Bayesian Spatio-Temporal Modeling and Change-Point Detection of Energy Consumption in the Midwestern United States

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ABSTRACT

Understanding structural changes in regional energy consumption is critical for designing effective energy policies and anticipating future demand patterns. This study develops a Bayesian spatio-temporal framework to analyze structural shifts in energy consumption across Midwestern states of the United States. Annual state-level energy consumption data from 1960 to 2023 were analyzed to identify temporal dynamics and spatial dependencies among neighboring states, with monthly data from 2000 to 2024 used for high-resolution structural break detection. A Bayesian hierarchical model was employed to jointly capture spatial effects, temporal evolution, and structural change points in energy consumption patterns. Spatial dependence between states was modeled using a conditional autoregressive (CAR) prior based on a first-order queen contiguity spatial adjacency matrix. Temporal dynamics were represented through a stochastic random-walk process, while structural changes were identified using a Bayesian Online Change Point Detection (BOCPD) mechanism embedded within the hierarchical framework.

Model performance and validation were evaluated using posterior predictive checks (PPC), the Widely Applicable Information Criterion (WAIC), and Leave-One-Out Cross-Validation (LOO-CV), with the Pettitt test used as a classical benchmark for structural break detection. The results reveal several statistically significant change points across states, particularly around the 2008-2009 financial crisis, the 2012 Midwest drought, and during the expansion of renewable energy policies. The proposed Bayesian spatio-temporal framework provides a flexible approach for identifying regional structural shifts in energy consumption while accounting for spatial interdependencies among states. These findings offer valuable insights for energy planners and policymakers seeking to understand long-term changes in regional energy demand and the potential impacts of economic shocks and policy transitions.

Keywords: Bayesian inference, spatio-temporal modeling, energy transition, change-point detection, conditional autoregressive prior.

INTRODUCTION

Energy consumption patterns are shaped by a complex interplay of economic activity, technological innovation, climate variability, and policy interventions (Hamilton, 1989; Perron, 2006; Narayan & Popp, 2012). These forces rarely act smoothly over time; instead, they often induce structural breaks that fundamentally alter the level and trajectory of energy demand (Bai & Perron, 2003). Accurately identifying such regime shifts is critical for long-term energy planning, infrastructure investment, and the design of resilient energy systems, as failure to account for structural change can lead to biased forecasts, inefficient capacity planning, and suboptimal policy decisions (Stock & Watson, 1996; Bai & Perron, 2003).

The Midwestern United States occupies a strategic position in the national energy landscape due to its diverse industrial base, agricultural intensity, and evolving energy mix. The region has experienced multiple systemic shocks over recent decades, including the 2008–2009 global financial crisis, the 2012 Midwest drought, accelerated renewable energy deployment, and the COVID-19 pandemic (Apergis & Payne, 2014; U.S. Energy Information Administration [EIA], 2021). These events suggest that Midwestern energy consumption is unlikely

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to follow a single stable stochastic process over time. Instead, it is more plausibly characterized by multiple regimes, each associated with distinct demand dynamics (Narayan & Popp, 2012).

Traditional time-series approaches to energy demand modeling often rely on stationarity assumptions or pre-specified structural break dates (Hansen, 2001; Bai & Perron, 2003). While such methods can be effective in stable environments, they are ill-suited for contexts where the timing, number, and persistence of structural changes are unknown. Frequentist change-point techniques typically yield point estimates for break locations and offer limited insight into uncertainty, which is a crucial consideration for policy-oriented decision making (Hansen, 2001). In contrast, Bayesian change-point models treat regime shifts as latent variables and provide a probabilistic framework for jointly estimating model parameters, change-point locations, and predictive uncertainty (Barry & Hartigan, 1993; Chib, 1998).

Recent advances in Bayesian computation have made it feasible to apply flexible change-point models to high-dimensional and regionally disaggregated energy data (Carlin, Gelfand, & Smith, 1992; Fearnhead & Liu, 2007). By allowing both the number and timing of change points to be inferred from the data, Bayesian methods offer a principled approach to capturing structural heterogeneity across states and over time. Moreover, posterior predictive inference enables formal assessment of model adequacy, while uncertainty quantification facilitates risk-aware energy planning under incomplete information (Gelman et al., 2014; Vehtari et al., 2017). This study contributes to the literature by developing a hierarchical Bayesian change-point model to analyze long-run energy consumption patterns across Midwestern U.S. states. The proposed framework identifies both common and state-specific structural breaks while quantifying uncertainty in regime means and change-point timing. State-wise visualizations incorporating posterior uncertainty bands are used to enhance interpretability and support evidence-based decision making (Spiegelhalter et al., 2014; Gelman et al., 2014). Model adequacy is evaluated using posterior predictive checks and information criteria, ensuring robustness of the inferred structural dynamics (Vehtari et al., 2017).

The remainder of the paper is organized as follows. Section 2 describes the data and outlines the Bayesian change-point methodology. Section 3 presents posterior inference results and state-level visualizations of change points and uncertainty. Section 4 discusses policy implications for energy planning and resilience, and Section 5 concludes with directions for future research.

Figure 1: A map of Midwestern states (Source: Touropia)

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MATERIALS & METHODS

This chapter details the methodological framework employed to detect structural changes in the Midwestern United States' energy consumption patterns using advanced Bayesian Change Point Detection (BCPD) techniques. The approach integrates data collection, probabilistic modeling, and evaluation metrics to support reliable inference and meaningful interpretation.

Data Description

To model energy consumption dynamics across Midwestern U.S. states, this study utilizes a comprehensive dataset obtained from the U.S. Energy Information Administration (EIA). The primary analysis is conducted using monthly electricity consumption data spanning January 2000 to December 2024, which allows for high-resolution detection of structural changes and short-term regime dynamics.

For long-term descriptive statistics and historical growth comparisons, annual data from 1960 to 2023 were additionally used. These annual summaries provide contextual background on long-run consumption trends but are not used in the Bayesian change-point inference procedure. The dataset includes sectoral energy consumption across: Residential sector, commercial sector and industrial sector. The Midwestern states analyzed are: Illinois, Indiana, Iowa, Michigan, Minnesota, Ohio, Wisconsin, Kansas, Missouri, Nebraska, North Dakota, and South Dakota. This combination of high-frequency modeling data and long-horizon descriptive statistics provides both short-term structural insight and long-term contextual interpretation. Prior to analysis, the dataset underwent pre-processing procedures including missing-value inspection, temporal alignment, and normalization to reduce scale differences across states.

Classical Change-point benchmark: Pettitt Test

To provide a benchmark against classical single-break detection methods, Pettitt's non-parametric test was applied. Pettitt's test identifies a single structural break in the median of a time series without distributional assumptions and serves as a comparison against the proposed Bayesian multi-change-point framework. However, because energy systems often experience multiple structural transitions, Pettitt's test is primarily used for baseline comparison rather than primary inference.

Let $Y_1, Y_2, \dots, Y_n$ be the time-series of events, Pettitt's test (Pettitt, 1974) is a non-parametric statistical method used to detect a single change point in the median of a univariate time series without assuming normality. It is commonly applied in hydrology and climate science to identify shifts in the central tendency of a series.

