs the underlying computations, including L-moment analysis, spatial autocorrelation, cumulative sum (CUSUM) analysis, and non-stationary diagnostics. The AI layer receives these computed results as structured inputs and synthesizes relationships among metrics that may otherwise require manual comparison across individual diagnostic outputs.

4.1. Contextual Data Ingestion

The AI assistant operates on the results of the active analysis rather than independently accessing or generating analytical data. When invoked, the platform constructs a structured payload containing the outputs available from the current analytical workflow. Depending on the selected analysis, the payload can include:

- **Descriptive Statistics and Flow Regimes:** mean, coefficient of variation, skewness, and flow-duration-curve (FDC) ratios for high- and low-flow quantiles.
- **Spatial Diagnostics:** variogram parameters, including nugget, sill, and range; global and local Moran's I ; and kriging variance.

- **Temporal and Non-Stationary Diagnostics:** Mann-Kendall τ , Sen's slope, Pettitt change-point results, spatial CUSUM diagnostics, and Augmented Dickey-Fuller (ADF) stationarity tests.
- **Performance Metrics:** Kling-Gupta Efficiency (KGE), Nash-Sutcliffe Efficiency (NSE), and continuous ranked probability score (CRPS).

The supplied metrics provide the analytical context for the generated interpretation. The AI layer does not replace the underlying statistical procedures or independently recompute their results; its output is derived from the diagnostic results provided by the platform.

4.2. Persona-Driven Analytical Lenses

The AI assistant provides several analytical lenses that constrain the interpretation to a selected aspect of the diagnostic workflow. These lenses are implemented through role-specific prompts and associated evaluation criteria:

1. **Frequency Analyst:** Evaluates extreme-flow statistics, including L-moment ratios and their consistency with the distributional assumptions used in regional frequency analysis. The analysis also considers sample size and detected temporal changes when interpreting return-period estimates and stationarity.
2. **Geostatistical Analyst:** Examines the spatial dependence structure represented by variogram parameters, spatial clustering, and kriging uncertainty. The interpretation considers whether the identified spatial structure is consistent with the observed monitoring network and whether station density provides adequate support for spatial prediction.
3. **Trend and Non-Stationarity Analyst:** Synthesizes temporal diagnostics, including Mann-Kendall trends, Sen's slope, Pettitt change points, and spatial CUSUM results. The analysis considers whether detected changes represent spatially coherent behavior or localized station-level changes.

These analytical lenses provide different interpretations of the same diagnostic outputs without altering the underlying statistical results.

4.3. Diagnostic Synthesis and User Interaction

The AI layer is intended to reduce the effort required to compare related diagnostics across the regional workflow. For example, a detected temporal change point can be considered alongside the spatial dependence structure when interpreting subsequent spatial analysis. Similarly, differences in FDC characteristics, L-moment ratios, and model performance metrics can be evaluated jointly to identify relationships among distributional and performance behavior. AI-generated responses are limited to the diagnostic information supplied by the platform and are presented as interpretive summaries rather than statistical estimates. The responses identify notable diagnostic patterns, relationships or inconsistencies among metrics, and potential follow-up considerations associated with the selected analytical lens. The underlying statistical results remain the basis for inference and are available independently of the AI-assisted interpretation. This subsystem connects to Large Language Model backends (such as OpenAI, Gemini, or Anthropic) via user-configured API keys. when no API key is configured, the deterministic fallback applies rule-based interpretations using the same data context.