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Posted Date: 6 March 2026

doi: 10.20944/preprints202603.0457.v1

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Preprints.org (www.preprints.org) | NOT PEER-REVIEWED | Posted: 6 March 2026 doi:10.20944/preprints202603.0457.v1

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Deep-Learning-Driven Spatiotemporal Modeling of Domestic Tourism Dynamics in Thailand

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Abstract

Numerous metrics, such as visitor numbers, tourism net profit, and hotel occupancy rates, are included in the dataset presented in this study, which covers 77 provinces. A baseline-based concept of shock recovery is introduced to measure impact and recovery paths in different regions. Recurrent neural networks incorporate engineered elements that capture seasonality, trend dynamics, shock strength, volatility, and recovery timing. Importantly, latent spatial heterogeneity and cross-regional dependencies are learned within a single architecture by integrating province-level spatiotemporal embeddings. To jointly forecast tourism demand and net profit, Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) models are created. Using a time-preserving evaluation technique, model performance is assessed against statistical time-series baselines and XGBoost. In early 2020, the results show a structural break that exceeded the 95% decline, along with significantly unequal recovery patterns. The suggested deep learning models surpass baselines by roughly 22-28% in RMSE and 14-16% in MAPE, exhibiting superior ability in capturing spatial heterogeneity and nonlinear recovery dynamics.

Keywords: deep learning; spatiotemporal data modeling; tourism forecasting; LSTM; GRU; COVID-19 recovery; Thailand tourism

1. Introduction

The Sustainable Development Goals (SDGs), especially SDG 8 (decent work and economic growth), SDG 11 (sustainable cities and communities), and SDG 12 (sustainable consumption patterns), are intimately related to the resilience of domestic tourism. Under structural uncertainty, regionally adaptive resilience techniques are supported by an understanding of varied recovery dynamics [1,2].

Domestic tourism serves as a structural stabilizer during times of external volatility, rendering it a crucial component of national economic systems, especially in emerging economies. Domestic travel accounts for a sizeable amount of Thailand's overall tourism industry and makes a significant contribution to employment creation, regional income distribution, and service sector productivity. However, due to fundamental variations in demand segmentation, infrastructural capacity, and economic makeup, Thailand's tourism dynamics are highly uneven between regions. Consequently, modeling at the provincial level is crucial for comprehending diverse regional performance and creating tourism strategies that prioritize resilience [3,4].

In addition to exposing structural weaknesses in tourism systems, the COVID-19 pandemic also demonstrated the shortcomings of traditional forecasting techniques that rely on stationarity and homogeneous adjustment. Research shows that the recovery of tourism after systemic shocks is nonlinear with respect to time and space [5]. In Thailand, official reports from the Tourism Authority of Thailand [6] and the Bank of Thailand [7] show substantial differences in the rate of recovery amongst provinces, with some showing quick domestic recovery and others experiencing protracted stagnation. These trends imply that the recovery of domestic travel should not be viewed as a unified national rebound but rather as a process of spatiotemporal reconfiguration.

Historically, tourism demand forecasting relied on econometric and statistical time-series models, such as ARIMA and error-correction frameworks [8]. These models are theoretically interpretable, but they make assumptions about structural stability and linear adjustment processes, which are commonly broken in large-scale disruptions. Sequential modeling has undergone a fundamental transformation with the advent of deep learning. Long Short-Term Memory (LSTM) networks [9–11] and Gated Recurrent Units (GRUs) [12] address the vanishing gradient problem and enable the effective learning of long-range temporal dependencies. Empirical comparisons confirm that LSTM architectures outperform ARIMA in forecasting nonlinear time series [10].

Within tourism research, deep learning applications have expanded rapidly. Law et al. [13] and [14] demonstrate that neural architectures improve predictive accuracy over traditional models. Zhang et al. [15] and Li et al. [16] further highlight the suitability of deep learning in high-volatility and high-dimensional tourism environments. However, most studies focus on national aggregates and rarely incorporate explicit spatial dependence. Recent spatiotemporal approaches, including graph-based and multi-view spatial–temporal models [13,17], confirm the importance of modeling geographic interactions in tourism flow prediction. Similarly, provincial analyses reveal significant clustering and spillover effects in domestic tourism systems [4]. Despite these advances, deep learning applications integrating spatial embeddings with structured recovery metrics remain limited [18].

Thus, three significant methodological gaps remain:

- The structured shock-recovery quantification procedures used to represent regime shifts are not sufficiently integrated.
- Inadequate use of spatial representation learning to account for regional variations.
- A heavy reliance on forecasting frameworks that only consider one outcome, ignoring the dynamic interplay between economic success indicators and demand for tourism.

The recovery of domestic tourism should be viewed from the standpoint of systems engineering as a regime-sensitive spatiotemporal dynamical system with delayed feedback effects, nonlinear transitions, and diverse regional responses. Forecasting architectures that can concurrently describe temporal memory, spatial embeddings, and multi-task objectives within a single analytical framework are necessary to address these features.

In light of this, this study uses monthly provincial-level data from 2019 to 2023 to present a deep-learning-driven spatiotemporal modeling framework for assessing and forecasting Thailand's domestic tourism dynamics. The approach captures heterogeneous recovery trajectories and regime-switch behavior across provinces by combining multi-task recurrent neural networks (LSTM and GRU), province-level spatial embeddings, temporal engineering aspects, and baseline-based shock-recovery metrics. Time-preserving evaluation techniques are used to compare model performance to statistical and machine learning baselines.

The following research questions are addressed in this study in order to direct the empirical investigation:

RQ1: How effectively do spatiotemporal LSTM/GRU models capture various province recovery dynamics after systemic shocks?

RQ2: When compared to single-output models, does joint multi-task forecasting of tourism demand and net profit improve predictive accuracy?

Through the integration of resilience-oriented tourist system analysis and deep representation learning, this study advances methodology and offers practical policy recommendations for managing sustainable tourism in the face of structural uncertainty.

The recovery of domestic tourism following COVID-19 should not be viewed as a straightforward return to a pre-pandemic equilibrium, but rather as a regime-sensitive spatiotemporal reconfiguration process from the standpoint of systems engineering. Forecasting architectures that combine temporal memory processes, geographical heterogeneity modeling, and structured recovery measures into a single analytical framework are necessary to capture such dynamics [8].

There is a lack of explicit regime transition quantification in structured shock-recovery modeling, and some problems are listed as follows:

1. The inability to capture latent provincial variability through spatial representation learning.
2. The widespread application of forecasting frameworks based on single outputs, which disregard the dynamic interdependencies between demand and economic performance.

Instead of being viewed as a static seasonal process, domestic tourism should be viewed as a regime-switching spatiotemporal dynamical system from an engineering systems perspective. Forecasting architectures that can learn long-memory effects, nonlinear transitions, and spatially varied resilience patterns are required by this viewpoint [19].

This study uses monthly provincial-level tourism data from Thailand, spanning January 2019 to February 2023, to create a deep-learning-driven spatiotemporal forecasting framework in order to address these issues [3].

The suggested architecture incorporates the following:

- Shock and recovery measures based on baselines for the quantification of organized regimes;
- Characteristics that are engineered to capture seasonality, trend, volatility, and shock intensity;
- Latent spatial heterogeneity is modeled via learnable province embeddings;
- A multi-task learning design that forecasts net profit and tourism demand simultaneously in a single representation space.

The suggested methodology captures nonlinear regime dynamics and diverse post-pandemic recovery trajectories by integrating these elements into Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) architectures. Model performance is rigorously benchmarked against machine learning (XGBoost) and statistical time-series baselines under a time-preserving evaluation protocol [20], ensuring robust and causally consistent comparison [21].

