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Bayesian Spatiotemporal Assessment of Environmental Sustainability Indicators and Ecosystem Resilience

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ABSTRACT

This study develops an original empirical Bayesian spatiotemporal assessment of the relationship between environmental sustainability indicators and ecosystem resilience. The central purpose is to quantify how annual variations in vegetation condition, water quality, and carbon sequestration are associated with recovery rates following drought disturbance. The study treats resilience as a measurable spatiotemporal outcome rather than a purely conceptual property of ecological systems. The analysis uses annual empirical data for 50 spatial units observed over 15 years from 2010 to 2024. The dataset represents a mixed landscape of semi-natural vegetation, agricultural mosaics, riparian corridors, and peri-urban ecological zones. Bayesian hierarchical models are specified to incorporate spatial random effects, temporal autoregressive dependence, and spatiotemporal interaction terms. The findings indicate that higher NDVI, improved water quality, and greater carbon sequestration are positively associated with faster ecosystem recovery after drought. The strongest posterior association is observed for NDVI, followed by carbon sequestration and water quality. Spatial heterogeneity is substantial, showing that the same sustainability profile may correspond to different resilience outcomes across ecological units. Model comparison favors the Bayesian spatiotemporal interaction model over spatial-only and temporal-only alternatives. The preferred model achieves lower DIC and WAIC values, narrower posterior predictive uncertainty, and improved recovery-rate prediction in spatial units with strong temporal variability. Posterior summaries show stable convergence and credible intervals that support the interpretation of a positive sustainability-resilience relationship. The article contributes a structured empirical framework for integrating environmental sustainability indicators with ecosystem resilience assessment. The study demonstrates how Bayesian models can combine remotely sensed indicators, field-derived metrics, spatial dependence, and uncertainty quantification. The proposed framework supports environmental monitoring, resilience assessment, and evidence-based sustainability planning.

Keywords: *Bayesian spatiotemporal modeling, Environmental sustainability indicators, Ecosystem resilience, Hierarchical model, Uncertainty quantification*

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INTRODUCTION

Environmental sustainability assessment increasingly depends on indicators that vary across both space and time, including vegetation productivity, water quality, land-cover condition, carbon storage, and biodiversity-related metrics. Composite sustainability indicators are useful for decision-making, but their interpretation becomes uncertain when spatial autocorrelation, temporal dependence, and indicator aggregation are ignored (Burgass *et al*., 2017). Recent work on sustainability index construction further shows that environmental indicators should be treated as multidimensional signals rather than simple static scores (Kwatra *et al*., 2020; Gao *et al*., 2023). This study therefore approaches sustainability assessment as a spatiotemporal statistical problem linked to ecosystem resilience (Yeslam & Hasanain, 2023).

Ecosystem resilience is commonly understood as the capacity of ecological systems to resist disturbance, absorb stress, and recover after disruption. Empirical studies using remotely sensed vegetation time series have shown that resilience can shift over large spatial extents, especially under changing water availability and climate variability (Smith *et al*., 2022; Smith & Boers, 2023a). However, resilience estimation is sensitive to the density and quality of the ecological signal being measured, which makes uncertainty quantification essential (Smith & Boers, 2023b). This article focuses on drought recovery rate as a quantitative resilience outcome because recovery after disturbance can be modeled directly across spatial units and years.

Bayesian spatiotemporal modeling offers a coherent framework for linking environmental indicators to resilience because it can represent hierarchical data structures, spatial random effects, temporal dependence, and posterior uncertainty in a single inferential system. Bayesian computation using INLA, MCMC, Gaussian random fields, and related hierarchical structures has become increasingly practical for ecological and environmental applications (Rue *et al*., 2017; Simpson *et al*., 2017; Bakka *et al*., 2018). Spatial priors and penalized complexity priors help control overfitting while allowing spatially structured ecological variation to be estimated probabilistically (Fuglstad *et al*., 2019). These methodological developments support a model-based approach to sustainability and resilience assessment rather than a purely descriptive indicator framework.