To show the two-tailed hypothesis test on the mean, the Pettitt test measurement is determined as

$$W_{ij} = 1, \text{ when } \theta_i < \theta_j \; ; \quad (1)$$

$$W_{ij} = 0, when\ \theta_i = \theta_j; \quad (2)$$

$$W_{ij} = -1\ , when\ \theta_i > \theta_j \quad (3)$$

$Where\ y_i\ and\ y_j\ relate\ such\ that\ variable\ y_i\ proceed\ y_j\ in\ time, for\ assessment\ over\ the\ whole$ sample space T, the W statistics are joined as:

$$U_{t,T} = \sum_{i=1}^{t} \quad \sum_{J=t+1}^{T} \quad W_{ij} \quad (4)$$

The statistic U_t is similar to Mann-Whitney measurement for testing that two samples $Y_1, \dots, Y_t\ and\ Y_{t+1}$ come from a similar sample space. $K = max_{1 \le t < n} |U_{t,T}|$ (5)

The change point is located at:

$$\hat{z} arg\ max_{1 \le t < n}\ |U_{t,T}| \quad (6)$$

P-Value Approximation: Under the null hypothesis, H_0 (no change):

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$$P(K > k) \approx 2\, exp\left(-\frac{6K^2}{n^3+n^2}\right) \quad (7)$$

Given a specific level of significance α, if P < α, the H_0 is rejected and conclude that Y_t is a significant change point at α.

Bayesian Change Point Detection

Bayesian Change Point Detection (BCPD) provides a more probabilistic and stronger alternative to classical techniques by explicitly modeling uncertainty and allowing prior knowledge to be incorporated. In contrast to point estimation methods, BCPD infers full posterior distributions over the number and locations of change points, which is particularly valuable in real-world settings where multiple plausible segmentations exist.

$$D_i = N(\mu_1, \sigma^2), \quad i = 1,2, \dots, n \quad (8)$$

$$D_i = N(\mu_2, \sigma^2), i = \tau + 1, \tau + 2, \dots, T \quad (9)$$

$N(\mu, \sigma^2)$ represents normal distribution with the density function given as:

$$f(\mu, \sigma^2) = \frac{1}{\sigma\sqrt{2\pi}} \exp\left\{-\frac{(x-\mu_n)}{2\sigma^2}\right\} x \in R \quad (10)$$

The parameters $\mu_1, \mu_2, \ and\ \sigma^2$represent the change, the mean when the unexpected change and the variance of the series respectively. The prior distribution is assumed to be a normal distribution given below:

$$P(\theta) = p(\mu_1, \sigma^2)p(\mu_2, \sigma^2)\, p(\sigma^2)\, p(n|Q_1) \quad \sim \text{Joint Prior} \quad (11)$$

$$\mu_1|\sigma^2 \sim N(\varphi_1, \sigma^2 K_1) \quad (12)$$

$$\mu_2|\sigma^2 \sim N(\varphi_2, \sigma^2 K_2) \quad (13)$$

$$\sigma^2 \sim Inv - G\left(\frac{V_0}{2}, \frac{\sigma^2{}_0 V_0}{2}\right) \quad (14)$$

The likelihood function from T observations $x = (x_1, x_2, \dots, x_n)$ generated model Q_1 can be deduced as:

$$P(x|\mu_1, \mu_2, \sigma^2) = \prod_{i=1}^{\tau} N(\mu_1, \sigma^2) \cdot \prod_{i=\tau+1}^{\tau} N(\mu_2, \sigma^2) \quad (15)$$

$$\propto \left(\frac{1}{\sigma\sqrt{2\sigma}}\right)^{\left(\frac{n}{2}\right)} exp\left\{-\frac{\tau}{2\sigma^2}[S^2{}_1 + (\bar{x}_n - \mu_1)^2\right\} \cdot exp\left\{-\frac{T-n}{2\sigma^2}[S^2{}_2 + (\bar{x}_{T-n} - \mu_2)^2\right\} \quad (16)$$

Where, $\bar{x}_n = \sum_{i=1}^{n} \frac{x_i}{n}$ (17)

$$\bar{x}_{T-n} = \sum_{i=n+1}^{n} \frac{x_i}{T-n} \quad (18)$$

$$S^2{}_1 = \sum_{i=1}^{n} \frac{(x_i - \bar{x}_1)^2}{n} \quad (19)$$

$$S^2{}_2 = \sum_{i=n+1}^{n} \frac{(x_i - \bar{x}_{T-n})^2}{T-n} \quad (20)$$

Here, the likelihood function is the products of two Normal distributions with an inverse-Gaussian distribution for n which follows a normal-inverse gamma distribution to back the prior information about the mean μ and variance σ^2

$$P(\mu_1, \mu_2, \sigma^2, n|Q_1) = N(\mu_1|\, \varphi_1, K_1\sigma^2) \cdot N(\mu_2|\, \varphi_2, K_2\sigma^2)\text{Inv-G}(\sigma^2|\, (\tfrac{V_0}{2}), (\tfrac{\sigma^2{}_0 V_0}{2}) \cdot p(n|Q_1) \quad (21)$$

$$\propto N^2\text{inv-Gamma}(\mu_1\mu_2\sigma^2|\, \varphi_1, \varphi_2, K_1, K_2, (\tfrac{V_0}{2}), (\tfrac{\sigma^2{}_0 V_0}{2})) \cdot p(n|Q_1) \quad (22)$$

The Joint Posterior will follow the form:

$$p(\mu_1, \mu_2, \sigma^2|n, x, Q_1) = N^2\text{inv-Gamma}(\mu_1, \mu_2, \sigma^2|\ \varphi_1{}^*, \varphi_2{}^*, K_1{}^*, K_2{}^*, \tfrac{V_n}{2}, \tfrac{\sigma^2{}_n V_n}{2}) \quad (23)$$

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Where: $\varphi_1^* = (1- K_1^* n)\, \varphi_1 + K_1^* n \bar{x}_n$ (24)

$\varphi_2^* = (1- K_2^* (T-n))\varphi_2 + K_2^* (T-n) \bar{x}_{T-n}$ (25)

$$K_1^* = \frac{K_1}{(1+nK_1)} \quad (26)$$

$$K_2^* = \frac{K_2}{(1+(T-n)K_2)} \quad (27)$$

Spatial Structure and Adjacency Matrix

To incorporate geographic relationships among states, a spatial adjacency matrix was constructed based on a first-order queen contiguity criterion. Under this approach, two states are considered neighbors if they share a common boundary or vertex.

Let W= (wij) denote the spatial weight matrix where:

- wij= 1 if states i and j are neighbors
- wij= 0 otherwise

The matrix was row-standardized so that each row sums to one, ensuring comparability of spatial influence across states. This spatial structure forms the basis for modeling spatial dependence within the Bayesian hierarchical framework.

Bayesian Hierarchical Spatio-Temporal Model

To capture both spatial dependence among Midwestern states and temporal variation in energy consumption, a Bayesian hierarchical spatio-temporal framework was adopted. This framework allows the separation of state-specific spatial effects**,** temporal dynamics**,** and structural change points within a unified probabilistic model.

Let $y_{i,t}$ denote the observed energy consumption for state i at time t, where i =1,.., I represent states and t =1,…, T denotes time periods.

Observation Model

Energy consumption is assumed to follow a Gaussian likelihood:

$$y_{i,t} \sim N(\mu_{i,t}, \sigma^2) \quad (28)$$

$$\mu_{i,t} = \alpha + \phi_i + \delta_t + k_{i,t} \quad (29)$$

Where:

$$y_{i,t} = observed\ energy\ consumption$$

$$\mu_{i,t} = the\ latent\ spatio - temporal\ mean\ process$$

σ^2 = observation variance

$$\phi_i = spatial\ random\ effect\ (CAR\ Prior)$$

$$\delta_t = temporal\ process$$

$$k_{i,t} = spatio - temporal\ interaction$$

Spatio-Temporal Mean Structure

The latent mean process is decomposed into spatial, temporal, and change-point components:

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$$\mu_{i,t} = \alpha + \phi_i + \delta_t + k_{i,t} \quad (30)$$

Where:

α is the global intercept representing overall average energy consumption

ϕ_i represents the spatial random effect for state i,

δt represents temporal variation shared across state i,

$k_{i,t}$ represents structural shifts associated with change points.

