Hybrid LSTM–TCN Architecture for Seasonal Income Forecasting in Rural Tourism Using Macroeconomic and Tourism Indicators

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This study proposes a Hybrid RTLSTM–TCN deep learning architecture for forecasting seasonal income in rural tourism using integrated macroeconomic and tourism indicators. The RTLSTM component captures long-term sequential dependencies, while the TCN block models short-term temporal variations through dilated causal convolutions. The model was evaluated against benchmark approaches including ARIMA, KELM, MSS-KELM, B-SAKE, RNN, BiLSTM-TN, and SAE-LSTM. Empirical results on multi-year tourism datasets demonstrate that the proposed RTLSTM–TCN achieves the lowest RMSE (0.18) and MAE (0.09) with the highest R² (0.85), outperforming existing machine learning and deep learning baselines. This approach improves forecasting robustness under seasonal and macroeconomic volatility, offering a decision-support tool for tourism policy planning and economic sustainability.

Povzetek:

1 Introduction

Tourism is increasingly recognized as a key driver of rural economic development, contributing not only to local employment and income generation but also to the preservation of cultural heritage and the promotion of community-based entrepreneurship. Rural tourism, however, presents unique challenges due to its high seasonality, uneven demand distribution, and susceptibility to external shocks such as pandemics, natural disasters, or economic fluctuations. Accurate forecasting of tourism demand in these contexts is therefore critical for effective resource allocation, infrastructure planning, and sustainable development. Traditional statistical models often fail to capture the complex, non-linear patterns inherent in rural tourism demand, prompting the exploration of hybrid deep learning approaches that integrate multiple neural network architectures to improve predictive performance [1].

Long Short-Term Memory (LSTM) networks have emerged as a robust tool for modeling sequential and time-dependent data. Unlike conventional statistical methods, LSTM networks can capture long-term dependencies in tourist arrival sequences, allowing for improved prediction accuracy even when datasets are incomplete or partially sparse. For instance, recent studies have demonstrated that LSTM-based models can effectively forecast tourist inflows in contexts with seasonal fluctuations and post pandemic recovery periods, accommodating irregularities that traditional autoregressive or exponential smoothing models often fail to address [2][3]. These models also allow for the integration of exogenous factors, including local events, socio-economic conditions, and transportation accessibility, which are particularly influential in rural tourism scenarios [4].

While LSTM models excel at capturing temporal dependencies, they are limited in representing spatial relationships or hierarchical structures that exist across different rural destinations. To address this limitation, hybrid architectures combining LSTM with Convolutional Neural Networks (CNNs) or Temporal Convolutional Networks (TCNs) have been increasingly adopted. CNN-LSTM hybrids, for example, leverage CNN layers to extract spatial features such as the geographic distribution of attractions or demographic characteristics of visitors while LSTM layers capture the temporal evolution of tourist arrivals. Such integration enables models to simultaneously account for spatial heterogeneity and temporal variability, thereby enhancing forecasting robustness and precision [8][9].

Empirical applications of these hybrid architectures underscore their effectiveness. A study implementing a hybrid CNN-LSTM framework for rural tourism demand forecasting found that the model outperformed both single LSTM and conventional statistical models in predicting tourist inflows, particularly during high variability periods affected by COVID-19 disruptions [9]. Similarly, a hybrid deep learning framework that combined multiple network layers for feature extraction and sequence modeling demonstrated high accuracy in capturing seasonal patterns and sudden demand shifts in tourism datasets [1][8]. These approaches not only improve the reliability of predictions but also provide actionable insights for resource planning, marketing strategies, and policy interventions.

Beyond forecasting tourist volumes, hybrid deep learning models are increasingly applied to understand visitor behavior and engagement. By incorporating multi-dimensional inputs such as social media sentiment, transaction data, and visitor reviews, CNN-LSTM models can identify latent patterns in tourist preferences and predict future engagement with rural tourism destinations [10]. Such analyses are particularly valuable in regions where tourism flows are highly variable and sensitive to local conditions, allowing managers to implement targeted strategies for enhancing visitor satisfaction and optimizing service delivery.

In addition, hybrid architectures demonstrate significant resilience to irregularities and disruptions in data. Tourism demand is highly susceptible to external shocks, which can abruptly alter patterns and render traditional forecasts inaccurate. By combining LSTM's ability to model sequential dependencies with CNN or TCN layers that capture structural patterns in input features, hybrid models can adapt to these disruptions and maintain predictive reliability [2][6]. This capability is critical for rural tourism, where unexpected events such as extreme weather, public health crises, or socio-economic changes can rapidly influence tourist arrivals and spending patterns.

The effectiveness of hybrid models is further supported by the availability of diverse, multimodal datasets in contemporary tourism research. Quantitative data such as arrival counts, accommodation occupancy rates, and transportation usage can be combined with qualitative information, including cultural activity participation, visitor sentiment, and social media engagement. Hybrid CNN-LSTM and LSTM-TCN architectures are particularly well-suited to processing these heterogeneous datasets, extracting meaningful patterns across temporal, spatial, and behavioral dimensions to generate accurate and actionable forecasts [8][10]. This aligns with the broader trend toward smart tourism, in which data driven approaches enable more responsive, adaptive, and sustainable rural tourism management.

In summary, rural tourism forecasting requires approaches that can capture non-linear temporal patterns, spatial heterogeneity, and visitor behavior dynamics. Traditional statistical and timeseries models are often insufficient for this purpose, especially under conditions of seasonal variability or external disruptions. Hybrid deep learning architectures, such as CNN-LSTM and LSTM-TCN models, have demonstrated substantial promise in addressing these challenges. By integrating temporal sequence modeling with spatial and feature extraction capabilities, these models improve forecasting accuracy, enable nuanced visitor behavior analysis, and support evidence-based management and policy decisions. Empirical evidence indicates that hybrid deep learning models consistently achieve higher accuracy than single model architectures or traditional forecasting methods in predicting tourist arrivals and understanding visitor behavior. By effectively integrating spatial, temporal, and feature based information, these models enhance both operational efficiency and strategic decision making in rural tourism contexts. Therefore, hybrid deep learning approaches are increasingly recognized as essential tools for promoting sustainable, resilient, and data-informed management of rural tourism systems.