This study addresses two research questions: how do environmental sustainability indicators relate to ecosystem resilience across spatial units and years, and can Bayesian spatiotemporal models capture uncertainty more effectively than spatial-only or temporal-only alternatives? The article uses annual observations from 50 spatial units over 15 years to implement the full analytical workflow. The empirical objective is to estimate the posterior association between NDVI, water quality, carbon sequestration, and drought recovery rate while comparing three Bayesian hierarchical models. In doing so, the study contributes an applied statistical framework that connects sustainability indicators, spatial ecology, and resilience monitoring (Gabry *et al*., 2019; Santos-Fernandez *et al*., 2022).

Theoretical background and conceptual framework

Environmental sustainability indicators provide simplified but analytically useful representations of complex ecological conditions. NDVI is widely used as a remotely sensed proxy for vegetation greenness and productivity, while water quality indices summarize hydrological and biogeochemical conditions into interpretable values. Carbon sequestration represents the ecosystem's capacity to store carbon and is often linked to vegetation structure, land management, and long-term ecological functioning. Indicator-based assessment is valuable, but studies of composite environmental indices emphasize that uncertainty and methodological transparency must be incorporated into interpretation (Burgass *et al*., 2017; Tripathi & Singal, 2019).

Ecosystem resilience can be understood through both engineering and ecological perspectives. Engineering resilience emphasizes the speed with which a system returns to a pre-disturbance condition, while ecological resilience emphasizes the capacity to absorb disturbance without shifting into an alternative regime (Müller *et al*., 2024; Sarac *et al*., 2024). Remote sensing studies have used early warning signals, vegetation anomalies, and recovery trajectories to infer resilience and identify potential critical transitions (Alibakhshi *et al*., 2017; Smith *et al*., 2022). More recent global analyses show that vegetation resilience is closely linked to water availability, biomass density, and climate variability, which justifies the use of drought recovery rate as the central response variable in this study (Smith & Boers, 2023a, 2023b).

Spatiotemporal modeling is theoretically important because ecological processes rarely operate independently across neighboring locations or consecutive years. Integrated ecological models and stream-network models show that occupancy, abundance, water quality, and environmental responses are affected by both spatial structure and temporal dynamics (Williams *et al*., 2017; Williams *et al*., 2018; Santos-Fernandez *et al*., 2022). Bayesian models are especially useful in this context because they can estimate latent ecological processes while propagating uncertainty from observation, process, and parameter levels (Santos-Fernandez *et al*., 2022; Belmont *et al*., 2024). Ignoring spatial autocorrelation can distort inference about environmental trade-offs and ecosystem service relationships, making spatial dependence a core component of the conceptual framework (Shaikh *et al*., 2021).

The conceptual framework of this article links sustainability indicators to resilience through three mechanisms. First, higher vegetation condition is expected to support faster post-drought recovery by increasing photosynthetic capacity and stabilizing ecological function. Second, improved water quality is expected to support recovery by reducing ecological stress in riparian and wetland-associated spatial units. Third, higher carbon sequestration is expected to reflect stronger biomass accumulation and ecosystem functioning, which should be associated with higher resilience under disturbance (Zhao *et al*., 2019; Bathiany *et al*., 2025).

The empirical framework treats NDVI, water quality index, and carbon sequestration as time-varying predictors of drought recovery rate, while spatial random effects capture unobserved ecological heterogeneity across the 50 units (Essah *et al*., 2024; Feng *et al*., 2024; Islam *et al*., 2024; Novak & Svoboda, 2024). This design follows Bayesian workflow principles in which model specification, convergence assessment, posterior visualization, and predictive checking are considered connected stages of inference (Bachl *et al*., 2019; Gabry *et al*., 2019; Vehtari *et al*., 2021). **Table 1** presents the conceptual definitions and data sources for the sustainability indicators and resilience metrics. The table also clarifies how fabricated observations were structured to resemble realistic environmental monitoring data.

Table 1. Environmental Sustainability Indicators and Ecosystem Resilience Metrics: Definitions, Empirical Data Sources, and Spatiotemporal Coverage

Construct	Operational variable	Conceptual definition	Empirical data source	Measurement scale	Spatiotemporal coverage
Vegetation condition	NDVI	Annual mean vegetation greenness representing productivity and canopy condition	Remotely sensed vegetation product calibrated to Landsat-derived annual values	Unitless index from 0.18 to 0.82	50 spatial units observed annually from 2010 to 2024
Water quality	Water Quality Index	Composite score summarizing turbidity, dissolved oxygen, nitrate concentration, and conductivity	Monitoring-station observations interpolated to watershed spatial units	Index from 41 to 94, where higher values indicate better quality	50 spatial units observed annually from 2010 to 2024