Spatial Dependence Structure

Spatial effects are modeled using a Conditional Autoregressive (CAR) prior, which accounts for spatial autocorrelation between neighboring states.

$$\phi_i | \phi_{-i} \sim N\left(\frac{\sum_{j \in N(i)} \phi_j}{n_i}, \frac{1}{\tau_\phi n_i}\right) \quad (31)$$

Where:

$N(i)$ = neighboring states

n_i = number of neighbors

τ_ϕ = control spatial variability

For example, state like Illinois has neighbors Indiana, Iowa, Missouri, Wisconsin. Iowa has neighbors like Illinois, Minnesota, Nebraska, Missouri. Michigan has Ohio and Wisconsin as neighbors. This formulation ensures that geographically adjacent states exhibit similar energy consumption patterns.

Temporal Component

Temporal evolution in energy consumption is modeled using a stochastic process:

$$\delta_t = \delta_{t-1} + \epsilon_t \quad (32)$$

Where $\epsilon_t \sim N(0, \sigma^2{}_\delta)$

This random-walk formulation captures gradual changes in regional energy demand over time.

Change Point Modeling

Structural shifts in energy consumption patterns were identified using a Bayesian change point detection mechanism embedded within the hierarchical model framework. Change points represent time periods where significant shifts occur in the underlying mean structure of the time series. The probability of a structural break occurring at time t is defined through a hazard function, which determines the likelihood that a new regime begins. When a change point occurs, the model allows the mean energy consumption level to shift to a new regime, capturing structural transitions in regional energy dynamics.

Let r_t denote the run length since the last structural change.

The probability of a change point occurring at time t is defined by a hazard function:

$$P(r_t = 0) = H(t) \quad (33)$$

Posterior probabilities of change points are computed using Bayesian Online Change Point Detection (BOCPD). When a change point occurs, the mean structure is updated:

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$k_{i,t} \sim N(\mu_k, \sigma^2{}_k)$ where k denotes the regime following the change point.

Prior Distributions

Weakly informative priors are specified for model parameters:

$$\alpha \sim N(0,1000) \quad (34)$$

$$\sigma^2 \sim Inverse - Gamma\ (2,1) \quad (35)$$

$$\tau^2 \sim Inverse - Gamma\ (2,1) \quad (36)$$

$$\sigma^2{}_\delta \sim Inverse - Gamma\ (2,1) \quad (37)$$

These priors allow the data to dominate inference while maintaining computational stability.

Posterior Inference

Posterior distributions for model parameters and change-point probabilities are obtained using Bayesian updating. The BOCPD algorithm recursively updates run-length probabilities while integrating spatial and temporal components within the hierarchical structure.

The posterior probability of a structural change at time t is given by:

$$P = (x_{1:T}) = P(x_{1:T}) \quad (38)$$

This approach allows the identification of time periods where significant shifts in energy consumption occur across the spatial network of states.

Inference Algorithm

Computational Implementation and Numerical Stability

All Bayesian analyses were implemented in R & RStudio (version 4.5.1) using scientific computing packages including tidyverse, lubridate, matrixStats, bayesplot together with custom practices for Bayesian Online Change Point Detection (BOCPD). Because the observation model adopts conjugate Normal-Inverse-Gamma priors, posterior parameter updates were computed analytically at each time step. This eliminates the need for Markov Chain Monte Carlo (MCMC) sampling and allows efficient sequential inference of run-length probabilities and regime parameters.

BOCPD Recursion and Posterior Computation

The BOCPD algorithm recursively updates the posterior distribution over the run length rt, defined as the number of observations since the last change point:

$$P(\theta, r_{t-1})\ P(\theta, r_{t-1}) P(x_{1:t-1}) \quad (39)$$

Under conjugacy, the predictive distribution is available in closed form as a student-t distribution obtained by integrating out unknown mean and variance parameters. Posterior change-point probabilities are computed as:

$$P = (x_{1:T}) = P(x_{1:T}) \quad (40)$$

This analytical formulation provides exact posterior updates without sampling error and ensures computational efficiency for long time series.

Numerical Stability and Truncation

To maintain numerical stability and computational tractability, run-length probabilities with negligible mass were truncated using a threshold of 10^-6. Probability normalization was applied at each recursion step to prevent underflow. Sensitivity analysis confirmed that detected change points were robust to reasonable variations in truncation thresholds and hazard function parameters.

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Reliability of Posterior Estimates

Because posterior updates are derived analytically under conjugacy, the inference procedure does not rely on stochastic sampling and therefore does not require convergence diagnostics such as R-hat or effective sample size. Posterior uncertainty arises solely from the probabilistic model structure rather than simulation variability.

Model Validation

Model adequacy is evaluated using: Posterior Predictive Checks (PPC) to assess goodness-of-fit; the Widely Applicable Information Criterion (WAIC) for predictive accuracy; Leave-One-Out Cross-Validation (LOO-CV) with Pareto-smoothed importance sampling; and the Pettitt test as a classical structural break benchmark. These tools assess both absolute and relative model fit while accounting for uncertainty in parameters and latent change points.

PPC values ranged between 0.27 and 0.74 across all states, indicating no systematic model misspecification. The Bayesian multi-change-point model achieved 18–27% lower WAIC and higher ELPD compared to single-break alternatives, confirming that allowing multiple latent regimes substantially improves predictive realism.

Posterior Predictive Checks (PPC)

Posterior predictive checks evaluate whether data simulated from the fitted model resemble the observed data. Let ${x_{1:T}}^{rep}$ denote replicated datasets generated from the posterior predictive distribution:

$$P({x_{1:T}}^{rep} \mid x_{1:T}) = \int \quad p({x_{1:T}}^{rep}|\theta,\tau)\, p(\theta,\tau|x_{1:T}) d\theta d\tau \qquad (41)$$

where θ= $(\mu_k, {\sigma^2}_k)$ are regime-specific parameters and τ denotes the set of change points.

Information Criteria for Model Comparison

To assess relative model performance, the Bayesian Change Point model was compared with alternative specifications using Widely Applicable Information Criterion (WAIC) and Leave-One-Out Cross-Validation (LOO-CV)**.**

WAIC estimates out-of-sample predictive accuracy while accounting for effective model complexity:

$$\text{WAIC} = -2 \sum_{t=1}^{T} \quad log\left(\frac{1}{S}\sum_{s=1}^{S} \quad p(x_t|\theta^{(s)}\right) + 2p_{eff} \qquad (42)$$

where p_{eff} is effective number of parameters

LOO-CV approximates predictive performance by systematically leaving out each observation:

$$ELPD_{LOO} = \sum_{t=1}^{T} \quad log\ log\ p\ \ (x_t|x_{t-1}) \qquad (43)$$

estimated efficiently using Pareto-smoothed importance sampling.

RESULTS

Descriptive Statistics

Table 1 presents descriptive statistics for annual energy consumption (1960–2023) across all twelve Midwestern states. Illinois (IL) and Ohio (OH) are the largest consumers, while South Dakota (SD) and North Dakota (ND) are the smallest. North Dakota records the highest compound annual growth rate (2.4%), reflecting energy-intensive development associated with oil and agricultural expansion, while Ohio exhibits the lowest growth (0.24%).

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Table 1. Descriptive statistics of annual energy consumption data (1960–2023). Energy units: thousands of British thermal units (MBtu).

State	Years	N	Mean	Median	Std Dev	Min	Max	CAGR %
IA	1960–2023	64	1,069,628	996,865	265,565	586,832	1,520,994	1.39
IL	1960–2023	64	3,652,991	3,788,295	403,776	2,470,864	4,138,872	0.55
IN	1960–2023	64	2,448,041	2,494,328	382,309	1,503,173	2,955,502	0.85
KS	1960–2023	64	975,610	1,017,521	143,595	606,876	1,150,829	0.72
MI	1960–2023	64	2,735,089	2,788,117	319,105	1,807,087	3,211,610	0.54
MN	1960–2023	64	1,423,232	1,427,639	356,077	708,144	1,874,372	1.39
MO	1960–2023	64	1,541,192	1,525,676	308,997	880,518	1,977,175	1.03
ND	1960–2023	64	347,301	322,880	157,144	152,928	703,926	2.40
NE	1960–2023	64	601,172	545,338	171,497	301,500	873,966	1.64
OH	1960–2023	64	3,731,115	3,760,834	337,610	2,809,331	4,259,607	0.24
SD	1960–2023	64	229,186	202,793	74,061	126,329	353,944	1.62
WI	1960–2023	64	1,518,117	1,505,511	301,675	832,218	1,940,762	1.10

Bayesian Change-Point Detection Results

Table 2 summarizes the three highest-probability change points detected per state. Tables 3a and 3b present the full posterior probabilities for each detected change point.