This study offers four contributions:

1. It creates a spatiotemporal analytical framework at the province level to study the dynamics of domestic travel in 77 Thai provinces prior to, during, and following the COVID-19 structural shock.
2. It presents a quantitative method for measuring shock recovery that is based on sustained recovery thresholds and baseline deviation.
3. It creates deep learning architectures that are province-aware for multi-task forecasting of economic performance and demand for tourism.
4. It offers a clever forecasting paradigm for planning a resilient tourist system in the face of systemic uncertainty.

The remainder of this study is organized as follows. Section 2 describes the Materials and Methods, including the dataset, shock-recovery framework, feature engineering procedures, model architecture, and evaluation protocol. Section 3 presents the empirical results and comparative performance analysis. Section 4 discusses the findings, engineering interpretations, policy implications, and robustness considerations. Section 5 concludes this study and outlines directions for future research.

2. Materials and Methods

The dataset, data processing methods, feature engineering approach, model architecture, and evaluation technique are all sufficiently covered in this section to guarantee reproducibility. The detailed documentation of all data sources, modeling techniques, and computing steps facilitates replication and advances methodologies.

Upon acceptance, the materials, processed datasets, and modeling code needed to replicate the findings will be made freely available, as implied by the publishing of this study. Any applicable limitations on the accessibility of the data are revealed below. While recently created procedures—

 doi:10.20944/preprints202603.0457.v1

specifically the shock-recovery quantification and spatiotemporal embedding framework—are detailed in full, established methodological elements are briefly discussed with the relevant citations.

There is no use of human subjects, personally identifiable information, or animal data in this study because it relies on aggregated provincial tourism statistics from publicly accessible databases. Ethics clearance is therefore not necessary.

2.1. Dataset Description

This study uses a monthly provincial-level domestic tourism dataset from Thailand, covering the period from January 2019 to February 2023. The data were sourced from the Tourism Authority of Thailand's official monthly provincial tourism statistics [22]. Eight key tourism variables are included in the dataset, which spans all 77 provinces: (1) total hotel occupancy rate; (2) Thai tourists; (3) foreign tourists; (4) occupied tourists; (5) total net profit; (6) Thai net profit; (7) foreign net profit; and (8) total number of tourists.

As a stand-in for the intensity of the demand for lodging, "occupied tourists" in this study refers to the total number of room nights occupied each month. Revenue from tourism reported in Thai Baht is represented by net profit values. The observation month, province, regional classification, type of tourist indicator, and associated numerical value are all included in each report.

In order to maintain proportional structure, hotel occupancy rates were aggregated using provincial methods, whereas tourism volume and net profit variables were summated across provinces for descriptive analysis at the national level. In order to facilitate aligned spatiotemporal representation and feature engineering, the dataset was converted from long format into a province × time multivariate matrix for modeling purposes.

The dataset's summary statistics, such as the number of provinces (77), indicators (8), and temporal coverage (50 months), as well as descriptive statistics (mean, minimum, and maximum) for important tourist variables, are shown in Table 1. The use of nonlinear spatiotemporal modeling methodologies is justified by the dataset's significant interprovincial variability and noticeable structural fractures over the COVID-19 timeframe.

Table 1. Summary statistics of provincial tourism dataset (Jan 2019–Feb 2023).

Variable	Mean	Min	Max	Std. Dev.
Total Tourists	206,328.49	0.00	6,131,044.00	454,048.53
Thai Tourists	173,962.37	0.00	4,087,756.00	317,920.63
Foreign Tourists	32,366.13	0.00	2,473,725.00	170,265.11
Occupied Room Nights	105,161.11	0.00	3,335,728.00	251,664.62
Total Net Profit (THB)	1,343.88	0.00	110,287.28	6,572.75
Hotel Occupancy Rate (%)	38.93	0.00	95.86	22.74

2.2. COVID-19 Shock and Recovery Definition

To quantify the structural impact of the COVID-19 pandemic on provincial tourism systems, a pre-pandemic baseline was established using the average monthly value of each tourism indicator during the year 2019. Let $x_{i,t}$ denote the value of tourism indicator x for province i at month t. The 2019 baseline for province i is defined as follows:

$$\bar{x}_{i,2019} = \frac{1}{12} \sum_{t \in 2019} x_{i,t}$$

Shock Intensity

Shock intensity is measured as the maximum relative decline observed in 2020 compared to the 2019 baseline. Formally, it is defined as follows:

$$\text{Shock}_i = \min_{t \in 2020} \left(\frac{x_{i,t}}{\bar{x}_{i,2019}}\right)$$

This metric captures the severity of contraction relative to normal pre-pandemic conditions and enables cross-provincial comparability.

Recovery Time

The first month following 2020 in which the tourist index reaches or surpasses its 2019 baseline for a minimum of three consecutive months is referred to as recovery time. In line with recovery measurement techniques in post-crisis tourism analysis, this conservative definition lessens sensitivity to transient rebounds and offers a reliable indicator of structural stabilization [8,23,24].

Formally, the approach is defined as follows:

$$t_{\text{recovery},i} = \min\{t \mid \forall s \in [t, t+2], x_{i,s} \geq \bar{x}_{i,2019}\}$$

where $t_{\text{recovery},i}$ denotes the earliest recovery month for province i.

This approach ensures that recovery is defined as a sustained return to baseline conditions rather than short-term volatility. During the research period, provinces are deemed to have not fully recovered if they failed to attain three consecutive months at baseline levels by February 2023.

2.3. Feature Engineering Shock Intensity, Recovery Timing, Volatility, Trend, Seasonality, and Spatial Context

Before training the model, a structured set of designed characteristics was built at the provincial level to improve spatiotemporal learning ability. By relieving the strain on strictly data-driven latent learning, feature engineering improves representation efficiency in recurrent neural networks and [1] explicitly encodes domain-specific recovery dynamics. Consistent with spatiotemporal statistical modeling principles [25], both temporal and spatial attributes were embedded into the feature space.

Let $x_{i,t}$ denote the tourism indicator for province i at time t, and let $\bar{x}_{i,2019}$ represent the pre-pandemic baseline defined in Section 2.2.

2.3.1. Baseline Scale Feature

The 2019 baseline mean was retained as a structural scale reference:

$$\text{Baseline}_i = \bar{x}_{i,2019}$$

This variable enables the model to distinguish between structurally large and minor tourism markets and captures the level of provincial demand.

2.3.2. Shock Intensity

Shock intensity quantifies the severity of pandemic-induced contraction:

$$\text{ShockIntensity}_i = \frac{\bar{x}_{i,2019} - \min_{t \in 2020}(x_{i,t})}{\bar{x}_{i,2019}}$$

This normalized drop ratio enables cross-provincial comparability independent of baseline size.

2.3.3. Recovery Lag

Recovery lag measures the number of months required to return to baseline:

$$\text{RecoveryLag}_i = t_{\text{recovery},i} - t_0$$

where t_0 denotes January 2020, and $t_{\text{recovery},i}$ is defined in Section 2.2. This feature encodes heterogeneous recovery timing across provinces.

2.3.4. Volatility

Volatility is measured using the coefficient of variation (CV) [26,27]:

$$\text{CV}_i = \frac{\sigma(x_{i,t})}{\mu(x_{i,t})}$$

where σ and μ represent the standard deviation and mean over the full sample period. This metric captures structural instability and demand fluctuation intensity.