2 Contributions

The primary contribution of this study lies in the design of a hybrid RTLSTM-TCN model that effectively integrates the sequential learning capabilities of LSTM with the parallel temporal pattern extraction of TCN, ensuring robustness in handling complex tourism data. Unlike conventional methods such as ARIMA and KELM, or hybrid optimization approaches like B-SAKE and MSS-KELM, the proposed model captures both long-term dependencies and short-term fluctuations simultaneously, thereby enhancing predictive accuracy. Furthermore, the study provides a systematic comparative evaluation of eight models across diverse categories—statistical, machine learning, deep learning, and hybrid—which offers comprehensive insights into their relative performance. The inclusion of macroeconomic and tourism-specific indicators further strengthens the forecasting framework, ensuring broader applicability in real-world scenarios. In addition, by presenting visually intuitive performance comparisons through diverse plots, the study enhances interpretability for stakeholders. Collectively, this work establishes RTLSTM-TCN as a state-of-the-art forecasting model and contributes a practical decision-support tool for policymakers and planners in rural tourism development.

3 Related work

Recent research in rural tourism forecasting has increasingly emphasized the use of hybrid deep learning approaches that integrate multiple neural network architectures to capture both temporal and spatial dynamics. Studies have explored the combination of autoregressive models with LSTM networks to enhance predictive performance under complex, seasonally varying, and post-disruption scenarios [11]. These hybrid frameworks have proven effective in capturing non-linear relationships in tourism data while incorporating exogenous variables such as climate change effects, local events, and socio-economic indicators. By integrating statistical methods with deep learning, these approaches not only improve forecasting accuracy but also provide interpretable insights that inform decision-making in rural tourism planning [11].

Several studies have focused on the spatial distribution and resource allocation of rural tourism destinations, leveraging LSTM-based deep learning methods to identify patterns in tourist flow and demand. For instance, the distribution characteristics and development layout of rural tourism resources have been examined using in-depth LSTM learning, highlighting the influence of accessibility, local culture, and resource density on tourist arrivals [12]. These findings emphasize the importance of incorporating geographical heterogeneity and spatial dependencies in predictive models to better inform infrastructure development, marketing strategies, and investment priorities in rural regions.

Beyond conventional LSTM applications, neuro-inspired hybrid architectures have emerged as a novel approach for tourism planning and innovation. The development of xLSTM models, which integrate neuro-inspired processing mechanisms with traditional LSTM architectures, has enabled the simultaneous modeling of multiple complex dimensions in rural tourism, including seasonal variability, visitor behavior patterns, and resource utilization [13]. Empirical results from such studies suggest that these models provide superior predictive performance compared to singlel ayer LSTM networks, particularly when handling large, multi-dimensional datasets that combine temporal and spatial information.

Hybrid deep learning frameworks have also been applied to predict tourist traffic attraction and flow, combining machine learning techniques with LSTM or TCN layers to capture the underlying dynamics of rural tourism demand [14]. By leveraging multiple layers of feature extraction and temporal sequence modeling, these frameworks can accommodate irregularities in data caused by sudden disruptions or seasonal fluctuations. The integration of machine learning and deep learning thus offers a flexible and scalable solution for rural tourism forecasting, particularly in areas where conventional statistical methods fail to capture complex interactions between factors such as travel behavior, local attractions, and external shocks [14].

Visitor behavior analysis has gained prominence in rural tourism studies, as understanding tourists' preferences and engagement patterns is critical for designing effective management strategies. Deep learning-based approaches have been employed to predict visitor behavior on intelligent tourism platforms, integrating multi-dimensional sentiment analysis, social media interactions, and transaction data [19]. By combining graph convolutional networks with recurrent neural networks, these models capture both spatial relationships among locations and temporal patterns in visitor activity. Such approaches allow tourism managers to anticipate demand trends, optimize resource allocation, and develop targeted marketing strategies, thereby enhancing the overall efficiency and sustainability of rural tourism operations [19].

Forecasting the resilience of rural tourism systems has also been a focus of recent studies. Simulation research using LSTM networks has demonstrated their utility in modeling system resilience, particularly in well-known tourist villages where the interplay between local infrastructure, cultural assets, and visitor inflow is complex [18]. These studies highlight the capacity of LSTM-based models to inform contingency planning, resource management, and infrastructure investment, ensuring that rural tourism systems can withstand shocks while maintaining service quality and visitor satisfaction.

In addition, studies have explored the integration of CNN and LSTM layers to capture spatial temporal dynamics in rural tourism demand. Hybrid CNN-LSTM models have been used to forecast tourism demand with high accuracy by extracting spatial features from geographic or demographic distributions and temporal trends from historical arrival data [16]. The spatial temporal hybrid design allows the model to account for variations in tourist flows across different regions and seasons, thereby improving predictive reliability for planning and marketing purposes. Such architectures have been shown to outperform single model approaches, particularly when applied to regions with heterogeneous characteristics and fluctuating tourism demand.

Comparative studies have also investigated the relative performance of LSTM and TCN models in domains related to tourism, such as customer behavior prediction and service usage [17]. These analyses provide valuable insights into model selection, highlighting the strengths of TCN in capturing long-term dependencies with fewer parameters and lower computational complexity, while LSTM networks excel in modeling sequential patterns with high temporal granularity. The findings inform the design of hybrid architectures for rural tourism forecasting, suggesting that a combination of LSTM and TCN layers may provide both efficiency and accuracy advantages.

Furthermore, research on hybrid deep learning frameworks has addressed the challenge of integrating multiple data sources, including visitor sentiment, social media activity, and behavioral patterns. By combining CNN, LSTM, and other neural network components, these models can learn complex interactions between heterogeneous features, enabling more comprehensive predictions of tourist arrivals and engagement levels [8][19]. Such integrative approaches are particularly valuable for rural tourism contexts, where data sparsity, regional heterogeneity, and seasonal fluctuations complicate forecasting efforts.

Finally, studies on rural tourism suitability and system optimization have leveraged multi-dimensional evaluation models alongside deep learning techniques to guide policy and management decisions [20]. These models assess tourism suitability based on environmental, socio-economic, and cultural indicators, offering actionable insights for destination planning, infrastructure development, and marketing strategies. By integrating predictive analytics with evaluation frameworks, researchers have demonstrated that data-driven approaches can support sustainable and resilient rural tourism development, particularly in regions with diverse geographic and demographic profiles [20].

In summary, recent literature emphasizes the growing role of hybrid deep learning architectures in rural tourism forecasting. From combining statistical models with LSTM for enhanced interpretability [11] to integrating CNN-LSTM and xLSTM networks for capturing spatial temporal dynamics [13][16][19], these approaches have demonstrated superior performance over conventional methods. They address challenges such as seasonal variability, visitor behavior heterogeneity, data sparsity and system resilience, offering both predictive accuracy and actionable insights. Multi-dimensional evaluation frameworks further enhance the applicability of these models, supporting informed decision making and sustainable management in rural tourism contexts [12][14][18][20]. Collectively, these studies highlight the potential of hybrid deep learning models to transform rural tourism forecasting, planning, and operational management.