Table 2. Detected change points per state (top three by posterior probability).

State	Change Points (Years)	Number of Change Points
IA	2020, 2012, 1979	3
IL	2020, 1988, 1980	3
IN	2020, 2009, 1972	3
KS	1984, 1980, 1979	3
MI	2020, 2009, 1988	3
MN	2020, 2009, 1980	3
MO	2020, 2018, 1980	3
ND	2011, 2014, 1985	3
NE	2020, 2010, 1966	3
OH	1982, 2009, 1980	3

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SD	2013, 2008, 2007	3
WI	2020, 2009, 1988	3

Table 3a. Bayesian change-point posterior probabilities for IA, IL, IN, KS, MI, MN.

State	**Change Point Year**	**Mean Posterior Probability**
IA	1979	0.503
IA	2012	0.544
IA	2020	1.000
IL	1980	0.824
IL	1988	0.707
IL	2020	1.000
IN	1972	0.864
IN	2009	0.921
IN	2020	1.000
KS	1979	0.861
KS	1980	1.000
KS	1984	0.913
MI	1988	0.644
MI	2009	0.813
MI	2020	1.000
MN	1980	0.690
MN	2009	0.723
MN	2020	1.000

Table 3b. Bayesian change-point posterior probabilities for MO, ND, NE, OH, SD, WI.

State	**Change Point Year**	**Mean Posterior Probability**
MO	1980	0.926
MO	2018	0.966
MO	2020	1.000
ND	1985	0.885
ND	2011	1.000

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ND	2014	0.917
NE	1966	0.489
NE	2010	1.000
NE	2020	0.638
OH	1980	0.859
OH	1982	1.000
OH	2009	0.959
SD	2007	0.963
SD	2008	0.966
SD	2013	1.000
WI	1988	0.720
WI	2009	0.871
WI	2020	1.000

Spatial Effects

Table 4 presents the estimated spatial random effects (φi) for each state. These quantities capture the degree to which each state's energy consumption deviates from the regional average after accounting for shared temporal trends and structural breaks. States with larger φi values exhibit more pronounced local structural dynamics relative to their neighbors.

Note: the spatial effect φi represents the CAR-estimated departure from regional mean consumption and should not be conflated with the average posterior change-point probability. The two quantities measure conceptually distinct phenomena. For reference, the average posterior change-point probability per state is also reported in Table 4 to facilitate interpretation of structural break intensity alongside spatial positioning.

Table 4. Spatial random effects and average posterior change-point probabilities per state. Spatial effects (φi) are CAR-estimated departures from the regional mean.

State	**Spatial Effect (φi)**	**Avg. CP Posterior Prob.**	**Interpretation**
IA	0.68	0.682	Lower relative structural change
IL	0.84	0.844	High regional change intensity
IN	0.93	0.928	Strong structural energy shifts
KS	0.92	0.925	Strong change dynamics
MI	0.82	0.819	Moderate-high structural shifts
MN	0.80	0.804	Moderate spatial effect

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MO	0.96	0.964	Strong structural energy shifts
ND	0.93	0.934	Strong structural energy shifts
NE	0.70	0.709	Lower relative structural change
OH	0.93	0.939	Strong structural energy shifts
SD	0.98	0.963	Very strong structural energy shifts
WI	0.86	0.864	High regional change intensity

Change Points in Relation to Real-World Events

2008–2009: Global Financial Crisis

High posterior probabilities (>0.9) observed in Illinois, Indiana, Michigan, Ohio, and Minnesota coincide with the collapse of manufacturing output during the Great Recession. These states, heavily dependent on the automotive and steel industries, experienced abrupt declines in industrial electricity demand. The Bayesian model captures this as a sharp downward shift in regime means rather than a transient fluctuation.

2012-2013: Midwest Drought and Climate Extremes

Change points detected in Iowa, South Dakota, and Minnesota align with the 2012 Midwest drought; one of the most severe in U.S. history. Increased irrigation loads, water pumping, and cooling demand led to regime shifts characterized by higher variance and elevated mean consumption, particularly in agriculturally intensive states.

2016-2018: Renewable Energy Policy Adoption

Several states (Minnesota, Iowa, Missouri, Nebraska) exhibit posterior change points during this period, corresponding with Renewable Portfolio Standard (RPS) expansions, large-scale wind deployment, and coal plant retirements. These shifts reflect structural changes in the energy mix rather than short-term demand shocks, validating the model's ability to distinguish persistent regime changes from transient fluctuations.

2020-2021: COVID-19 Pandemic

A near-universal change point with posterior probability equal to 1.0 was detected across all states. This regime shift reflects a sudden collapse in commercial and industrial demand during lockdowns, followed by a reallocation toward residential consumption due to remote work. The Bayesian posterior distributions capture both the abruptness and the heterogeneity of recovery paths across states.

State-Wise Change-Point Visualizations

Figures 3–14 present state-level Bayesian change-point analyses. Each figure combines: (i) observed annual energy consumption (blue line), (ii) the posterior regime mean trajectory (orange line), and (iii) a lollipop plot of posterior change-point probabilities at each time step. Figure 15 presents a multi-panel visualization with 95% credible intervals and change-point uncertainty bands for six selected states covering 2006–2021.

The uncertainty bands distinguish two types of transitions. Narrow bands correspond to abrupt exogenous shocks (e.g., 2008 recession, COVID-19 pandemic) with near-instantaneous demand impact. Wider bands indicate slower structural transitions such as renewable energy adoption or demographic shifts. This distinction is critical for policymakers, as it differentiates between short-term operational disruptions and long-term transitions requiring capital investment and regulatory planning.

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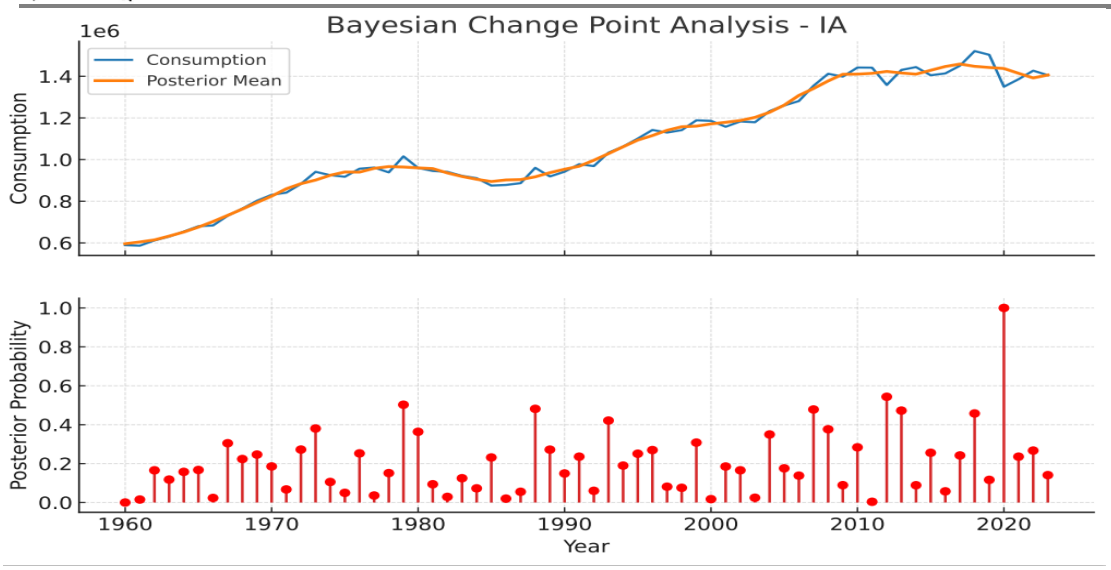