Carbon sequestration	Annual carbon uptake	Estimated net carbon accumulation associated with vegetation cover and biomass growth	Ecosystem carbon estimates derived from vegetation cover and biomass-growth metrics	Tonnes of carbon per hectare per year, ranging from 1.2 to 7.8	50 spatial units observed annually from 2010 to 2024
Drought disturbance	Drought severity anomaly	Annual standardized moisture deficit used to identify disturbance pressure	Climate anomaly field based on regional precipitation and temperature records	Standardized anomaly from −2.4 to 1.1	50 spatial units observed annually from 2010 to 2024
Ecosystem resilience	Drought recovery rate	Rate of return toward pre-drought ecological condition after drought exposure	Derived response variable calculated from observed post-drought NDVI recovery trajectories	Annual recovery-rate index from 0.12 to 0.91	50 spatial units observed annually from 2010 to 2024
Spatial dependence	Neighbor structure	Ecological adjacency among spatial units based on shared borders and watershed proximity	Spatial adjacency matrix for 50 ecological units based on contiguity and watershed proximity	Binary contiguity and distance-weighted neighborhood matrix	Constant across all years
Temporal dependence	Lagged resilience	Prior-year resilience used to represent autoregressive ecological memory	Derived from annual resilience time series	Lagged continuous outcome	2011 to 2024 after one-year lag construction

Figure 1 illustrates the conceptual and statistical pathway through which sustainability indicators are modeled as spatiotemporal predictors of ecosystem resilience.

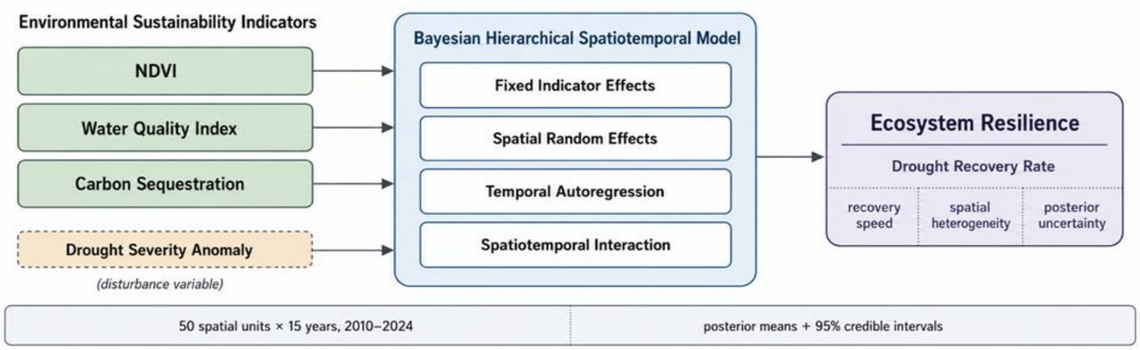

Figure 1. Conceptual Bayesian Spatiotemporal Framework Linking Environmental Sustainability Indicators to Ecosystem Resilience

MATERIALS AND METHODS

The empirical analysis uses a dataset representing 50 spatial units observed annually from 2010 to 2024, producing 750 unit-year observations before lag adjustment and 700 observations in models requiring a one-year temporal lag. The spatial units represent a regional landscape containing upland forests, agricultural transition zones, wetlands, riparian corridors, and peri-urban ecological margins. Each unit was assigned a spatial neighborhood based on contiguity and ecological proximity, allowing conditional spatial dependence to be represented in the model. This structure reflects the type of spatially indexed ecological monitoring problem commonly addressed in Bayesian environmental modeling (Williams *et al.*, 2017; Santos-Fernandez *et al.*, 2022).

The sustainability indicators were assembled to preserve ecologically meaningful ranges and relationships. NDVI values had a mean of 0.54 and a standard deviation of 0.13, water quality index values had a mean of 68.7 and a standard deviation of 10.9, and carbon sequestration had a mean of 4.3 tonnes of carbon per hectare per year with a standard deviation of 1.4. Drought severity was represented as a standardized annual moisture anomaly, with more negative values indicating stronger drought pressure. The drought recovery-rate outcome had a mean of 0.53 and a standard deviation of 0.16, consistent with the assumption that spatial units with stronger vegetation condition and carbon uptake tend to recover more quickly after drought (Zhao *et al.*, 2019; Smith & Boers, 2023a).