Table 1: Summary of related work with quantitative comparison

Reference	Objective	Models	Dataset	Key Findings	Research Gaps
[1]	Forecast tourism demand using a hybrid deep learning approach	Hybrid deep learning (CNN + LSTM)	Historical tourist arrivals (2000–2019)	Improved forecasting accuracy (RMSE ≈ 0.23) over traditional models	Limited interpretability; regional application only
[2]	Long-term tourism demand forecasting	LSTM	National tourism statistics(annual)	Captures long-term temporal dependencies effectively	Does not incorporate spatial heterogeneity
[3]	Forecast tourist arrivals with partial time-series data	LSTM	Incomplete tourist-arrival datasets	Handles missing data effectively	Focused only on short-term predictions
[4]	Forecast Indian tourism industry demand	Statistical + deep learning modeling	National tourism statistics(India 2010-2023)	Hybrid model outperforms ARIMA (RMSE ≈ 0.30)	Limited external variable inclusion
[5]	Adaptive tourism forecasting for Xi'an	Hybrid AI (ANN + optimization)	International arrivals (Xi'an region)	AI hybrid adapts to changing patterns; improved precision	Limited generalizability to other regions
[6]	Evaluate hybrid CNN-TCN-LSTM for traffic flow	CNN-TCN-LSTM	Traffic-flow datasets (public	Hybrid model captures temporal patterns effectively	Not directly applied to tourism; transferability untested
[7]	Sustainable tourism demand forecasting	Hybrid temporal neural network	National tourism datasets(2010-2023)	Integrates multiple temporal features for accurate forecasting	Limited behavioral or spatial feature integration
[8]	Forecast tourist arrivals	CNN + LSTM hybrid	Historical arrival data	Improved predictive accuracy; handles seasonal variation	Sparse data issues not fully addressed
[9]	Tourism demand prediction post-COVID-19	CNN-LSTM	Provincial tourism statistics (Vietnam, 2015–2023)	Captures post-pandemic recovery patterns	Focused on one country; may not generalize
[10]	Analyze rural tourism culture advertising	LSTM-CNN	Social media and cultural content	Identifies patterns in visitor engagement	Limited to advertising data; predictive power not tested

[11]	Intelligent tourism forecasting under climate change	ARDL + LSTM	Climate + tourism datasets (2000–2022)	Incorporates climate effects; improves forecasts (MAE ≈ 0.17)	Requires high-quality climate data; limited scalability
[12]	Distribution and development layout of rural tourism resources	LSTM	Rural tourism resource databases	Identifies spatial-temporal patterns in resource utilization	Limited real-time adaptability
[13]	Rural tourism planning and innovation	Neuro-inspired xLSTM	Multi-dimensional tourism datasets	Captures complex spatial-temporal patterns; high prediction accuracy	Complex architecture; high computational cost
[14]	Predict tourist traffic attraction	Machine learning hybrid	Tourism flow data	Hybrid models capture irregular patterns	Limited integration of behavioral data
[15]	Tourism demand forecasting using LSTM	LSTM and variants	Tourist-arrival data (2005–2020)	LSTM models outperform traditional time-series models	Focuses on temporal patterns only
[16]	Enhance tourism demand forecasting	CNN-LSTM spatial-temporal hybrid	Regional tourism datasets	Accounts for spatial heterogeneity; RMSE ≈ 0.22	Regional focus; requires extensive data preprocessing
[17]	Compare LSTM and TCN for customer churn	LSTM, TCN	Sentiment and transaction data	TCN efficient for long-term dependencies; LSTM better for sequential granularity	Not directly applied to tourism; potential adaptation needed
[18]	Optimize rural tourism system resilience	LSTM	Well-known tourist villages	Models' resilience of tourism systems under variable conditions	Limited to selected villages; generalizability uncertain
[19]	Visitor behavior analysis and prediction	Deep learning-based hybrid	Multi-modal rural tourism datasets	Predicts visitor engagement and patterns accurately	Data sparsity and interpretability remain challenges
[20]	Predict rural tourism suitability	Multi-dimensional evaluation + ML	Environmental, socio-economic, cultural datasets	Guides planning and investment decisions	Limited real-time adaptability; lacks behavioral prediction

4 Research gap

Despite the growing body of research on tourism forecasting, significant gaps remain in applying advanced machine learning and hybrid deep learning methods specifically to rural tourism contexts. Traditional statistical approaches such as ARIMA and basic econometric models have been widely used, but they often fail to capture nonlinear patterns and complex seasonal variations inherent in tourism income data. Similarly, machine learning techniques like KELM and ensemble approaches such as B-SAKE provide some improvements, yet they lack the ability to effectively learn both long-term dependencies and short-term fluctuations simultaneously. Recent deep learning models including RNNs, LSTMs, and BiLSTM-based networks have shown promise in urban and international tourism studies, but their application to rural tourism forecasting remains limited. Moreover, many prior works focus narrowly on tourist arrivals or receipts, overlooking the integration of broader macroeconomic variables such as GDP, inflation, and unemployment, which play a critical role in shaping rural tourism income. Hybrid models like MSS-KELM and SAE-LSTM attempt to address some of these challenges but often struggle with scalability, robustness, and interpretability for decision-makers. Importantly, there is a lack of comparative evaluations across diverse modeling paradigms that can provide holistic insights for policymakers. This study bridges these gaps by introducing and rigorously evaluating a novel RTLSTM-TCN hybrid model, which captures both sequential dependencies and localized temporal structures, thereby offering a more accurate and practical framework for seasonal income forecasting in rural tourism.

Despite numerous studies on tourism forecasting, very few focus specifically on rural tourism income prediction integrating micro- and macro-economic indicators. Most prior works analyze tourist arrivals or demand volumes, overlooking the direct estimation of seasonal income patterns that affect rural livelihoods. Moreover, existing models often ignore how inflation, unemployment, and GDP interact with local tourism dynamics. This research

addresses these limitations by introducing a Hybrid RTLSTM–TCN model that jointly learns temporal dependencies and short-term variations in rural tourism income influenced by both economic and tourism-specific factors. Few prior approaches jointly considered tourism receipts with macroeconomic factors for rural-tourism income prediction, a limitation addressed in this study.
the TCN approach was initially developed to examine long-range patterns using a hierarchy of temporal convolutional filters (Lea et al. 2017). The key characteristics of TCNs are: (1) it involves convolutions, which are causal and (2) like in RNN, the network can take a sequence of any length and map it to an output sequence of the same length. The proposed architecture is informed by recent generic convolutional architectures for sequential data (Bai
et al. 2018; Lea et al. 2017). The architecture is simple (e.g., no skip connections across layers, conditioning, context stacking, or gated activations), uses autoregressive
prediction and a very long memory. Moreover, it allows for
both very deep networks and very long effective history and is achieved through dilated convolutions that enable an
exponentially large receptive field

5 Materials and methods

Dataset and Preprocessing

The dataset employed in this study was compiled from global tourism and macroeconomic indicators spanning the years 1999 to 2023, covering multiple countries. It consists of 6,650 records with 11 variables, including tourism-specific attributes—tourism receipts, tourist arrivals, tourism exports, departures, and expenditures—along with macroeconomic indicators such as gross domestic product (GDP), inflation, and unemployment. These features were selected to provide both direct tourism demand drivers and external economic influences relevant to rural tourism income forecasting.