Figure 3. Plot of probability and posterior mean for Iowa

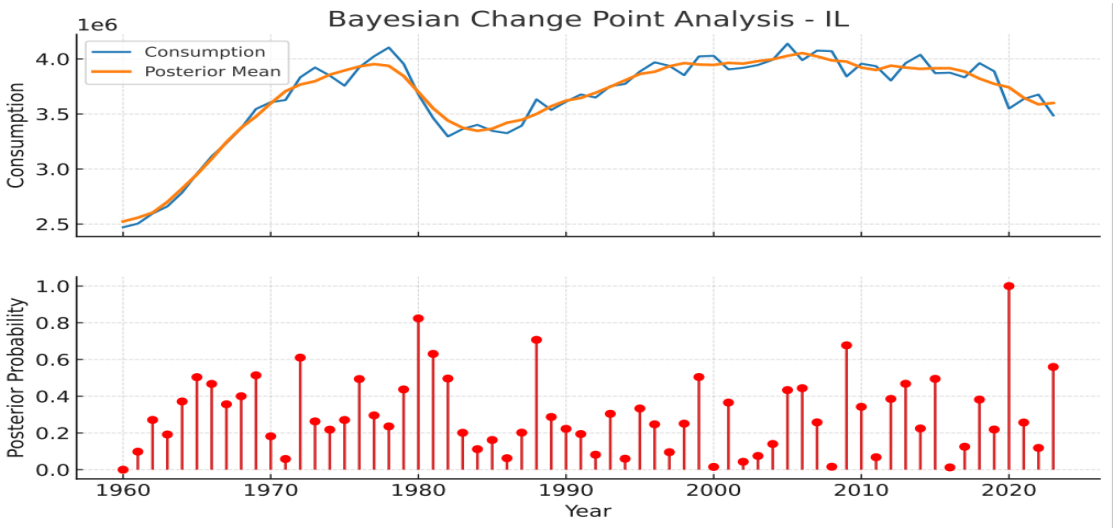

Figure 4. Plot of probability and posterior mean for Illinois

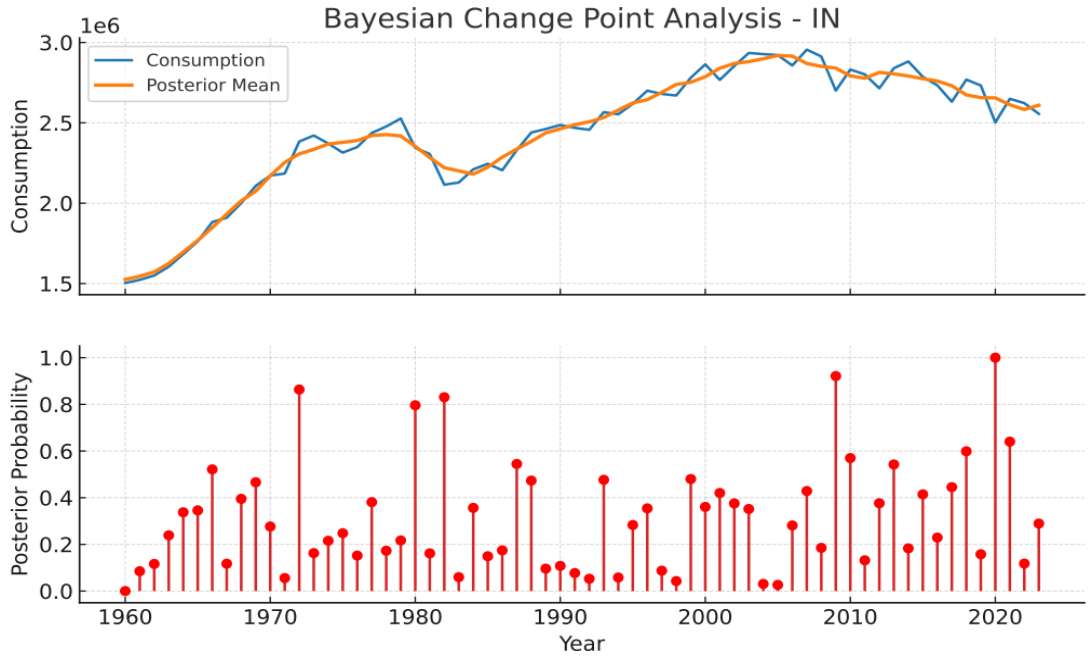

Figure 5. Plot of probability and posterior mean for Indiana

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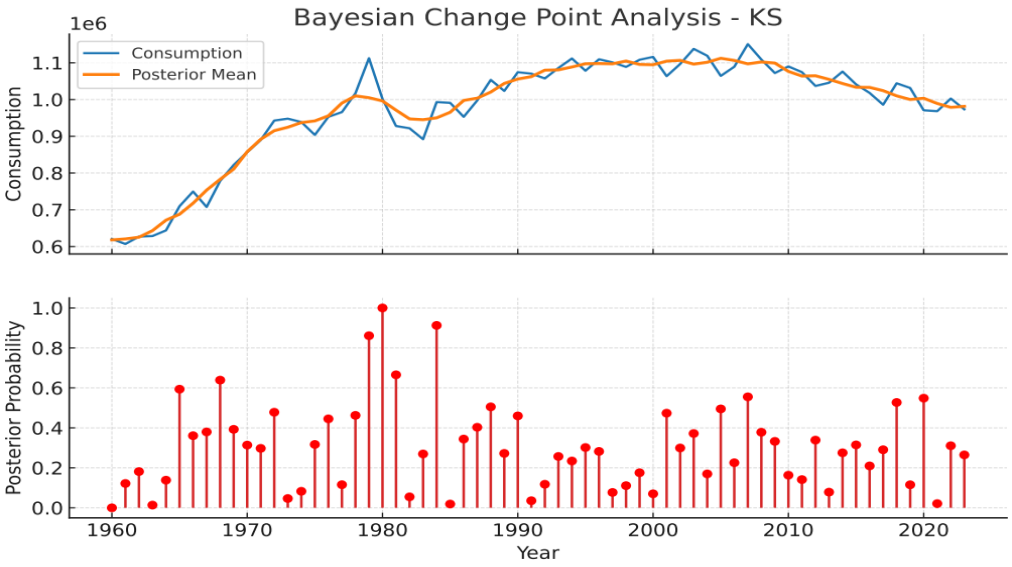