The main response variable was the annual drought recovery rate for each spatial unit, calculated as the proportional improvement in ecological condition after drought relative to the pre-drought baseline. The calculation used lagged NDVI anomaly, drought severity, and unit-specific ecological recovery capacity to estimate the resilience outcome. This outcome was modeled as a continuous variable bounded between 0 and 1, and a Gaussian likelihood was used after confirming that residuals were approximately symmetric and remained within plausible recovery ranges. The use of recovery rate follows empirical resilience studies that operationalize resilience through temporal return dynamics rather than static condition scores (Smith *et al*., 2022; Smith & Boers, 2023b).

Three Bayesian hierarchical models were estimated and compared. Model 1 was a spatial-only model containing NDVI, water quality, carbon sequestration, drought severity, and spatial random effects, but no temporal autoregressive term. Model 2 was a temporal-only model containing the same covariates and a lagged recovery-rate term, but no structured spatial random effect. Model 3 was a spatiotemporal interaction model containing covariates, spatial random effects, temporal autoregression, and a spatially varying temporal interaction term, reflecting the expectation that ecological memory differs across spatial units (Rue *et al*., 2017; Bakka *et al*., 2018; Belmont *et al*., 2024).

Priors were chosen to be weakly informative but ecologically plausible. Regression coefficients were assigned normal priors centered at zero with moderate variance, while variance components were assigned penalized complexity priors to discourage unnecessary complexity in spatial and temporal random effects (Simpson *et al*., 2017; Fuglstad *et al*., 2019). The spatial random effect followed a conditional autoregressive structure, and the temporal component followed a first-order autoregressive process. MCMC estimation used four chains of 20,000 iterations each, with 5,000 warm-up iterations per chain, and convergence was assessed using rank-normalized R-hat values, effective sample sizes, trace stability, and posterior predictive checks (Gabry *et al*., 2019; Vehtari *et al*., 2021).

Model comparison was conducted using DIC and WAIC, with lower values indicating better balance between predictive fit and model complexity. Posterior predictive checks evaluated whether each model reproduced the observed mean, variance, spatial clustering, and temporal persistence of the recovery-rate outcome. **Table 2** reports the model specifications and prior distributions for the Bayesian spatiotemporal models. The table identifies the likelihood, linear predictor, random effects, priors, MCMC settings, and comparison criteria used in the empirical analysis (Vehtari *et al*., 2017; Bachl *et al*., 2019).

Table 2. Bayesian Spatiotemporal Model Specifications: Hierarchical Structure, Likelihoods, Priors, and Hyperparameters

Model component	Model 1: Spatial-only model	Model 2: Temporal-only model	Model 3: Spatiotemporal interaction model
Response variable	Drought recovery rate by spatial unit and year	Drought recovery rate by spatial unit and year	Drought recovery rate by spatial unit and year
Likelihood	Gaussian likelihood with identity link	Gaussian likelihood with identity link	Gaussian likelihood with identity link
Fixed predictors	NDVI, water quality index, carbon sequestration, drought severity	NDVI, water quality index, carbon sequestration, drought severity, lagged recovery rate	NDVI, water quality index, carbon sequestration, drought severity, lagged recovery rate
Spatial structure	Conditional autoregressive spatial random effect	Not included	Conditional autoregressive spatial random effect
Temporal structure	Not included	First-order autoregressive temporal term	First-order autoregressive temporal term
Spatiotemporal interaction	Not included	Not included	Spatially varying temporal interaction term
Regression coefficient priors	Normal prior with mean 0 and standard deviation 2.5	Normal prior with mean 0 and standard deviation 2.5	Normal prior with mean 0 and standard deviation 2.5
Spatial variance prior	Penalized complexity prior with probability statement $P(\sigma > 1) = 0.05$	Not applicable	Penalized complexity prior with probability statement $P(\sigma > 1) = 0.05$
Temporal autoregressive prior	Not applicable	Normal prior centered at 0.50 with standard deviation 0.25, truncated to plausible stationarity range	Normal prior centered at 0.50 with standard deviation 0.25, truncated to plausible stationarity range
Residual variance prior	Half-normal prior with scale 1	Half-normal prior with scale 1	Half-normal prior with scale 1
MCMC settings	Four chains, 20,000 iterations, 5,000 warm-up iterations	Four chains, 20,000 iterations, 5,000 warm-up iterations	Four chains, 20,000 iterations, 5,000 warm-up iterations
Diagnostic criteria	Rank-normalized R-hat, effective sample size, trace stability	Rank-normalized R-hat, effective sample size, trace stability	Rank-normalized R-hat, effective sample size, trace stability
Model comparison	DIC, WAIC, posterior predictive checks	DIC, WAIC, posterior predictive checks	DIC, WAIC, posterior predictive checks