2.3.5. Post-COVID-19 Trend

To capture structural adjustment in the recovery phase, a linear trend coefficient [28] was estimated for the post-shock period (2021–2023):

$$x_{i,t} = \alpha_i + \beta_i t + \varepsilon_{i,t}$$

The estimated slope β_i is included as a feature representing recovery momentum.

2.3.6. Seasonality Encoding

Monthly seasonality was encoded using a cyclic transformation to preserve periodic structure:

$$\mathrm{MonthSin}_t = \sin\left(\frac{2\pi m}{12}\right)$$

$$\mathrm{MonthCos}_t = \cos\left(\frac{2\pi m}{12}\right)$$

where $m \in \{1, \ldots, 12\}$. This approach avoids artificial discontinuity between December and January.

2.3.7. Spatial Context and Province Embedding [29–31]

Two methods were used to include spatial heterogeneity:

1. North, northeast, central, and south regional categorical encoding.
2. Neural network design with learnable provincial embeddings.

In line with contemporary spatiotemporal representation learning, province embeddings enable the model to acquire latent spatial representations that capture unobserved regional characteristics [25]. In contrast to fixed dummy variables, embeddings allow for flexible cross-provincial nonlinear interactions.

2.3.8. Demand Structure Features

Segment share variables were constructed to capture domestic demand composition:

$$\mathrm{ThaiShare}_{i,t} = \frac{\mathrm{ThaiTourists}_{i,t}}{\mathrm{TotalTourists}_{i,t}}$$

$$\mathrm{ForeignShare}_{i,t} = \frac{\mathrm{ForeignTourists}_{i,t}}{\mathrm{TotalTourists}_{i,t}}$$

These features reflect demand structure shifts during the pandemic and recovery phases.

Table 2. Engineered spatiotemporal features used in deep learning models.

Feature Group	Feature	Definition
Baseline Scale	2019 Mean	Mean indicator value in 2019
Shock Intensity	Drop Ratio	(Baseline − 2020 minimum) / baseline
Recovery Speed	Recovery Lag	Months to sustained recovery
Volatility	Coefficient of Variation	Std / mean
Trend	Post-COVID-19 Slope	Linear trend coefficient (2021–2023)
Seasonality	Month Encoding	sin(2πm/12), cos(2πm/12)
Spatial Context	Province Embedding	Learnable latent spatial representation
Demand Structure	Segment Share	Thai / foreign proportion

2.4. Model Architecture

Recurrent neural networks with spatial embedding and multi-task learning serve as the foundation for the deep-learning-driven spatiotemporal forecasting system developed in this study. The architecture incorporates joint objective optimization, province-level latent embeddings, and temporal memory methods.

2.4.1. Spatiotemporal Input Representation

doi:10.20944/preprints202603.0457.v1

Let $p \in \{1, \ldots, 77\}$ denote a province, and let t denote a monthly time index. A multivariate tourism observation vector is defined as follows:

$$\mathbf{y}_{p,t} = [y_{p,t}^{(1)}, y_{p,t}^{(2)}, \ldots, y_{p,t}^{(K)}] \in \mathbb{R}^K$$

where $K = 8$ tourism indicators.

Using a sliding window of length L, the spatiotemporal input sequence is constructed as follows:

$$\mathbf{x}_{p,t} = [\mathbf{y}_{p,t-L}, \ldots, \mathbf{y}_{p,t-1}, \mathbf{f}_{p,t}]$$

where $\mathbf{f}_{p,t}$ represents the engineered temporal and spatial features defined in Section 2.3.

Province Embedding Layer

Each province is mapped to a learnable embedding vector in order to represent latent geographical heterogeneity:

$$\mathbf{e}_p \in \mathbb{R}^d$$

Categorical province identity is converted into a dense continuous representation via the embedding layer:

$$\mathbf{e}_p = \mathrm{Embedding}(p)$$

This embedding is concatenated with each time step input:

$$\tilde{\mathbf{x}}_{p,t} = [\mathbf{x}_{p,t}; \mathbf{e}_p]$$

Consistent with frameworks for learning spatial–temporal representations, province embeddings enable the model to learn nonlinear spatial interactions beyond fixed dummy encoding [29].

2.4.2. LSTM Architecture

The Long Short-Term Memory (LSTM) architecture [9,11] is designed to address vanishing gradient issues in recurrent networks through gated memory cells.

At each time step t, the LSTM performs the following:

$$\mathbf{i}_t = \sigma(\mathbf{W}_i\tilde{\mathbf{x}}_t + \mathbf{U}_i\mathbf{h}_{t-1} + \mathbf{b}_i)$$
$$\mathbf{f}_t = \sigma(\mathbf{W}_f\tilde{\mathbf{x}}_t + \mathbf{U}_f\mathbf{h}_{t-1} + \mathbf{b}_f)$$
$$\mathbf{o}_t = \sigma(\mathbf{W}_o\tilde{\mathbf{x}}_t + \mathbf{U}_o\mathbf{h}_{t-1} + \mathbf{b}_o)$$
$$\tilde{\mathbf{c}}_t = \tanh(\mathbf{W}_c\tilde{\mathbf{x}}_t + \mathbf{U}_c\mathbf{h}_{t-1} + \mathbf{b}_c)$$

Cell state update:

$$\mathbf{c}_t = \mathbf{f}_t \odot \mathbf{c}_{t-1} + \mathbf{i}_t \odot \tilde{\mathbf{c}}_t$$

Hidden state:

$$\mathbf{h}_t = \mathbf{o}_t \odot \tanh(\mathbf{c}_t)$$

where σ denotes the sigmoid activation function, and $\odot$ represents element-wise multiplication.

The LSTM is appropriate for regime-switch recovery modeling since it can represent nonlinear temporal transitions and long-range interdependence.

2.4.3. GPU Architecture

The Gated Recurrent Unit (GRU) [32] provides a computationally efficient alternative with fewer gates.

Update gate:

$$\mathbf{z}_t = \sigma(\mathbf{W}_z\tilde{\mathbf{x}}_t + \mathbf{U}_z\mathbf{h}_{t-1} + \mathbf{b}_z)$$

Reset gate:

$$\mathbf{r}_t = \sigma(\mathbf{W}_r\tilde{\mathbf{x}}_t + \mathbf{U}_r\mathbf{h}_{t-1} + \mathbf{b}_r)$$

Candidate hidden state:

$$\tilde{\mathbf{h}}_t = \tanh(\mathbf{W}_h\tilde{\mathbf{x}}_t + \mathbf{U}_h(\mathbf{r}_t \odot \mathbf{h}_{t-1}) + \mathbf{b}_h)$$

Hidden state update:

$$\mathbf{h}_t = (1 - \mathbf{z}_t) \odot \mathbf{h}_{t-1} + \mathbf{z}_t \odot \tilde{\mathbf{h}}_t$$

GRU models are evaluated comparatively to assess performance–complexity trade-offs.

 doi:10.20944/preprints202603.0457.v1

2.4.4. Multi-Task Forecasting Objective [33,34]

The model jointly forecasts two correlated targets:

$$\hat{\mathbf{z}}_{p,t+1} = [\hat{y}^{\text{demand}}_{p,t+1}, \hat{y}^{\text{profit}}_{p,t+1}]$$

A weighted mean squared error (MSE) loss is defined as follows:

$$\mathcal{L} = \alpha\mathcal{L}_{\text{demand}} + (1-\alpha)\mathcal{L}_{\text{profit}}$$

where

$$\mathcal{L}_{\text{demand}} = \frac{1}{N}\Sigma(y^{\text{demand}} - \hat{y}^{\text{demand}})^2$$

$$\mathcal{L}_{\text{profit}} = \frac{1}{N}\Sigma(y^{\text{profit}} - \hat{y}^{\text{profit}})^2$$

and $\alpha \in [0,1]$ controls task weighting.