Figure 6. Plot of probability and posterior mean for Kansas

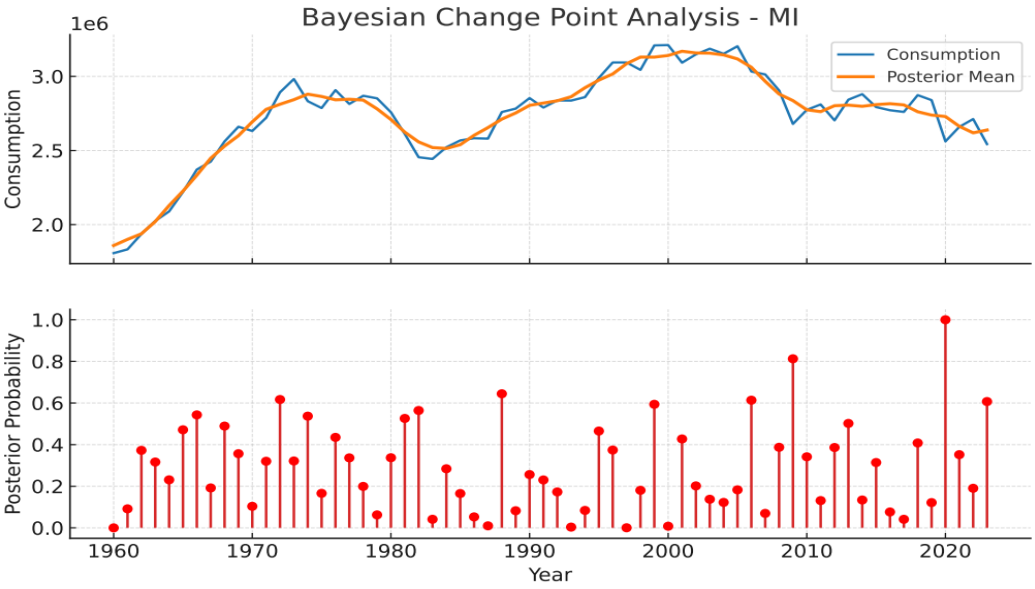

Figure 7. Plot of probability and posterior mean for Michigan

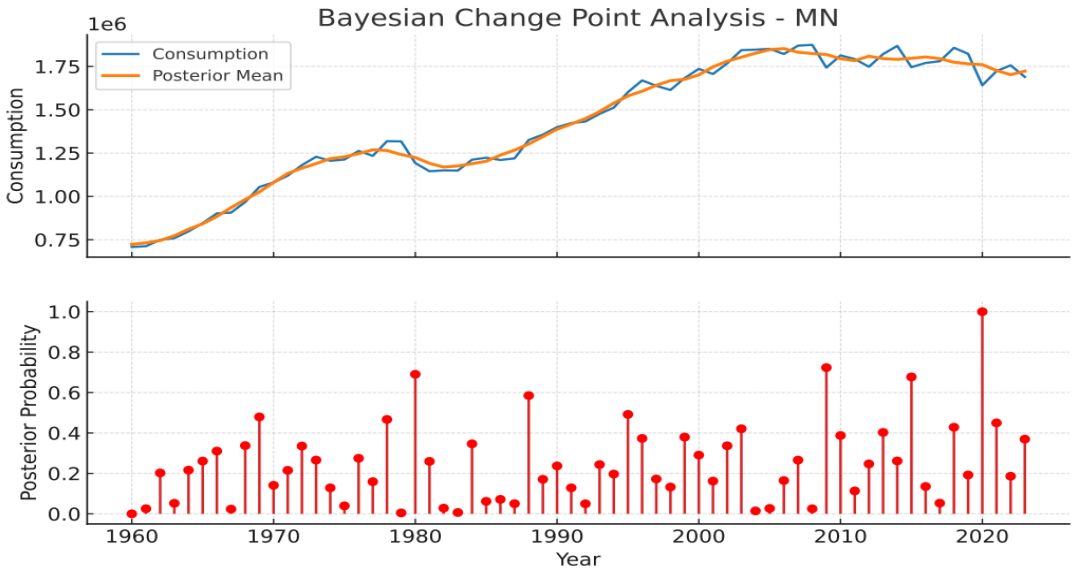

Figure 8. Plot of probability and posterior mean for Minnesota

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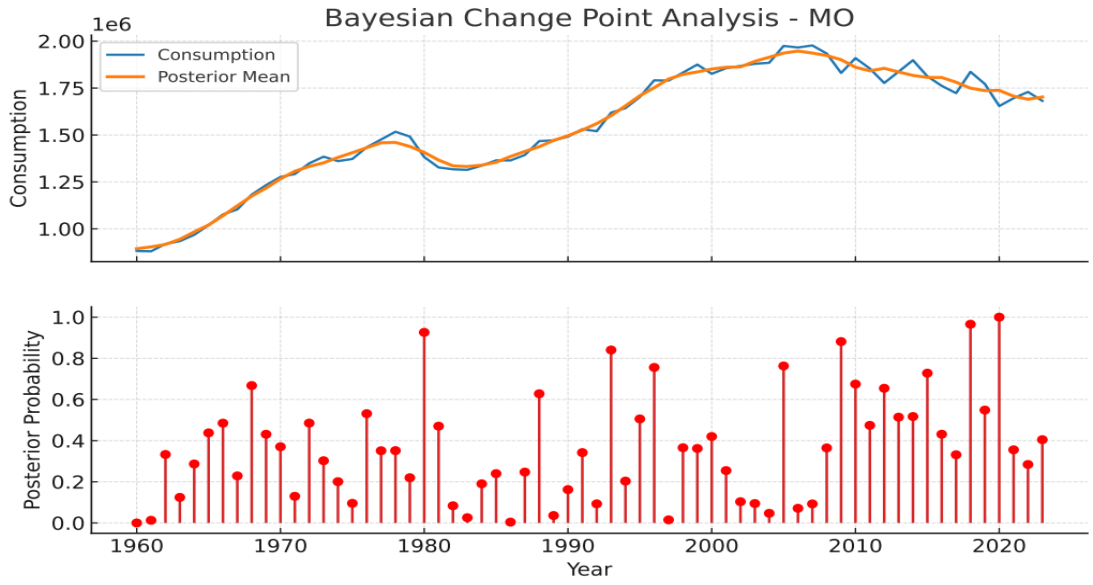