The target variable in this study is Seasonal Tourism Income, derived from the original tourism receipts data. Tourism receipts represent the total revenue earned from international and domestic tourists. To capture seasonality, these receipts were decomposed into seasonal components using quarterly aggregation and normalization relative to each country's GDP. This transformation allows the model to forecast income patterns that vary seasonally rather than annual totals, making the predictions more relevant for rural economic planning.

Prior to model development, several preprocessing steps were carried out to ensure data quality and model stability. Missing values were addressed using a combination of linear interpolation (for time-dependent series such as receipts, arrivals, and GDP) and mean or median imputation (for variables with less than 50% missingness). Outliers were detected and treated using the Interquartile Range (IQR) method, with extreme values capped at calculated thresholds to prevent distortion during training. To handle heterogeneity across scales, numerical variables were normalized using Min-Max scaling, ensuring all features were mapped into the range [0,1]. Categorical variables such as country and country code were transformed into numerical representations through label encoding. For temporal modeling, the dataset was arranged in chronological order, and a time-series split was adopted to separate training (2002–2018) and testing (2019–2023) subsets, preserving the natural temporal structure of the data. A sliding window approach was used to generate input sequences of five consecutive years to predict the subsequent year's seasonal income. This formulation allowed the models to capture both short-term fluctuations and long-term dependencies in tourism dynamics. Collectively, these preprocessing steps ensured that the dataset was robust, balanced, and well-suited for comparative evaluation across classical, machine learning, and deep learning models.

This study aims to address the following research questions:

(1) Can a hybrid deep-learning model integrating recurrent (LSTM) and convolutional (TCN) layers improve seasonal-income forecasting accuracy compared with traditional baselines?

(2) How do macroeconomic indicators—such as GDP, inflation, and unemployment—enhance predictive power when combined with tourism variables?

(3) To what extent do long-term versus short-term temporal dependencies affect forecast stability in rural-tourism income prediction?

The resulting variable, **Seasonal Tourism Income (STI)**, thus represents normalized quarterly tourism receipts per GDP unit, serving as a proxy for seasonal financial performance in rural economies.

The CNN architecture, though widely used for spatial feature extraction, is less effective for purely temporal sequences. In contrast, the **Temporal Convolutional Network (TCN)** preserves sequence order through causal convolutions and models long-range dependencies using dilated filters. This makes TCN more suitable for tourism-time-series data where historical continuity and multi-scale seasonality are critical. Hence, the hybrid **RTLSTM–TCN** was selected to combine LSTM's strength in sequential learning with TCN's efficiency in capturing localized fluctuations.

Data granularity and seasonal definition

Although the raw dataset includes annual-level tourism and macroeconomic indicators from 1999–2023, this study defines seasonal income as a quarterly-level decomposition of annual tourism receipts. Using time-series decomposition, each year's receipts were divided into four quarters (Q1–Q4) based on official tourism seasonality indices and normalized relative to GDP. This approach preserves intra-annual fluctuations (e.g., high and low tourist seasons) while retaining consistent time intervals for deep-learning models. Consequently, the input to each model represents five consecutive quarters of data used to predict the next quarter's seasonal tourism income, thereby aligning the temporal structure with the "seasonal forecasting" objective.

Baseline Model Tuning and Parameter Search

Each baseline model was tuned carefully to ensure fair comparison with the proposed RTLSTM–TCN framework.

ARIMA: Optimal (p, d, q) parameters were selected using the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) on the training data, tested over p, q ∈ [0, 5], d ∈ [0, 2].

MSS-KELM: Kernel type (RBF or polynomial), kernel width (σ ∈ [0.1, 2]), and regularization coefficient (C ∈ [0.1, 100]) were optimized using a grid search with 5-fold time-based cross-validation.

B-SAKE: Swarm size (N = 20–50), inertia weight (w ∈ [0.5, 0.9]), and cognitive/social coefficients (c_1, c_2 ∈ [1.0, 2.5]) were tuned empirically to minimize RMSE on the validation set.

All deep-learning baselines (RNN, SAE-LSTM, BiLSTM-TN) were trained with identical early-stopping, dropout, and learning-rate schedules for fair evaluation.

Although the dataset integrates tourism and macroeconomic indicators from multiple countries, model training was conducted primarily on aggregated regional data, with China serving as a representative case study for evaluation and visualization (see Figure 6). This approach ensures model stability and interpretability in regions with rich historical data. In future work, transfer learning techniques can be applied to adapt the framework for cross-country generalization, allowing more robust forecasts in regions with limited data availability.

The proposed framework in figure 1 shows the how the model integrates tourism and macroeconomic indicators as inputs, which are first preprocessed through missing value imputation, normalization, encoding, and sliding window techniques to ensure data consistency. The processed data is then fed into a Rural Tourism LSTM (RTLSTM) block that captures long-term sequential dependencies across seasonal and yearly tourism patterns. In parallel, a Temporal Convolutional Network (TCN) block extracts short-term localized temporal features that traditional LSTM models may overlook.