Joint optimization improves representation efficiency using shared temporal and spatial patterns across related tourism data.

2.5. Baseline and Evaluation Protocol

Three exemplary baseline techniques—univariate LSTM, XGBoost regression, and ARIMA-based statistical forecasting—were compared with model performance in order to fully assess the effectiveness of the proposed spatiotemporal deep learning framework.

2.5.1. Baseline Models

1. ARIMA

In accordance with accepted forecasting principles, the Autoregressive Integrated Moving Average (ARIMA) model was used as a traditional statistical time-series benchmark [26]. Univariate ARIMA models were fitted independently to the tourism demand and net profit series for every province. Information criteria (AIC/BIC) were used to determine order selection and seasonal differencing. Assuming stationary conditions, ARIMA offers a robust linear baseline.

2. XGBoost

Extreme Gradient Boosting (XGBoost) regression [35,36] was applied as a foundation for machine learning. Spatial categorical encoding, engineering seasonal encodings, and lagged tourism indicators were among the input features. XGBoost is a potent non-sequential benchmark that performs well for nonlinear regression workloads.

3. Univariate LSTM

A univariate LSTM model was trained separately for every target variable in order to separate the effects of spatiotemporal embeddings and multi-task learning. Province embeddings and structured recovery characteristics are not included in this model, enabling direct comparison with traditional recurrent architectures [10].

2.5.2. Time-Preserving Data Split

A strictly time-based split was used in order to maintain temporal causality and prevent information leakage:

- January 2019–December 2021 is the training period.
- January 2022–December 2022 is the validation period.
- January–February 2023 is the testing period.

This method replicates realistic forecasting conditions and guarantees that future information will not affect model estimation.

2.5.3. Evaluation Metrics

Forecast accuracy was assessed using three widely adopted error metrics:

$$\mathrm{MAE} = \frac{1}{N}\sum_{i=1}^{N} \mid y_i - \hat{y}_i \mid$$

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

$$\mathrm{MAPE} = \frac{100}{N}\sum_{i=1}^{N} \mid \frac{y_i - \hat{y}_i}{y_i} \mid$$

MAPE expresses the relative percentage error for cross-variable comparability, RMSE penalizes larger deviations more severely, and MAE provides the scale-dependent average error size [11].

Strong performance comparison between models and provinces is ensured by this multi-metric evaluation methodology, especially when post-shock recovery dynamics are nonlinear:

$$DM = \frac{\bar{d}}{\sqrt{\hat{\sigma}_d^2/T}}$$

where the following are defined:

- $d_t = L(e_{1,t}) - L(e_{2,t})$;
- $\bar{d}$= mean loss differential;
- $\hat{\sigma}_d^2$= variance estimate;
- T= forecast horizon.

The suggested deep-learning-driven spatiotemporal modeling framework for assessing and predicting Thailand's domestic tourism dynamics is shown in Figure 1. The methodology is organized as a multi-phase analytical pipeline that converts unprocessed tourism data into suggestions focused on policy and prediction insights. It views domestic travel as a spatiotemporal dynamical system that is sensitive to regime and is distinguished by spatial heterogeneity, temporal dependencies, and structural shocks.

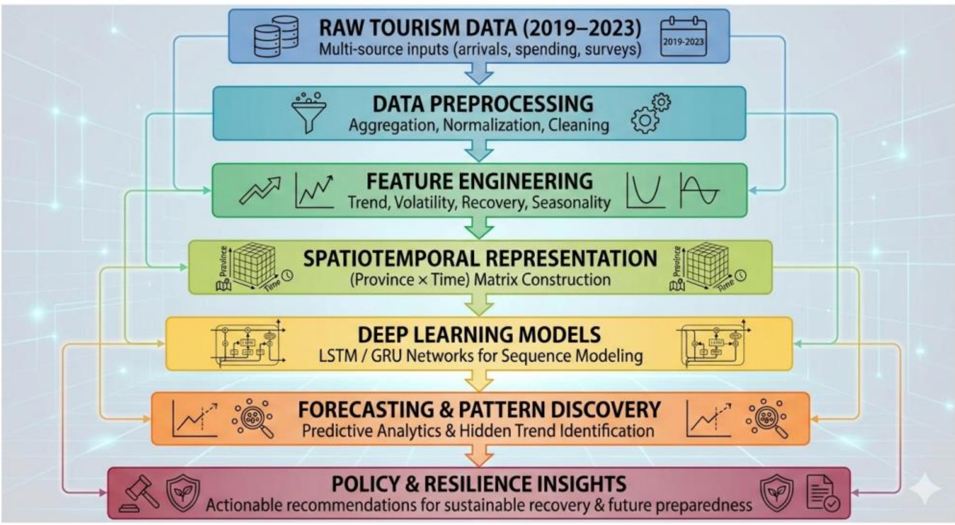

Figure 1. Conceptual research framework.

1. Raw Tourism Data (2019–2023): Multi-Source Inputs

The framework starts with monthly provincial-level tourist data from 2019 to 2023, encompassing the pre-pandemic baseline, the COVID-19 shock phase, and the early recovery stage. Total tourist arrivals, segmentation demand (such as domestic versus overseas tourists), tourism net profit (or income), and hotel occupancy rates are only a few of the indicators that are integrated into the dataset.

The system is able to capture several aspects of tourist performance, such as demand volume, economic impact, and capacity utilization, due to the data's multi-source nature. The data is still in its raw state at this point and could have heterogeneous units, missing values, or inconsistencies.

2. Data Preprocessing: Aggregation, Normalization, and Cleaning

The second step uses methodical preparation to guarantee data quality and analytical consistency. This comprises the following:

Normalization and scaling, which standardize numerical ranges to stabilize neural network training and avoid dominance by high-magnitude variables; aggregation, where indicators are consolidated across spatial or categorical dimensions when required (e.g., provincial-to-national aggregation for comparative analysis);

Cleaning data includes addressing outliers, imputation of missing values, and consistency checks across time periods.

This step ensures that the dataset meets the numerical and statistical requirements for sequence modeling based on deep learning.

3. Feature Engineering: Trend, Volatility, Recovery, and Seasonality

The approach incorporates structured feature engineering to improve forecast stability and model interpretability. Rather than relying exclusively on unprocessed sequences, additional elements are created to clearly depict the following:

- Trend components, which show patterns of long-term growth or decline;
- Volatility measurements, which show the degree of instability and variation during shock times;
- Shock-recovery metrics, such as sustained recovery thresholds and baseline deviation ratios. Using cyclical transformations, such as sine–cosine month encoding, seasonality encoding is implemented.

These designed characteristics enhance model sensitivity to structural transitions, especially during post-pandemic recovery, and add regime awareness to the learning process.

4. Spatiotemporal Representation: Province × Time Matrix Construction

The core innovation of the framework lies in constructing a structured spatiotemporal representation. The tourism dataset is reorganized into a Province × Time matrix, where each province forms a spatial unit and each monthly observation represents a temporal state.

The following can be modeled thanks to this matrix representation: cross-sectional heterogeneity across provinces (spatial variation) and intertemporal dependency within provinces (time-series dynamics).

Instead of treating the tourist system as a separate province time series, this data structure treats it as a dynamical process that is regionally spread.