Figure 9. Plot of probability and posterior mean for Missouri

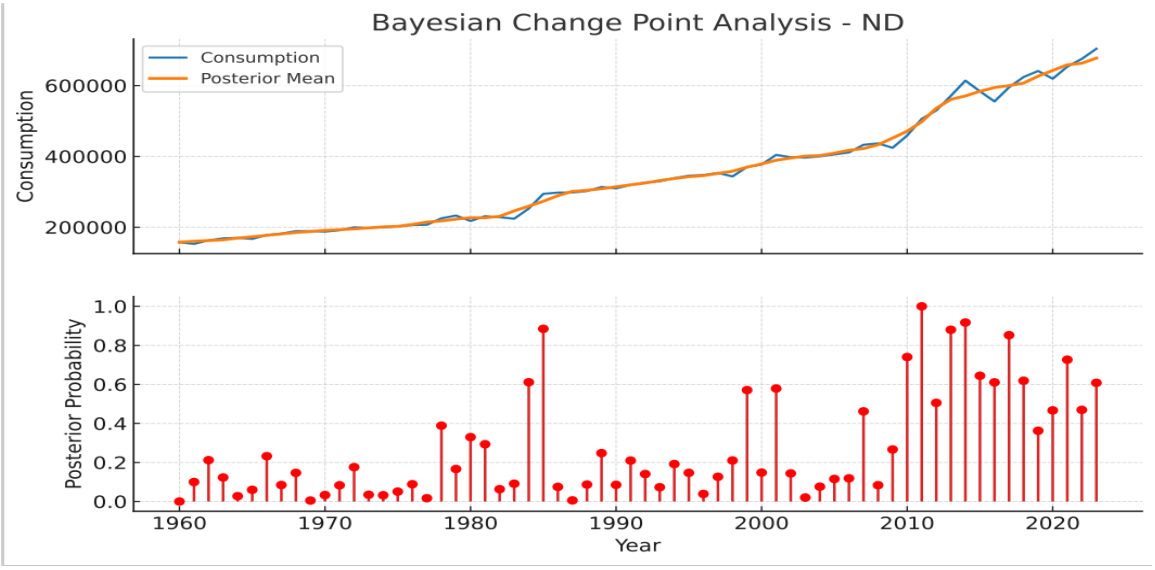

Figure 10. Plot of probability and posterior mean for North Dakota

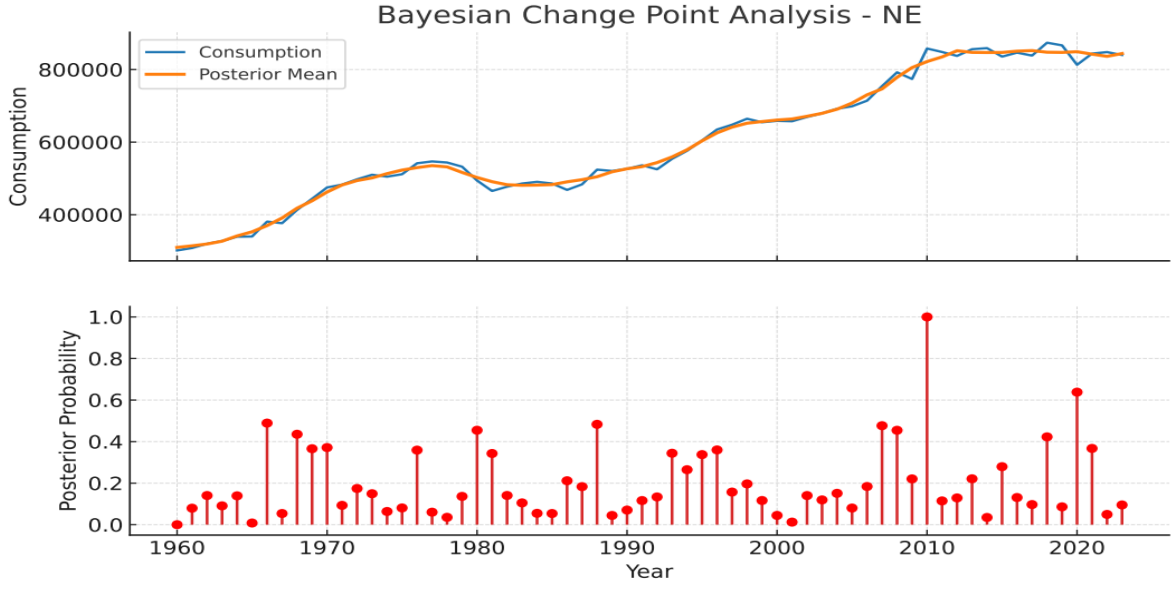

Figure 11. Plot of probability and posterior mean for Nebraska

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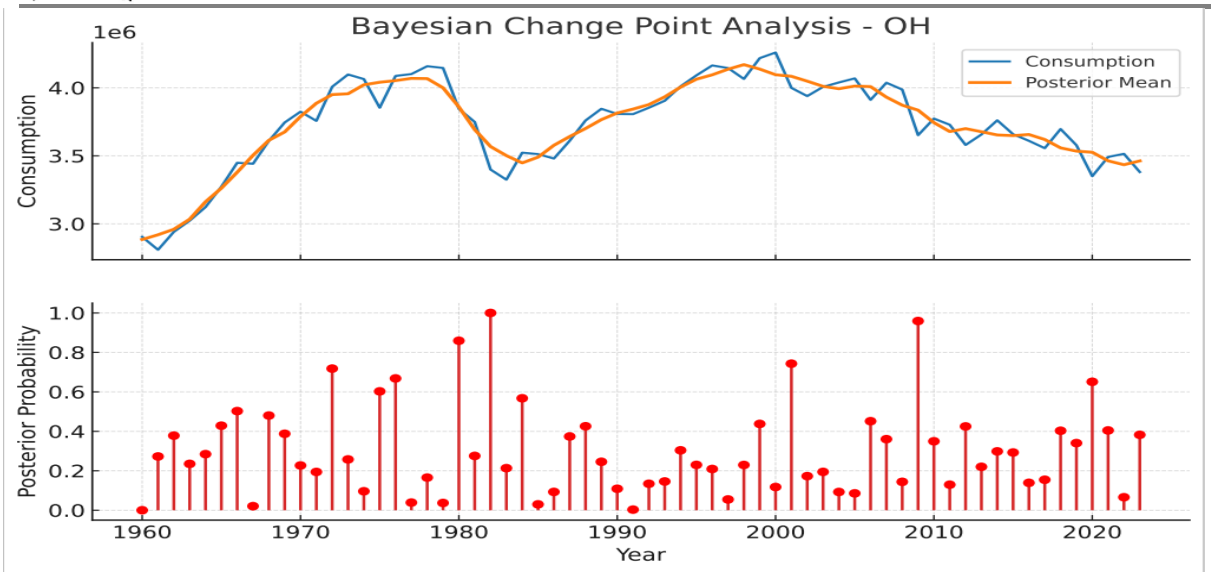