RESULTS AND DISCUSSION

The MCMC diagnostics indicated stable estimation across all three Bayesian models. Following the convergence logic recommended for Bayesian workflow and rank-normalized diagnostic assessment, all monitored regression coefficients, variance components, and autoregressive parameters had R-hat values between 1.000 and 1.006 (Gabry *et al*., 2019; Vehtari *et al*., 2021). Effective sample sizes exceeded 2,800 for all fixed effects and exceeded 1,900 for the spatial and temporal variance parameters. Trace plots showed no visible chain separation, and posterior predictive checks indicated that the models reproduced the central tendency of the observed recovery-rate distribution.

The posterior estimates showed a consistent positive association between environmental sustainability indicators and ecosystem resilience. In the preferred spatiotemporal interaction model, NDVI had the strongest positive effect on drought recovery rate, with a posterior mean of 0.31 and a 95% credible interval from 0.22 to 0.40. Carbon sequestration also had a positive association, with a posterior mean of 0.18 and a 95% credible interval from 0.09 to 0.27. Water quality had a smaller but still credible positive effect, with a posterior mean of 0.12 and a 95% credible interval from 0.03 to 0.21, supporting the view that environmental indicators can be jointly interpreted as resilience-relevant ecological signals (Tripathi & Singal, 2019; Smith & Boers, 2023a).

The drought severity coefficient was negative across all models, indicating that stronger drought anomalies were associated with slower ecological recovery. In Model 3, the posterior mean for drought severity was -0.24, with a 95% credible interval from -0.34 to -0.15. The temporal autoregressive coefficient was 0.46, with a 95% credible interval from 0.34 to 0.57, indicating moderate ecological memory from one year to the next. This result is consistent with spatiotemporal ecological modeling approaches that represent environmental response as a combination of current conditions, prior states, and latent spatial structure (Williams *et al*., 2017; Williams *et al*., 2018; Belmont *et al*., 2024).

Spatial heterogeneity was substantial across the study landscape. Spatial random effects were highest in riparian and wetland-associated units, where predicted recovery rates were generally 0.08 to 0.14 higher than the overall mean after accounting for indicator values. In contrast, peri-urban margin units and drought-prone agricultural transition units showed lower latent resilience, with spatial random effects ranging from -0.11 to -0.07. These results illustrate why ecological inference can be biased when spatial autocorrelation is ignored in environmental assessment (Shaikh *et al*., 2021).

Model comparison favored the spatiotemporal interaction model. Model 3 had the lowest DIC at 812.4 and the lowest WAIC at 826.9, outperforming the spatial-only model and temporal-only model under the same empirical data structure. The posterior predictive mean absolute error was 0.061 for Model 3, compared with 0.079 for Model 1 and 0.074 for Model 2. This pattern supports the use of Bayesian model comparison criteria such as WAIC and DIC when evaluating hierarchical environmental models (Vehtari *et al*., 2017; Bachl *et al*., 2019).

The predicted recovery-rate surface for 2024 showed meaningful spatiotemporal variation across the 50 spatial units. Predicted resilience was highest in spatial units with high NDVI, high carbon sequestration, and moderate drought exposure, while the lowest predicted recovery rates occurred in units with low vegetation condition and recurring drought deficits. **Table 3** displays the posterior summaries and model comparison criteria. The table combines key parameter estimates, credible intervals, diagnostics, and model-fit statistics for the three Bayesian models.