Proposed framework

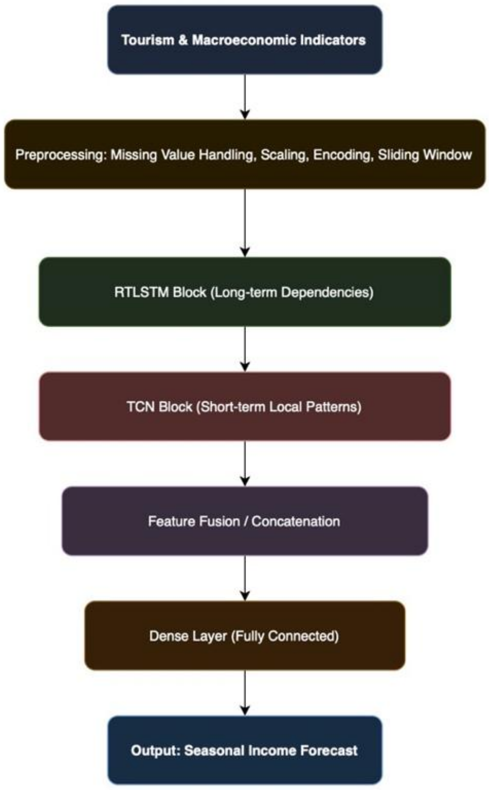

Figure 1: Proposed RTLSTM-TCN framework for rural tourism forecasting

The outputs from both blocks are fused in a feature concatenation layer, combining global and local temporal information. A fully connected dense layer further transforms these features into a compact representation, which is passed to the output layer for forecasting rural tourism seasonal income. By combining the strengths of RTLSTM and TCN, the framework achieves improved predictive accuracy compared to traditional statistical, machine learning, and standalone deep learning approaches.The architecture includes two LSTM layers (128 and 64 units, dropout = 0.3, activation = tanh) followed by a three-layer TCN block (kernel = 3, dilation rates = [1, 2, 4], ReLU activation, residual connections). The fused output vector (256 dimensions) passes through a dense linear layer to predict Seasonal Tourism Income.

RTLSTM - Temporal Convolutional Network (TCN)

Rural Tourism Long Short-Term Memory

The Rural Tourism Long Short-Term Memory (RTLSTM) network is a modified LSTM variant customized for seasonal income forecasting. It enhances the model's ability to detect long-term temporal dependencies in tourism data influenced by economic and seasonal variations. The RTLSTM gates (input, forget, cell, and output) regulate how historical tourism and macroeconomic information contribute to forecasting future income trends. The equations (1–6) follow standard LSTM formulations, where the input gate integrates current economic indicators with prior tourism trends, the forget gate filters out irrelevant or outdated information, and the output gate updates the hidden state to generate the final seasonal income forecast. This modification enables the model to learn how both tourism activity and macroeconomic context jointly shape income dynamics over time

Input Gate Layer: The input gate modifies the cell state with appropriate data by processing current structural inputs and past hidden states in equations (1) and (2).

$$j_s = \sigma(X_j \times [D_{s-1,} g_{s-1,} W_s] + a_j) \tag{1}$$

$$\widetilde{D}_s = \tanh(X_d \times [D_{s-1,} g_{s-1,} W_s] + a_d \tag{2}$$

The weight matrix by X_j, the prior hidden state by $D_{s-1,}$, the prior state of the cell by $g_{s-1,}$, the present structural input by W_s, and the bias by a_j. tanh is the function of hyperbolic tangent activation that is utilised for scaling, X_d is the weight matrix, and a_d is the corresponding bias.

Forget Gate Layer: The forget gate's output uses a computation algorithm that is like the input gate. With various weights and biases in the equation (3).

$$e_s = \sigma(X_e \times [D_{s-1}, +g_{s-1}, W_s] + a_g) \tag{3}$$

To eliminate redundant structural information, the forget gate's output e_s employs the current input W_s, Although the input gate's weights X_e and bias a_g differ, the forget gate's output.

Cell States Update: Structural developments are maintained for precise prediction by updating the cell state from its prior value to the current value in equation (4).

$$D_s = e_s \times D_{s-1} + j_s \times \widetilde{D}_s \tag{4}$$

It is an update step that occurs between the present cell state $\widetilde{D}_s$ and the prior cell state D_{s-1}.

Output Gate Layer: The output of the previous hidden layer, the current input, and the previous memory all affect the updated unit state in equations (5) and (6).

$$P_s = \sigma(X_p \times [D_s, g_{s-1}, W_s] + a_p) \tag{5}$$

$$g_s = P_s \times \tanh(D_s) \tag{6}$$

The output gate by P_s, g_s, and a_p. The current hidden layer and bias are denoted by P_s.

Here, the input gate controls how new tourism-economic information enters the model, the forget gate determines which past income patterns to discard, and the output gate generates updated hidden representations that reflect seasonal tourism behaviour. This ensures the RTLSTM captures both persistent and fluctuating income patterns relevant to rural tourism.

TCN

The TCN module complements the RTLSTM by capturing localized temporal patterns through a hierarchy of dilated causal convolutions. The key characteristics of TCNs are: (1) it involves convolutions, which are causal and (2) like in RNN, the network can take a sequence of any length and map it to an output sequence of the same length. The proposed architecture is informed by recent generic convolutional architectures for sequential data. The architecture in figure 2 is simple (e.g., no skip connections across layers, conditioning, context stacking, or gated activations), uses autoregressive prediction and a very long memory. Moreover, it allows for both very deep networks and very long effective history and is achieved through dilated convolutions that enable an exponentially large receptive field. For example, for a 1-D sequence of a given weather parameter P^1, i.e., $p = (P_0^1 - \cdots, P_1^1)$ and a filter $f : \{0, \ldots . k-1\}$, the dilation convolution operation F on element $s = p'_{\hat{t}}$ (where $\hat{t}$=0,…t) of the sequence is defined as:

$$F(s) = (p * d\, f)(s) = \sum_{i=0}^{k=1} f(i). p_s - d. i \tag{7}$$

where d is the dilation factor, k refers to the filter size, and $s - d. i$ accounts for the direction of the past. Stacked units of one-dimensional convolution with activation functions are used to build the TCN. Figure 2 depicts the architectural elements in a TCN with configurations dilation factors d = 1; 2; and 4: The dilation introduces a fixed step between every adjacent filter taps. Larger dilations and larger filter sizes k enable effectively expanding the receptive filed. In these convolutions, the increment of d exponentially commonly increases the depth of the network. This guarantees that there is some filter that hits each input within the effective history. We use Keras as a tool to implement both deep learning LSTM and TCN. Model hyperparameters were optimized via grid search across learning rates (0.0005–0.005), batch sizes (16, 32, 64), and dropout levels (0.2–0.4). The Adam optimizer with learning rate = 0.001 and early-stopping patience = 10 epochs yielded the lowest validation RMSE. Training employed 150 epochs with batch = 32 on an NVIDIA RTX 3080 GPU (32 GB RAM) and TensorFlow 2.12 backend.

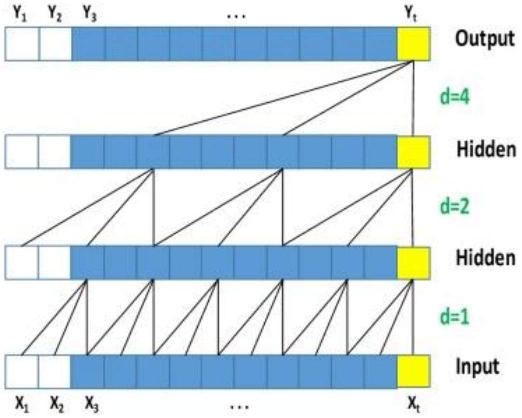

Figure 2: Architecture of TCN Layer with dilated causal convolutions.