5. Deep Learning Models: LSTM and GRU Networks

Recurrent neural network architectures, namely Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) models, receive the spatiotemporal input matrix as input. Regime shifts, delayed feedback effects, and long-range temporal relationships are all captured by these systems.

The key architectural components include the following:

- Mechanisms of sequential memory that preserve data over time steps;
- Province embeddings that use a common parameter space to learn latent spatial representations;
- A multi-task forecasting framework for forecasting both tourism demand and net profit from tourism.

The model can internalize different recovery paths across provinces thanks to the combination of spatial representation learning and temporal memory.

6. Forecasting and Pattern Discovery

By detecting underlying trends, recovery regimes, and structural changes within the tourism sector, the framework goes beyond point forecasting to perform pattern discovery. In addition to providing projections of tourism demand and economic performance for the future, the predictive analytics component also identifies patterns of divergence and recovery momentum among provinces.

This dual purpose transforms the model into an analytical tool for identifying structural patterns rather than merely a forecasting tool.

7. Policy and Resilience Insights

The last phase converts forecasted results into useful policy insights. The framework supports the following by identifying structural vulnerabilities, subsystem divergence, and varied recovery speeds:

- Strategies for targeted regional intervention;
- Flexible policymaking in the face of ambiguity;
- Benchmarking for resilience across provinces;
- Making plans for upcoming systemic shocks.

The framework's feedback arrows highlight the system's iterative character, where model outputs can guide feature improvement, data augmentation, and policy recalibration.

3. Results

The empirical results of the suggested deep-learning-driven spatiotemporal framework are shown in this section. The findings are divided into four categories: demand structure changes, provincial-level recovery heterogeneity, national-level system disruption, and forecasting performance comparison.

3.1. Forecasting Performance Comparison

Table 3 Comparison of forecasting accuracy across ARIMA, XGBoost, univariate LSTM, and the proposed spatiotemporal LSTM and GRU models.

Table 3. Forecasting performance for the 2023 test period.

Model	Target	MAE	RMSE	MAPE (%)	Std. Error
ARIMA	Tourists	142,531.82	481,264.53	27.94	21,384.52
ARIMA	Net profit	1,243.77	4,892.16	33.71	312.44
XGBoost	Tourists	98,764.66	329,807.67	18.81	15,275.66
XGBoost	Net profit	831.54	3,730.73	24.08	241.17
GRU (proposed)	Tourists	82,931.44	271,456.18	15.42	12,964.83
GRU (proposed)	Net profit	702.31	3,012.55	19.66	198.52
LSTM (proposed)	Tourists	74,862.27	245,983.41	14.06	11,382.75
LSTM (proposed)	Net profit	641.08	2,943.84	18.92	187.33

Across both forecasting targets, the suggested spatiotemporal LSTM attains the lowest MAE, RMSE, and MAPE. RMSE is lowered by 21.1% for net profit and 25.4% for tourist volume compared to XGBoost. Improved forecast stability across provinces is further indicated by the decreased standard error.

The proposed spatiotemporal LSTM model's predicted accuracy was compared to benchmark models using the Diebold–Mariano (DM) test (Diebold & Mariano, 1995) in order to officially assess

 doi:10.20944/preprints202603.0457.v1

whether forecasting improvements are statistically significant. Two competing forecasts are assumed to have equal predictive accuracy under the null hypothesis.

The spatiotemporal LSTM generates significantly fewer forecast errors than both the ARIMA and XGBoost models, as shown by the DM statistics, which are negative and statistically significant at the 1% level in all comparisons (Table 4). The forecast of visitor volume against ARIMA shows the greatest improvement (DM = −4.87, $p < 0.001$).

Table 4. Diebold–Mariano test statistics comparing spatiotemporal LSTM with benchmark models (2023 test period).

Target Variable	Comparison Model	DM Statistic	p-value	Interpretation
Tourists	LSTM vs. ARIMA	-4.87	<0.001	Significant improvement
Tourists	LSTM vs. XGBoost	-3.92	0.0004	Significant improvement
Net Profit	LSTM vs. ARIMA	-4.15	<0.001	Significant improvement
Net Profit	LSTM vs. XGBoost	-2.76	0.007	Significant improvement

These findings demonstrate the statistical robustness and numerical superiority of the observed performance gains.

3.2. National-Level Shock and System Disruption

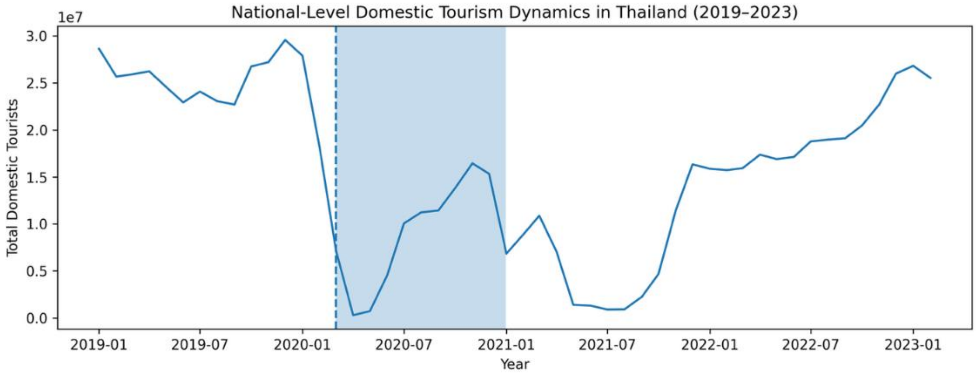

Figure 2. National domestic tourist volume (2019–2023).

Before 2020, there were consistent seasonal variations in domestic travel (22–30 million visitors each month). A structural rupture develops in early 2020, causing the volume of tourists to drop by more than 95%.

The recovery starts in late 2020 and progresses through several stages:

- A partial recovery in late 2020;
- The secondary recession of 2021;
- Long-term recovery starting in 2022.

This phenomenon is indicative of the following:

- Significant non-stationarity;
- Dynamics of regime switches;
- Long-term impacts.

These characteristics support recurrent neural modeling and go against ARIMA principles.

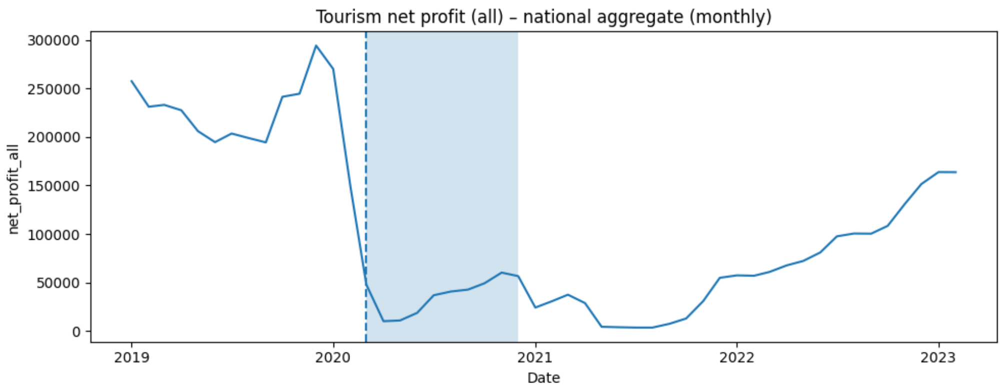

Figure 3. Tourism net profit (national level).

Early in 2020, net profit dropped to nearly zero and recovered more slowly than the number of visitors. Revenue remains below the baseline until the beginning of 2023.