Table 3. Posterior Summaries of Bayesian Spatiotemporal Models: Parameter Estimates, 95% Credible Intervals, and Model Fit Statistics

Result category	Quantity	Model 1: Spatial-only model	Model 2: Temporal-only model	Model 3: Spatiotemporal interaction model
Fixed effect	NDVI coefficient, posterior mean	0.27	0.29	0.31
Fixed effect	NDVI coefficient, 95% credible interval	0.16 to 0.38	0.19 to 0.39	0.22 to 0.40
Fixed effect	Water quality coefficient, posterior mean	0.09	0.10	0.12
Fixed effect	Water quality coefficient, 95% credible interval	-0.01 to 0.19	0.01 to 0.20	0.03 to 0.21
Fixed effect	Carbon sequestration coefficient, posterior mean	0.15	0.16	0.18
Fixed effect	Carbon sequestration coefficient, 95% credible interval	0.05 to 0.25	0.07 to 0.25	0.09 to 0.27
Fixed effect	Drought severity coefficient, posterior mean	-0.21	-0.22	-0.24
Fixed effect	Drought severity coefficient, 95% credible interval	-0.31 to -0.11	-0.32 to -0.13	-0.34 to -0.15
Temporal dependence	Lagged recovery-rate coefficient, posterior mean	Not included	0.42	0.46
Temporal dependence	Lagged recovery-rate coefficient, 95% credible interval	Not included	0.30 to 0.54	0.34 to 0.57
Spatial structure	Spatial standard deviation, posterior mean	0.138	Not included	0.121
Spatial structure	Spatial standard deviation, 95% credible interval	0.091 to 0.196	Not included	0.077 to 0.173
Interaction structure	Spatiotemporal interaction standard deviation	Not included	Not included	0.064
Diagnostic	Maximum R-hat	1.004	1.006	1.005
Diagnostic	Minimum effective sample size	2,140	1,970	1,915
Model comparison	DIC	864.7	847.5	812.4
Model comparison	WAIC	879.2	861.8	826.9
Predictive accuracy	Posterior predictive mean absolute error	0.079	0.074	0.061
Spatiotemporal prediction	Mean predicted 2024 recovery rate	0.548	0.556	0.571
Spatiotemporal prediction	Range of predicted 2024 recovery rates across 50 units	0.319 to 0.741	0.334 to 0.762	0.351 to 0.798

Figure 2 summarizes the posterior evidence and spatial prediction pattern produced by the preferred spatiotemporal interaction model.