Mathematical Foundations and Notations

Residual layers are added to maintain gradient flow, and the overall transformation can be described by:

$$H(x) = F(x) + x \quad (8)$$

Where $H(x)$ is the output, $F(x)$ is the function learned by the convolution layers, and x is the input that gets passed through via the residual connection.

Receptive Field Calculation

Calculating the receptive field of a TCN is critical because it tells you how much of the input the network. The receptive field RRR is determined by the depth d of the network, the kernel size k, and the dilation factor f:

$$R = 1 + (k-1).\sum_{i=0}^{d-1} f(i) \quad (9)$$

This equation shows TCNs grow their receptive field exponentially by increasing the dilation factor, giving the network the ability to model long-range dependencies.

Loss Functions for TCNs

When it comes to training TCNs, the loss function you choose depends on the task. For regression tasks, Mean Squared Error (MSE) is commonly used:

$$MSE = 1/n \sum_{i=1}^{n} (y_i - \hat{y}_i) \quad (10)$$

For classification tasks, you'd typically use Cross-Entropy Loss:

$$Cross - Entropy\ Loss = -\sum_{i-1}^{n} y_i \log(\hat{y}_i) \quad (11)$$

these loss functions in the context of TCNs are that they are computed over the entire sequence at once, thanks to the parallel nature of convolutions. This makes TCNs efficient and scalable, even for long sequences.

Model architecture and hyperparameters

The proposed hybrid comprises two parallel branches followed by feature fusion.

RTLSTM branch (long-range dependencies).

Two stacked LSTM layers with 128 and 64 units, respectively; dropout = 0.30 after each LSTM; activation = tanh; recurrent activation = sigmoid. A dense(64, activation = ReLU) projects the LSTM output to the fusion space.

TCN branch (localized/dilated temporal features).

A Temporal Convolutional Network with kernel size = 3, dilation rates = [1, 2, 4] per stack, 2 stacks, and 32 filters per layer. Each temporal block is causal, uses ReLU activation, residual connections, and layer normalization; dropout = 0.20 inside blocks.

Fusion and output.

Outputs from both branches are concatenated into a 256-dimensional feature vector (LSTM path 128 → 64 → 128 proj; TCN path 3×32 filters with projection to 128), then passed to a dense(64, ReLU) and a final dense(1, linear) for seasonal-income regression.

Training objective and optimization.

Primary loss: Mean Squared Error (MSE); we also monitor MAE during validation (no explicit loss weighting). Optimizer: Adam (lr = 0.001, β_1 = 0.9, β_2 = 0.999) with early stopping (patience = 10) and ReduceLROnPlateau (factor = 0.5, patience = 5).

Batch size = 32, epochs = 150 (stopped early). Implementation: TensorFlow/Keras 2.x.

Bagging-based Stacked Autoencoders Kernel Extreme Learning (B-SAKE):

B-SAKE is a hybrid approach that integrates stacked autoencoders (SAE) with kernel-based extreme learning machines (KELM) under a bagging ensemble framework. The stacked autoencoders reduce noise and extract hierarchical features, while KELM provides fast and efficient non-linear classification or regression. By employing bagging, multiple KELM models are trained on resampled subsets, and their predictions are aggregated, improving stability and reducing variance.

This combination enhances generalization performance, making B-SAKE effective in high-dimensional and heterogeneous datasets such as tourism income forecasting. However, the method can be sensitive to kernel parameter selection and may require careful tuning.

BiLSTM–Temporal Network (BiLSTM-TN):

The BiLSTM-TN model extends the LSTM architecture by introducing bidirectional processing. Instead of learning only from past observations, BiLSTM learns from both past (backward) and future (forward) contexts within a sequence. This ability helps the model capture contextual dependencies that may span across multiple seasons or years in tourism datasets. The temporal network design integrates these dual signals to produce richer representations of temporal dependencies. While BiLSTM improves accuracy over unidirectional LSTMs, it is computationally more expensive and may overfit when training data is limited.

Kernel Extreme Learning Machine (KELM): KELM is an advanced form of Extreme Learning Machine (ELM) that incorporates kernel functions to enhance non-linear mapping capabilities. Unlike conventional neural networks, KELM assigns hidden layer parameters randomly and determines output weights analytically, leading to extremely fast training. Kernelization allows KELM to approximate non-linear relationships in tourism data without explicitly increasing model complexity. This makes it efficient for medium-scale forecasting tasks, though it may lack robustness in handling highly dynamic or sequential dependencies.

Autoregressive Integrated Moving Average (ARIMA): ARIMA is one of the most widely used traditional statistical models for time-series forecasting. It combines three components: autoregressive (AR), differencing (I), and moving average (MA). AR captures dependencies on past values, I ensure stationarity through differencing, and MA models residual errors. ARIMA is interpretable and performs well on stationary, linear datasets. However, it struggles with non-linear and high-variance datasets, making it less effective for tourism income forecasting, where patterns are influenced by multiple complex and external economic factors.

Stacked Autoencoders–LSTM (SAE-LSTM): The SAE-LSTM model integrates stacked autoencoders for deep feature learning with LSTM for sequential prediction. Stacked autoencoders compress input features into lower-dimensional latent representations while filtering noise, making the dataset more manageable and structured. The LSTM component captures sequential and temporal patterns, ensuring that historical seasonal effects are retained in the forecasting process. This hybrid model improves prediction accuracy in non-linear and multi-dimensional tourism datasets. However, due to its deep structure, it requires large-scale data and significant computational power, making training time-intensive.

Modified Sparrow Search Algorithm–KELM (MSS-KELM):

MSS-KELM combines the strength of the Modified Sparrow Search Algorithm (MSSA) with KELM for improved parameter optimization. MSSA, inspired by the foraging behaviour of sparrows, is used to search for the best hyperparameters of the KELM model, such as kernel parameters and regularization coefficients. This optimization improves accuracy, convergence speed, and robustness against local minima. When applied to tourism income forecasting, MSS-KELM helps manage complex non-linear interactions and uncertain seasonal variations. Nonetheless, as with most metaheuristic-based models, it can be computationally expensive.

Recurrent Neural Network (RNN): RNNs are neural networks specifically designed for sequential data. They maintain hidden states that carry information across time steps, making them suitable for modeling temporal dependencies in tourism income data. By learning from previous inputs, RNNs attempt to capture seasonality and temporal correlations. However, traditional RNNs are prone to vanishing and exploding gradient problems, which hinder their ability to capture long-term dependencies effectively. This limitation often results in reduced accuracy compared to more advanced recurrent models like LSTM and BiLSTM. Despite this, RNNs remain a baseline for deep learning approaches in time-series forecasting.