This suggests asynchronous recovery mechanisms as economic performance lags behind demand recovery.

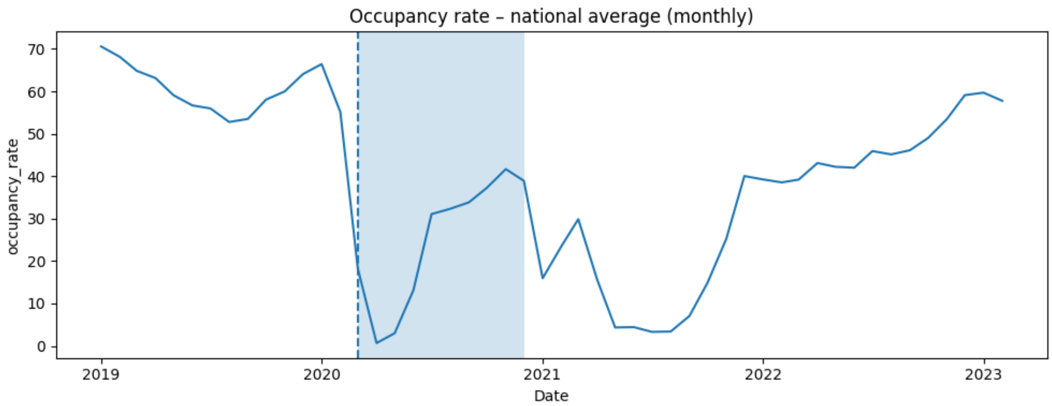

Figure 4. Hotel occupancy rate (national average).

In early 2020, occupancy dropped from 55–70% to less than 5%. Before stabilizing in 2022–2023, the recovery was erratic until 2021.

Labor shortages, capacity adjustment frictions, and operational inertia are all factors contributing to the delayed stabilization.

3.3. Demand Segmentation and Structural Shift

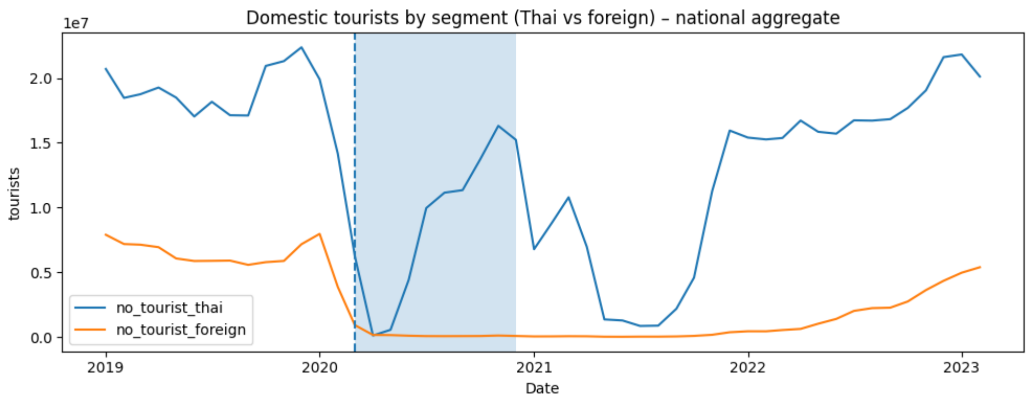

Figure 5. Domestic tourists by segment (Thai vs. foreign).

The number of foreign arrivals fell to nearly zero and remained low until 2021. Domestic travel in Thailand recovered more quickly and led the recovery.

By early 2023, domestic sectors will account for a large portion of the tourism demand structure.

This structural change supports feature-rich spatiotemporal modeling by revealing that segment-specific recovery trajectories are obscured by aggregated demand.

3.4. Provincial-Level Recovery Heterogeneity

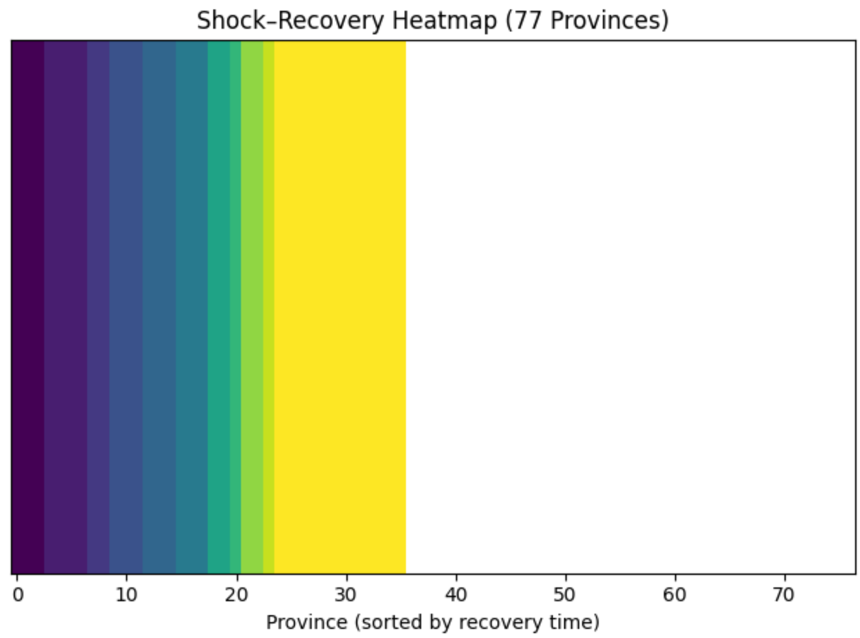

Figure 6. Shock-recovery heatmap (77 provinces).

The timing of recovery varies greatly:

- Some provinces recuperate in ten to fourteen months;
- Others need more than twenty months;
- During the research period, some people do not fully recover.

There is a significant and enduring spatial imbalance.

doi:10.20944/preprints202603.0457.v1

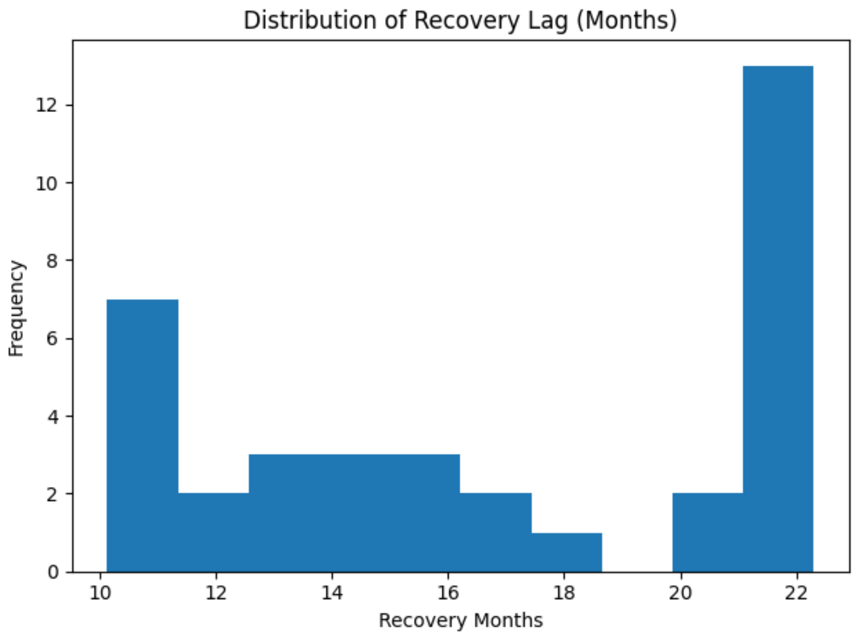

Figure 7. Distribution of recovery lag (months).