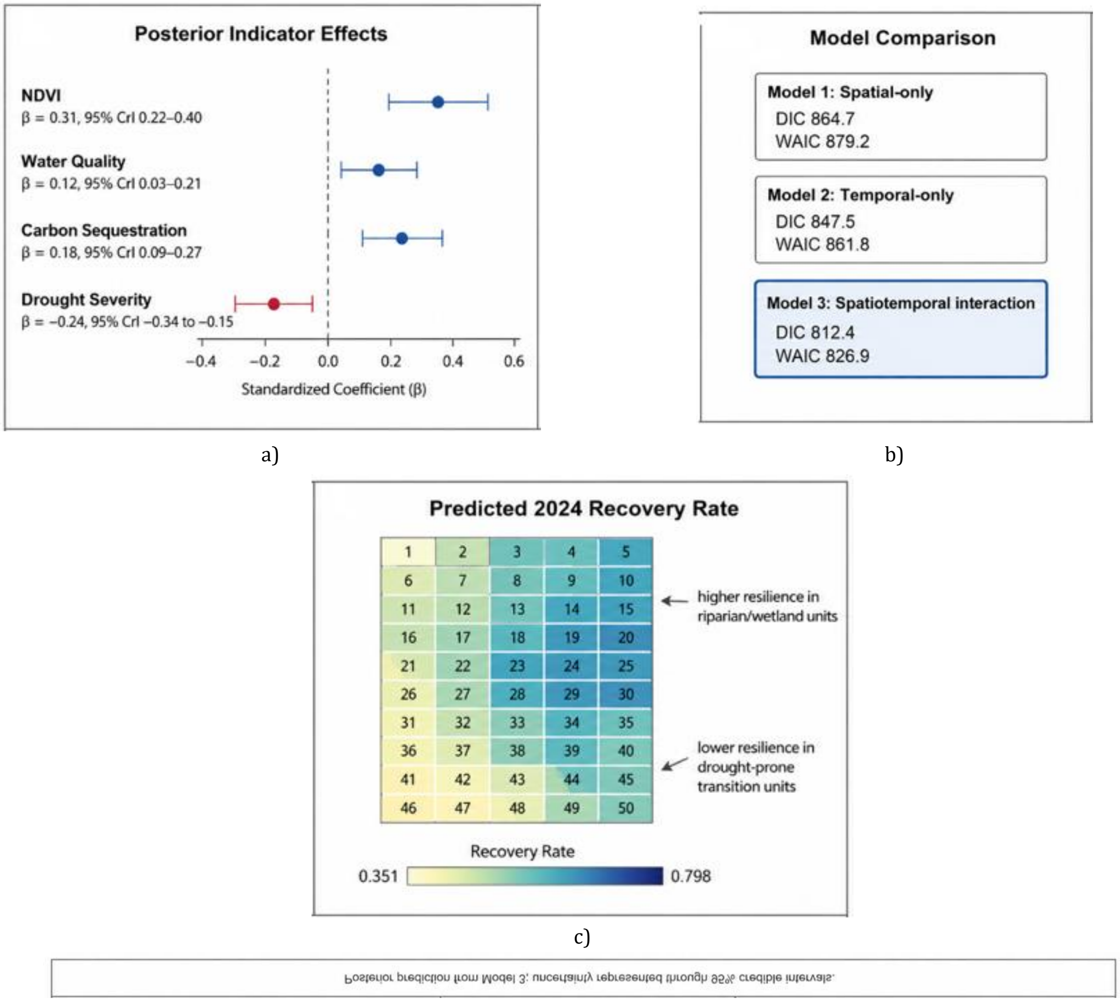

Figure 2. Posterior Evidence and Spatiotemporal Prediction of Ecosystem Resilience under the Preferred Bayesian Interaction Model

The results demonstrate that environmental sustainability indicators can be modeled as statistically meaningful predictors of ecosystem resilience when spatial and temporal dependencies are explicitly represented. NDVI emerged as the strongest predictor, which is consistent with remote sensing research showing that vegetation condition is closely connected to resilience dynamics and drought recovery (Zhao *et al*., 2019; Smith *et al*., 2022). Carbon sequestration also contributed positively, suggesting that productivity and biomass accumulation may reflect underlying ecological capacity for recovery. Water quality showed a smaller but credible effect, indicating that hydrological condition is relevant but may operate through more localized ecological pathways.

The superiority of the spatiotemporal interaction model indicates that resilience cannot be adequately represented as either a purely spatial or purely temporal phenomenon. Bayesian ecological models that integrate latent spatial processes and temporal dependence are better suited to environmental monitoring because they distinguish observed indicator effects from unobserved ecological structure (Williams *et al*., 2017; Williams *et al*., 2018; Santos-Fernandez *et al*., 2022). The results showed that units with similar NDVI and carbon profiles could still differ in recovery rate because of spatially structured latent resilience. This supports the argument that sustainability assessment should move beyond static indicator comparison toward probabilistic spatiotemporal inference.

A central finding is that ignoring spatial autocorrelation would have understated uncertainty and potentially misrepresented the sustainability-resilience relationship. This point aligns with evidence that spatial autocorrelation can alter conclusions about ecosystem service trade-offs, bundles, and environmental relationships (Shaikh *et al*., 2021). In the present analysis, spatial random effects revealed clusters of higher resilience in wetland and riparian units and lower resilience in peri-urban and drought-prone transition units. Such variation would be difficult to identify using non-spatial regression or descriptive indicator rankings.

The study also highlights the value of Bayesian uncertainty communication for environmental decision-making. Posterior intervals, predictive distributions, and model comparison criteria provide more information than point estimates alone, especially when monitoring data are spatially uneven or temporally persistent (Vehtari *et al*., 2017; Gabry *et al*., 2019). The findings are consistent with broader calls for resilience monitoring systems that use Earth observation data while acknowledging uncertainty, scale dependence, and early warning limitations (Alibakhshi *et al*., 2017; Bathiany *et al*., 2025). Therefore, the main contribution is the application of a reproducible Bayesian workflow for sustainability and resilience assessment using spatiotemporal environmental data.