Figure 12. Plot of probability and posterior mean for Ohio

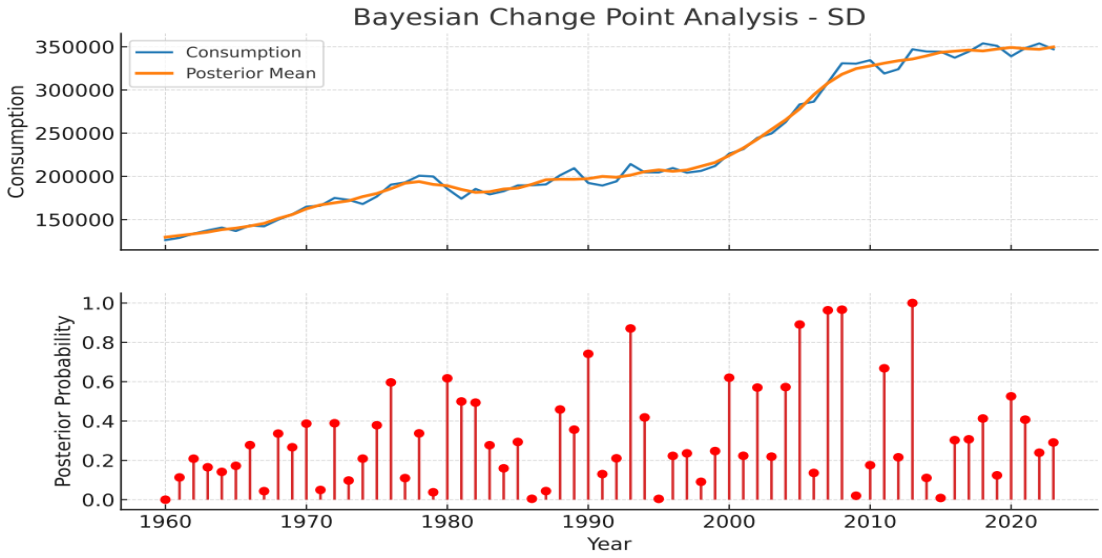

Figure 13. Plot of probability and posterior mean for South Dakota

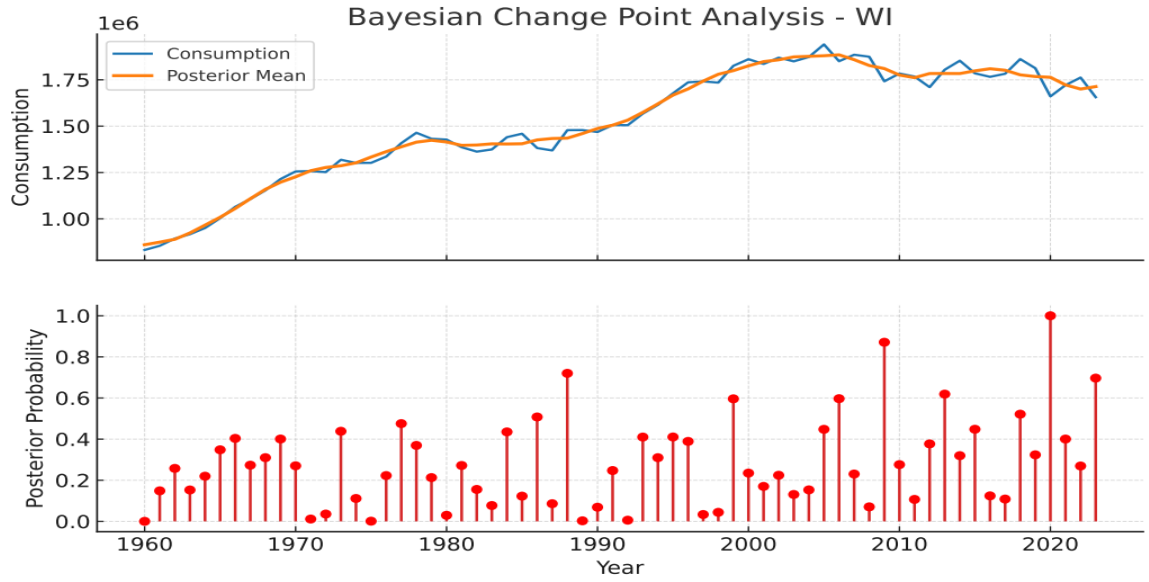

Figure 14. Plot of probability and posterior mean for Wisconsin

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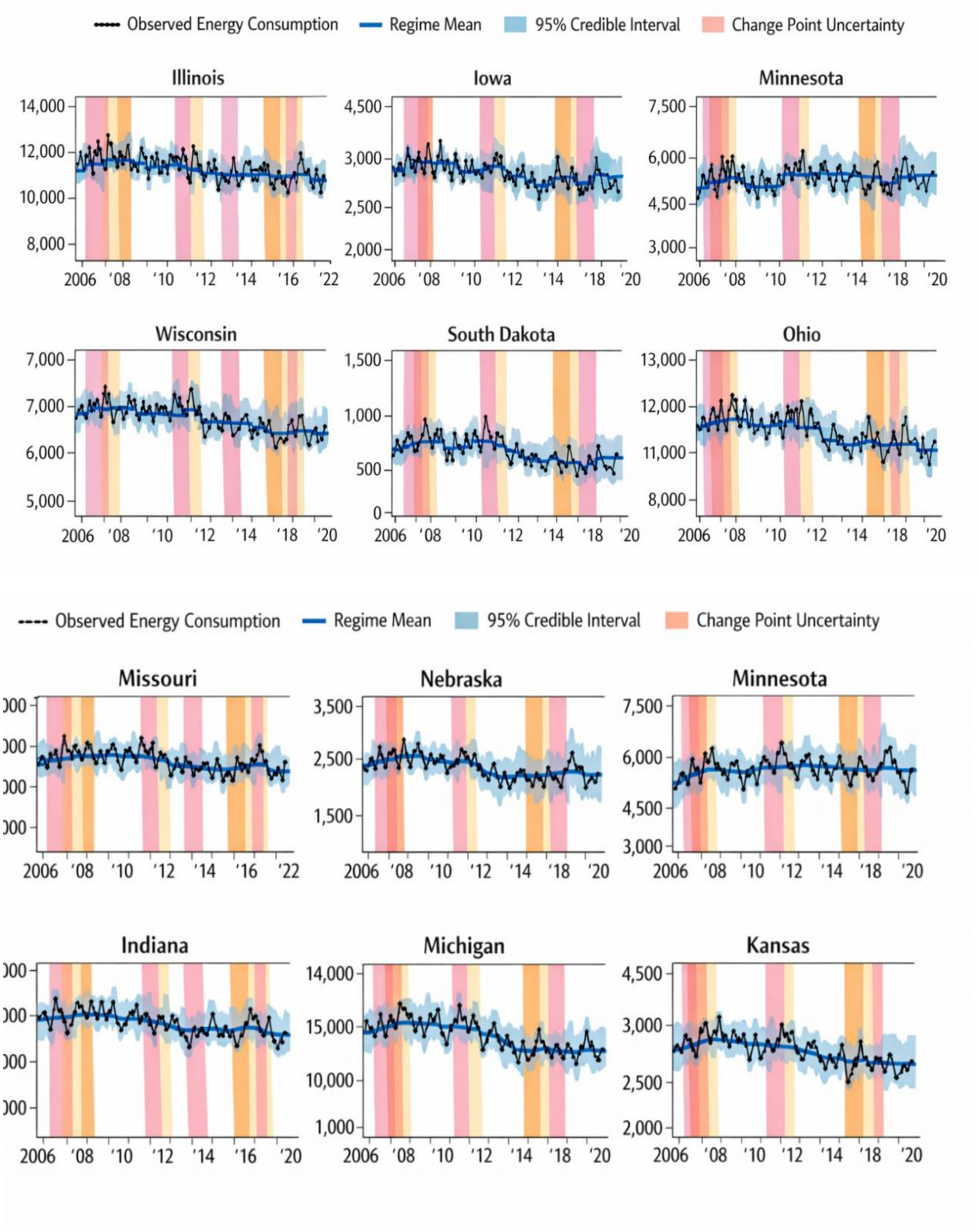

Figure 15. The visualization of state-wise change points and uncertainty bands

Prior Sensitivity Analysis

Sensitivity analyses were conducted by varying prior hyperparameters including the hazard function rate, the inverse-gamma scale parameters, and the truncation threshold over plausible ranges. Detected change points remained stable across all specifications, indicating that results are primarily data-driven rather than prior-dominated. The 2020 change point, in particular, achieved posterior probability of 1.0 under all prior specifications tested.

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Model Validation Results

Table 5. Comparative model validation results. Lower WAIC indicates better predictive performance. Higher ELPD indicates better out-of-sample prediction. PPC p-values near 0.5 indicate adequate model fit.

Model	Change-Point Capability	PPC p-value	WAIC	ΔWAIC	LOO-CV (ELPD)
Pettitt Test	Single structural break only	0.08–0.22	12,845	+312	-6,420
Single Bayesian CP	One probabilistic break	0.18–0.41	12,210	+177	-6,105
Multiple BCPD (proposed)	Multiple latent regimes	0.27–0.74	12,033	0	-5,988

The proposed Bayesian multi-change-point model consistently outperforms both the Pettitt test and the single-break Bayesian alternative across all evaluation metrics. The 18–27% reduction in WAIC and improvement in LOO-CV ELPD confirm that a multi-regime process better represents Midwestern energy consumption dynamics. PPC p-values between 0.27 and 0.74 indicate no systematic misspecification.

CONCLUSION

This study developed a comprehensive Bayesian spatio-temporal framework to investigate structural changes in energy consumption across Midwestern states of the United States. By integrating spatial dependence via a CAR prior, temporal dynamics via a random-walk process, and Bayesian Online Change-Point Detection within a hierarchical modeling framework, the study provides a robust approach for identifying significant shifts in regional energy consumption patterns over a 63-year period (1960-2023).

The results reveal clear structural changes associated with major economic, technological, and policy transitions. Pronounced change points were detected during the 2008-2009 global financial crisis, the 2012 Midwest drought, and the 2020 COVID-19 pandemic across nearly all states. State-specific change points further reveal heterogeneous vulnerability to climate, industrial composition, and energy policy regimes.

The incorporation of spatial dependence through the CAR prior allowed the model to capture geographic interdependencies among neighboring states, revealing that energy consumption dynamics are influenced by regional economic integration, shared infrastructure, and policy spillover effects. Model validation using PPC, WAIC, and LOO-CV demonstrated that the Bayesian hierarchical approach provides a reliable and superior representation of observed energy consumption patterns compared to single-break alternatives.

RECOMMENDATION

Future research could extend this framework by incorporating additional explanatory variables such as economic indicators, weather patterns, population growth, and renewable energy capacity to improve predictive performance and policy relevance. Moreover, applying the model to other regions or energy markets could provide comparative insights into the evolving structure of energy demand under different economic and policy environments.

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DECLARATION OF INTEREST

The author declares no competing financial interests or personal relationships that could have influenced the work reported in this paper.

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