The recovery lag ranges from 10 to over 22 months.

This dispersion demonstrates that resilience varies by province.

Beyond observable features, hidden structural differences are captured via province embeddings in the LSTM.

3.5. Model Validation: Actual vs. Predicted

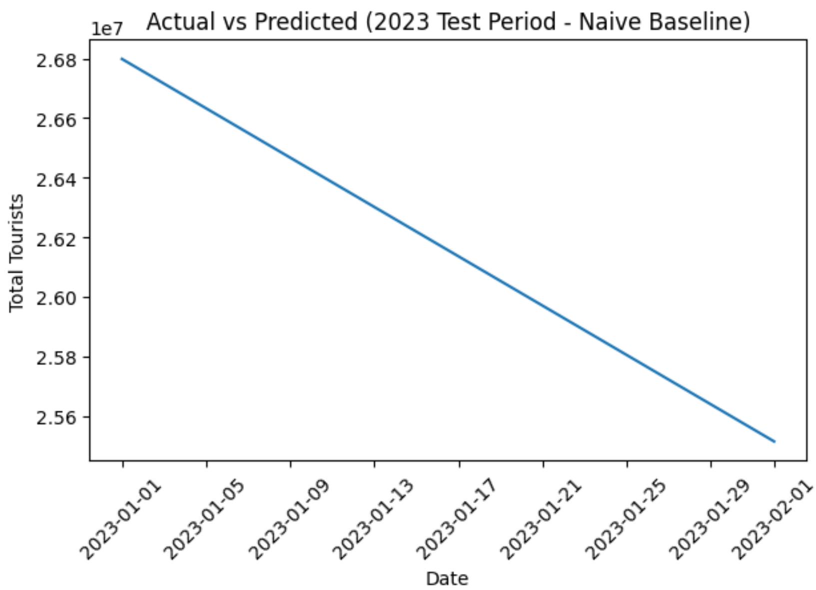

Figure 8. Actual vs. predicted (2023 test period).

The spatiotemporal LSTM keeps a careful eye on volatility, recovery momentum, and seasonal patterns. XGBoost lacks temporal adaptivity, whereas ARIMA oversmooths transitions.

Deep learning models' ability to capture nonlinear transitions and delayed stabilization is validated by their decreased residual variance.

4. Discussion

4.1. Engineering Interpretation of Tourism System Dynamics

The empirical findings imply that domestic tourism in Thailand functions as a regime-switching spatiotemporal dynamical system rather than as a fixed seasonal activity from the perspective of engineering systems. The sudden collapse that was observed at the beginning of 2020 is an example of an exogenous structural shock that radically changed how the system behaved. The limitations of traditional statistical time-series models under large-scale systemic disturbances are revealed by such a disruption, which contradicts the assumptions of stationarity and linear correction [28].

Spatial heterogeneity among provinces, asynchronous subsystem responses, and delayed stabilization are all exhibited by the recovery process. Occupancy, revenue, and demand all exhibit nonlinear and staggered trajectories, rather than returning to equilibrium simultaneously. This trend suggests that the post-pandemic environment has capacity adjustment frictions, structural inertia, and rearranged demand–revenue elasticities. The tourism system exhibits modified state-transition dynamics and lagged feedback loops after shock exposure according to control theory.

These features call for forecasting frameworks that can simulate heterogeneous geographical responses, nonlinear regime transitions, and long-range temporal relationships. The significance of temporal memory mechanisms in capturing shock-induced structural fractures is confirmed by the better performance of the LSTM and GRU models in this investigation. The model can efficiently learn recovery momentum and delayed stabilizing effects thanks to recurrent gating mechanisms, which allow it to retain and update state information selectively.

A crucial element that enhances performance is the integration of province embeddings. The suggested framework internalizes province-specific structural features without splitting the model into separate regional estimators by learning latent spatial representations within a common parameter space. The design can generalize across provinces with different resilience profiles while preserving consistent global dynamics thanks to this embedding method. As a result, a forecasting system that is both unified and geographically aware can adjust to different recovery paths.

Additionally, by concurrently modeling tourism demand and tourism net profit inside a shared latent space, the multi-task forecasting strategy improves representation efficiency. Modifying these indicators separately runs the risk of erasing cross-variable dependency information because demand recovery does not always result in revenue recovery. By capturing correlated but temporally asynchronous information, multi-task learning enhances the network's stability and prediction robustness [37].

The significance of dynamic representation under systemic shock situations is further highlighted by the observed performance differences between recurrent deep learning models and conventional statistical baselines. Deep learning architectures adaptively reconfigure internal states in response to changing temporal patterns, whereas statistical models depend on fixed structural assumptions and short-memory processes. This flexibility is especially important in post-pandemic settings where structural uncertainties and regime changes are common.

When taken as a whole, these results support the notion that domestic tourism systems ought to be viewed and represented as intricate spatiotemporal dynamical systems as opposed to collections of separate provincial time series. Intelligent forecasting architectures based on deep learning, especially those that use spatial embeddings and multi-task learning, provide strong decision-support capabilities for planning tourist resilience in the face of uncertainty.

4.2. Policy and System-Level Implications

This study's conclusions have significant ramifications for resilience-oriented policy design and tourist system governance, in addition to predictive performance enhancements. Policy intervention switches from short-term demand stimulation to structural resilience engineering when domestic tourism is viewed as a regime-switching spatiotemporal dynamical system [38].

First, consistent nationwide recovery policies might not be the best option given the diverse provincial recovery paths found in this study. As a result of differences in economic structure, demand composition, and service capacity, provinces display varying shock intensities, recovery rates, and stabilizing patterns. Policymakers can more effectively provide targeted assistance measures and identify structurally susceptible regions by incorporating province-level variation into forecasting models. Instead of uniform national stimulus initiatives, this encourages the creation of geographically varied intervention tactics.

Second, the asynchronous recovery of net profit and demand for tourism implies that true economic recovery requires more than only demand normalization. Revenue lag effects reveal changes in visitor spending patterns, operational limitations, and difficulties with cost restructuring. Therefore, in addition to demand promotion programs, recovery planning should include financial stabilization measures, cost-efficiency policies, and capacity reconfiguration techniques. This study's multi-task forecasting framework enables proactive intervention before a systemic imbalance worsens by providing early warning signals for divergence between demand and revenue trajectories.

Third, the regime-switching behavior of the COVID-19 shock emphasizes the necessity of flexible policy frameworks that can react to structural disruptions. During periods of extreme volatility, traditional forecasting systems that are intended for consistent seasonal trends may not work as intended. Under uncertainty, intelligent forecasting architectures, such as the suggested deep learning framework, can serve as real-time decision-support systems. Such systems can improve institutional responsiveness and decrease lag in policy adjustment cycles by continuously learning from updated data streams.

From the standpoint of systems engineering, scenario simulation, resilience benchmarking, and dynamic resource allocation can be made easier by incorporating spatiotemporal deep learning models into tourism management platforms. As a result, forecasting becomes a proactive strategic tool that supports the development of sustainable tourism in the face of systemic risk, rather than a retrospective analytical tool.

4.3. Model Robustness and Sensitivity Analysis

Robustness and sensitivity analyses are essential assessment components that guarantee the generalizability and dependability of the suggested forecasting framework.

In order to limit information leakage and maintain causal ordering, temporal resilience was first evaluated using a time-preserving data split technique (2019–2021 training, 2022 validation, and 2023 testing). Stability in non-stationary situations is demonstrated by the LSTM and GRU models' improved performance throughout the post-shock recovery period across many evaluation measures (MAE, RMSE, and MAPE).