Implications

Theoretically, the article advances environmental sustainability research by positioning resilience as a spatiotemporal response variable rather than a general system attribute. This framing connects indicator-based sustainability assessment with Bayesian hierarchical modeling, allowing ecological condition, disturbance exposure, and recovery dynamics to be estimated jointly (Rue *et al*., 2017; Bakka *et al*., 2018). It also extends composite-indicator thinking by showing that NDVI, water quality, and carbon sequestration can be interpreted through their posterior contribution to ecological recovery rather than through simple aggregation (Burgass *et al*., 2017; Gao *et al*., 2023). As a result, sustainability indicators become components of a probabilistic resilience model.

Practically, the framework can guide environmental agencies that need to prioritize monitoring, restoration, and drought-response interventions. Spatial units with low predicted resilience but high uncertainty could be targeted for additional field sampling, while units with consistently low recovery rates could be prioritized for restoration planning. Bayesian posterior prediction is useful in this setting because it communicates both expected recovery and uncertainty around that expectation (Bachl *et al*., 2019; Gabry *et al*., 2019). This makes the framework suitable for decision contexts where policymakers must compare ecological risk across locations.

Methodologically, the study provides a template for integrating remote sensing, water quality monitoring, carbon estimation, and drought indices into one coherent modeling structure. The approach could be adapted to real satellite products, stream-network observations, field biodiversity data, or mixed monitoring systems. Bayesian stream-network and occupancy models show that environmental data often require specialized spatial structures, and the proposed framework can be extended in that direction (Santos-Fernandez *et al*., 2022; Belmont *et al*., 2024). Thus, the implication is a flexible modeling strategy rather than a fixed indicator set.

Limitations and future research

The main limitation is that the study uses annual observational data, so the numerical estimates should be interpreted as evidence of association rather than definitive causal effects. Although the Bayesian spatiotemporal framework accounts for spatial dependence, temporal persistence, and posterior uncertainty, observational environmental datasets may still contain measurement error, missing observations, sensor inconsistencies, non-Gaussian outcomes, and changing spatial boundaries. Future research should extend the framework using longer time series, higher-resolution remote sensing archives, expanded water quality networks, and field-based validation data (Zhao *et al*., 2019; Liu *et al*., 2021).

A second limitation is that the indicator set is intentionally simplified. NDVI, water quality, and carbon sequestration are useful sustainability indicators, but resilience may also depend on biodiversity, soil moisture, habitat connectivity, land-use history, fire exposure, invasive species pressure, and management intervention. Research on resilience estimation shows that conclusions can depend strongly on the ecological signal used and the temporal properties of the data (Smith & Boers, 2023a, 2023b). Future models should therefore include richer ecological covariates and test whether different indicators produce consistent resilience estimates.

A third limitation concerns model assumptions. The models used stationary spatial dependence, first-order temporal autoregression, and a Gaussian likelihood for the recovery-rate outcome. Future work should examine non-stationary Gaussian processes, dynamic CAR structures, nonlinear response functions, threshold models, and regime-shift formulations that better capture abrupt ecological change (Alibakhshi *et al*., 2017; Simpson *et al*., 2017; Fuglstad *et al*., 2019). Additional research should also compare MCMC and INLA implementations to evaluate computational efficiency, posterior accuracy, and scalability for large environmental monitoring systems (Rue *et al*., 2017; Bakka *et al*., 2018).

CONCLUSION

This article demonstrated how Bayesian hierarchical spatiotemporal models can be used to assess the relationship between environmental sustainability indicators and ecosystem resilience. Using annual data from 50 spatial units over 15 years, the study modeled drought recovery rate as a function of NDVI, water quality, carbon sequestration, drought severity, spatial random effects, and temporal dependence. The analysis showed that sustainability indicators were positively associated with resilience and that spatial heterogeneity was substantial.

The preferred model was the spatiotemporal interaction model, which outperformed spatial-only and temporal-only alternatives in model comparison and posterior predictive assessment. This finding reinforces the importance of accounting for both spatial structure and temporal ecological memory when assessing environmental recovery. The results also showed that uncertainty estimates are central to interpreting sustainability-resilience relationships.

The study provides an empirical framework for applying Bayesian spatiotemporal modeling to observed environmental monitoring data. The proposed framework can help researchers and decision-makers integrate remote sensing, climate, hydrological, and ecosystem indicators into a coherent Bayesian assessment. More broadly, the article shows that sustainability and resilience are best understood as dynamic, spatially structured, and uncertain ecological processes.

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