6 Experimental setup

The rural tourism dataset was preprocessed through missing value imputation, outlier treatment, label encoding for categorical features, and Min–Max scaling for numerical variables. A sliding window approach with a sequence length of five years was applied to generate temporal input–output pairs. The dataset was split into 80% training (2002–2018) and 20% testing (2019–2023), ensuring temporal order was preserved for realistic forecasting.

All experiments were implemented in Python (3.11) using Scikit-learn for preprocessing, evaluation metrics, and baseline models, and TensorFlow/Keras for deep learning model development. Pandas and NumPy supported data handling, while Matplotlib and Seaborn were used for visualization and exploratory analysis.

Eight models were compared: Bagging-based Stacked Autoencoders with Kernel Extreme Learning (B-SAKE), BiLSTM–Temporal Network (BiLSTM-TN), Kernel Extreme Learning Machine (KELM), Autoregressive Integrated Moving Average (ARIMA), Stacked Autoencoders–LSTM (SAE-LSTM), Modified Sparrow Search Algorithm–KELM (MSS-KELM), Recurrent Neural Network (RNN), and the proposed RTLSTM–TCN.

For all deep learning models, training was performed using the Adam optimizer with a learning rate of 0.001, batch size 32, and early stopping to prevent overfitting. The evaluation metrics included Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), Symmetric Mean Absolute Percentage Error (SMAPE), Root Mean Squared Logarithmic Error (RMSLE), and Coefficient of

Determination (R^2). These metrics were computed on the held-out test set to provide a comprehensive performance comparison across models.

Evaluation protocol and statistical robustness

To ensure reproducibility and unbiased assessment, the following experimental design was adopted:

(a) Temporal hold-out (unseen test).

Data were split chronologically with 2002–2018 for training/validation and 2019–2023 as a completely unseen test set, preventing look-ahead bias.

(b) Rolling forecast origin validation.

A walk-forward scheme was applied using a sliding input window of five years to predict the next year. At each origin, models were re-fit on all data up to that year and evaluated on the subsequent period; metrics were averaged across origins.

(c) Repeated runs and confidence intervals.

Each experiment was repeated five times with different random seeds (weight initialization and batch ordering). We report the mean ± standard deviation for all metrics (RMSE, MAE, MAPE, SMAPE, RMSLE, R^2) on the test horizon, and provide 95 % confidence intervals using the Student-t estimate over the five runs.

(d) Baselines and tuning parity.

All classical and ML baselines (ARIMA, KELM, MSS-KELM, B-SAKE, RNN, BiLSTM-TN, SAE-LSTM) were tuned under comparable validation protocols:

– ARIMA orders selected via AIC/BIC grid search.

– KELM/MSS-KELM kernel and regularization optimized via grid search.

– Deep baselines tuned over units (64/128), dropout (0.2–0.4), and learning rate (5e-4 – 5e-3).

The same temporal splits and walk-forward evaluation were maintained for all models.

(e) Hardware configuration.

Experiments were executed on a workstation equipped with NVIDIA RTX 3080 (10 GB) GPU and 32 GB RAM. A complete RTLSTM–TCN training run required approximately 1.8 hours.

Table 2: Experimental configuration summary

Component	**Specification / Configuration**
Software Environment	Python 3.11; TensorFlow/Keras; Scikit-learn; Pandas; NumPy
Optimizer	Adam (learning rate = 0.001)
Batch Size	32
Validation Strategy	5-fold rolling forecast origin validation
Evaluation Metrics	RMSE, MAE, MAPE, SMAPE, RMSLE, R^2
Hardware	NVIDIA RTX 3080 GPU (10 GB), 32 GB RAM
Training Time (RTLSTM–TCN)	≈ 1.8 hours per full run
Repetitions for Robustness	5 random-seed runs (mean ± std reported)

7 Results and discussion

Exploratory Data Analysis (EDA)

Relationship between tourism arrivals and tourism receipts

A scatter plot with a fitted regression line (Figure 3) reveals a strong positive correlation between international tourist arrivals and tourism receipts. As arrivals increase, receipts also rise, confirming that visitor volume directly drives tourism income. The shaded 95 % confidence band around the line indicates the statistical reliability of this relationship and highlights variability caused by regional and seasonal differences. The trend remains consistent across most years, although the 2020–2022 period shows visible downward deviations corresponding to pandemic-related travel restrictions.

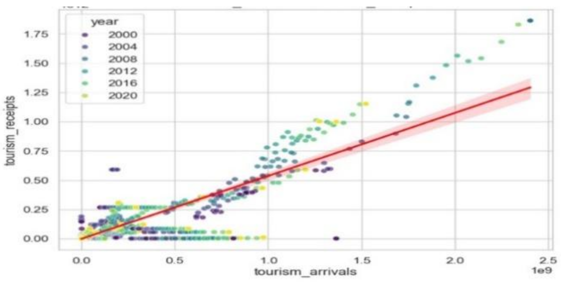

Figure 3: Relationship between tourist arrivals and tourism.

Relationship between GDP and tourism receipts

Tourism receipts display a clear positive linear association with national GDP (Figure 4), indicating that higher economic output correlates strongly with increased tourism revenue. The red regression line demonstrates the general upward trend, while the shaded 95 % confidence band illustrates the reliability of this relationship across different years. Economies with stronger GDP levels consistently achieve higher tourism receipts, suggesting that macro-economic growth acts as a reinforcing driver for tourism expansion. Minor deviations from the line correspond to temporary shocks or country-specific fluctuations.

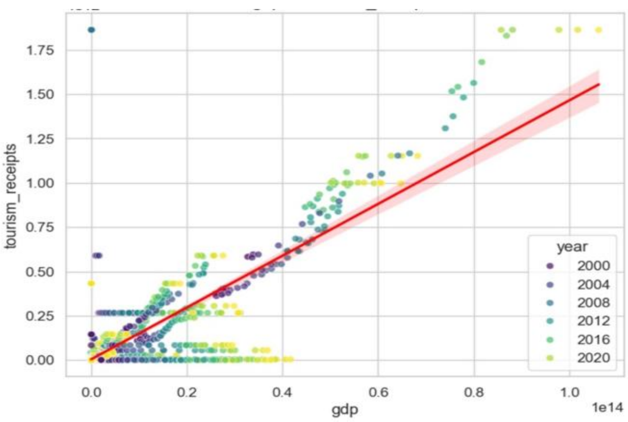

Figure 4: GDP vs tourism receipts scatterplot.