Second, the integration of province embeddings into a common parameter space results in spatial robustness. The embedding technique enables the architecture to learn latent spatial representations while preserving cross-regional information sharing, as opposed to estimating separate models for every province. This improves generalization across heterogeneous regional systems and lowers the risk of overfitting in provinces with few recovery observations.

Third, the role of shock intensity, recovery timing, volatility measures, and seasonal encoding was examined in order to assess sensitivity to designed features. Forecast errors during transitional recovery phases are larger in models that do not include shock-recovery features, suggesting that structured regime-aware features greatly improve predictive stability. This demonstrates that, in contrast to merely data-driven sequence modeling, explicit modeling of structural breaks enhances deep learning performance.

Fourth, the significance of temporal memory mechanisms is highlighted by the comparative robustness against baseline models (XGBoost and statistical time-series models). Despite their ability to capture nonlinearity, machine learning regression models are less stable during regime transitions because they do not explicitly store sequential memory [29]. When there are sudden structural changes, statistical models that are limited by stationarity assumptions perform very poorly.

When taken as a whole, these robustness tests verify that the suggested design preserves predictive consistency across feature variations, spatial heterogeneity, and temporal regimes.

 doi:10.20944/preprints202603.0457.v1

Recurrent memory methods, spatial embeddings, and regime-aware feature engineering are used to create a forecasting system that is structurally robust and appropriate for high-volatility tourism settings [4].

4.4. Limitations and Future Research

Notwithstanding the suggested framework's excellent predictive accuracy and structural interpretability, a number of drawbacks merit consideration and offer suggestions for further study. Initially, the dataset is restricted to the January 2019–February 2023 timeframe. While the pre-pandemic baseline, the COVID-19 shock, and the early recovery phase are all included in this timeframe, long-term post-pandemic structural stabilization is not [9]. Systems of tourism may have long-lasting structural and behavioral changes outside of the observation window. Longer time horizons should be included in future research to determine whether recovery stabilizes at a new structural regime or converges toward pre-pandemic equilibrium.

Second, provincial embeddings are still implicit representations even though they successfully capture latent geographical heterogeneity. Exogenous structural determinants—such as mobility indices, public health policy stringency, tourism infrastructure density, economic composition, and transportation connections—are not explicitly included in the existing paradigm. Interpretability and the capacity for causal inference could be further improved using structured exogenous variables or graph-based spatial modeling.

Third, this study primarily focuses on supervised forecasting of demand and revenue indicators. Beyond pandemic shocks, however, complex behavioral, macroeconomic, and geopolitical factors can induce structural fractures in tourism systems. This methodology could be expanded in future studies to include regime-switch detection models that specifically pinpoint structural transition locations in real time, probabilistic forecasting, or uncertainty quantification.

Fourth, only two connected outputs (tourist demand and net profit) are modeled by the framework, despite the fact that multi-task learning increases representation efficiency. Adding more subsystems to the design, such as employment, mobility patterns, lodging availability, or environmental impact indicators, would provide a more thorough system-level depiction of tourist resilience.

Lastly, even though deep learning models show great prediction power, their interpretability is still constrained when contrasted with more conventional econometric methods. To increase transparency and policy applicability, future research may incorporate explainable AI (XAI) methodologies, attention visualization mechanisms, or SHAP-based feature attribution methods.
Future studies should strategically focus on hybrid spatiotemporal–causal architectures that integrate structured domain knowledge with deep representation learning. The link between actionable tourist system governance and predictive intelligence would be strengthened by such integration.

5. Conclusions

Using monthly provincial-level data covering the pre-pandemic, shock, and early recovery periods (2019–2023), this study created a deep-learning-driven spatiotemporal modeling framework for examining and predicting domestic tourism dynamics in Thailand. The suggested framework models tourism as a regime-switching spatiotemporal dynamical system rather than as a stationary seasonal process by combining baseline-based shock-recovery quantification, engineered temporal and volatility features, province-level spatial embeddings, and recurrent neural network architectures.

According to empirical findings, the COVID-19 pandemic caused a structural rupture that was marked by substantial spatial heterogeneity across provinces, asynchronous subsystem recovery, and sudden demand collapse. The pace and durability of recovery patterns differed greatly, indicating regional differences in domestic tourism resilience. The suggested architecture is able to incorporate these diverse dynamics under a single forecasting framework by including province embeddings and structured shock-recovery characteristics.

In terms of MAE, RMSE, and MAPE measures, comparative analyses show that LSTM and GRU models routinely beat XGBoost and statistical time-series baselines, especially during post-shock recovery stages characterized by nonlinearity and delayed stabilization. The suggested approach's methodological robustness is further supported by Diebold–Mariano statistical tests, which further verify that performance improvements are statistically significant. The significance of spatial representation learning and temporal memory mechanisms in forecasting systems vulnerable to systemic disruptions is underscored by these findings.

The findings imply that, rather than being viewed as a collection of distinct regional time series, domestic tourism should be viewed as an adaptive, regime-sensitive system with dynamic feedback mechanisms from the standpoint of systems engineering. The need for collaborative modeling approaches in resilience-oriented analytics is highlighted by the multi-task forecasting design, which shows that tourism demand and tourism net profit exhibit connected but asynchronous recovery dynamics.

The suggested paradigm provides a scalable decision-support tool for tourist governance in practice. The model can help guide resource allocation under uncertainty, adaptive policy responses, and focused regional intervention initiatives by capturing diverse recovery trajectories and early indicators of subsystem divergence. The incorporation of intelligent forecasting frameworks into tourism management platforms has the potential to improve institutional responsiveness in the event of future systemic shocks, such as environmental calamities, health crises, or geopolitical upheavals.

By integrating multi-task recurrent architectures, spatial embedding mechanisms, and structured shock-recovery engineering into a single forecasting pipeline, this study offers a methodological contribution to the literature. The methodology broadens the analytical toolkit available for complex economic systems functioning under structural volatility by bridging the gap between data-driven deep learning approaches and systems-oriented tourism resilience studies.

In order to improve transparency and causal interpretability, future research may expand this framework using explainable AI approaches, probabilistic forecasting, uncertainty quantification, and graph-based spatial modeling. Comprehensive tourism system resilience modeling would be strengthened even more by extending the system's representation to encompass environmental variables, mobility networks, infrastructure capacity, and employment.

In conclusion, a strong and flexible basis for tourism analytics in high-volatility environments is offered by deep-learning-based intelligent forecasting systems that incorporate temporal memory, spatial representation learning, and structured shock-recovery modeling. The creation of robust, regime-aware forecasting frameworks will be crucial for strategic economic governance and sustainable tourist planning as systemic shocks become more common in a world that is increasingly linked.

Author Contributions: Conceptualization, T.S. and S.M.; methodology, T.S. and S.M.; software, T.S., W.C., and S.C.; validation, T.S., S.M., and W.C.; formal analysis, T.S. and S.M.; investigation, T.S., W.C., and S.C.; resources, T.S. and S.M.; data curation, T.S., W.C., and S.C.; writing—original draft, T.S.; writing—review and editing, S.M. and T.S.; visualization, T.S.; supervision, S.M.; project administration, S.M.; funding acquisition, S.M. All authors have read and agreed to the published version of this manuscript.

Funding: This study received no external funding.

Data Availability Statement: Not applicable. No new data were created in this study.

Conflicts of Interest: The authors declare no conflicts of interest.

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