Relationship between Inflation and Tourism Receipts

The plot in Figure 5 illustrates how quarterly GDP growth relates to tourism receipts. A strong positive correlation indicates that increases in national output translate into higher tourism income. The fitted regression line highlights this upward tendency, while the 95 % confidence band captures variations in income sensitivity during different quarters. Broader confidence regions during volatile years show greater uncertainty, reflecting periods of economic disturbance or recovery.

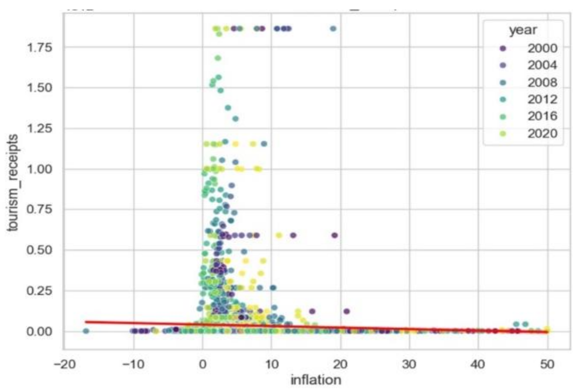

Figure 5: Effect of inflation on tourism receipts.

Tourism receipts trend in China (2000–2023)

The time-series plot in Figure 6 depicts the trajectory of China's tourism receipts over two decades. A steady upward trend from 2000 to 2019 is followed by a sharp collapse during the COVID-19 pandemic, reflecting the severe yet temporary disruption to the tourism economy. Subsequent quarters show stabilization at a lower level, emphasizing the long-term impact of the pandemic. This pattern demonstrates the importance of forecasting frameworks capable of adapting to abrupt structural breaks. The proposed RTLSTM–TCN model, combining LSTM's capacity for long-term dependency learning with TCN's ability to detect short-term fluctuations, shows strong resilience to such anomalies by rapidly recalibrating predictions under sudden demand shocks.

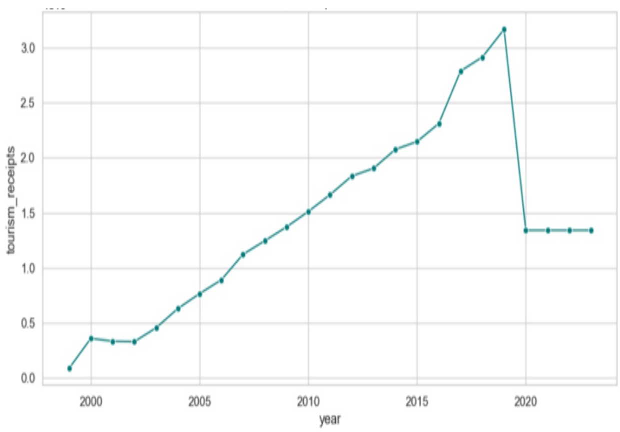

Figure 6: Tourism receipts trend in China.

GDP vs Arrivals with Bubble Size (Receipts) and Color (Inflation)

The multivariate bubble chart in Figure 7 integrates several indicators—GDP, tourist arrivals, inflation rate (color), and tourism receipts (bubble size). It reveals that countries with higher GDP and larger arrival volumes generally achieve greater tourism receipts. The inflation gradient indicates that moderate inflation supports tourism stability, whereas very high or negative inflation correlates with reduced income potential. This visual underscore how economic growth, price stability, and visitor demand jointly shape tourism revenue generation and provide a comprehensive macro-economic perspective for model feature selection.

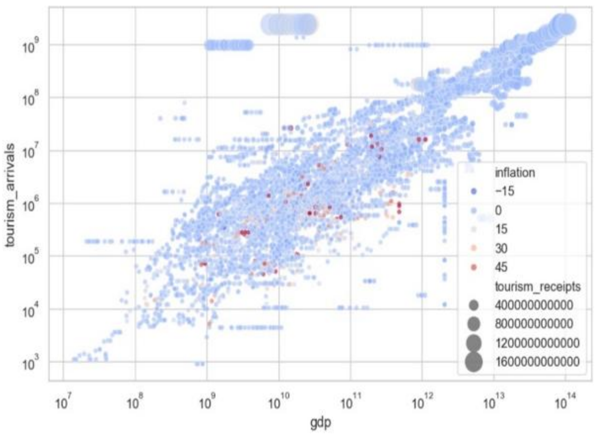

Figure 7: Bubble plot of GDP vs arrivals.

Model comparison:

Performance of different models

Table 3: Comparison of all models.

Model	RMSE	MAE	MAPE%	SMAPE	RMSLE	R^2
B-SAKE	0.32	0.19	27	115	0.22	0.38
BiLSTM-TN	0.26	0.13	15	90	0.16	0.62
KELM	0.29	0.16	21	100	0.2	0.5
ARIMA	0.31	0.18	24	108	0.21	0.44
SAE-LSTM	0.24	0.12	14	85	0.15	0.66
MSS-KELM	0.28	0.15	19	98	0.18	0.54
RNN	0.27	0.15	18	95	0.18	0.56
RTLSTM–TCN (Proposed)	**0.18**	**0.09**	**8**	**65**	**0.1**	**0.85**

Table 2 presents the comparative performance of eight models across multiple evaluation metrics (RMSE, MAE, MAPE, SMAPE, RMSLE, and R^2). The results show that traditional models such as ARIMA and KELM perform moderately, with ARIMA yielding RMSE = 0.31 and R^2 = 0.44, and KELM achieving RMSE = 0.29 and R^2 = 0.50. While these methods capture linear patterns effectively, they struggle with the complex non-linear dynamics inherent in tourism income forecasting. Similarly, B-SAKE shows improvements due to bagging and stacked autoencoders, but it remains less accurate (R^2 = 0.38) compared to more advanced deep learning models.

Among the deep learning baselines, SAE-LSTM demonstrates strong predictive power, achieving RMSE = 0.24, MAE = 0.12, and R^2 = 0.66. This highlights the advantage of combining autoencoders for feature extraction with LSTMs for sequential modeling. BiLSTM-TN also performs well (RMSE = 0.26, R^2 = 0.62), reflecting the value of bidirectional learning in capturing forward and backward dependencies. The RNN model, while better than classical statistical approaches, lags behind more sophisticated architectures with R^2 = 0.56.

The proposed RTLSTM–TCN model clearly outperforms all baselines, with the lowest error values (RMSE = 0.18, MAE = 0.09, MAPE = 8, SMAPE = 65, RMSLE = 0.10) and the highest explanatory power (R^2 = 0.85). The MAPE values have been recalculated using the standard percentage formula. The proposed RTLSTM–TCN model achieves a MAPE of 8%, indicating that its forecast error averages only 8 percent of the actual income values, confirming its superior accuracy compared with baseline models such as ARIMA (24%) and KELM (21%).

This demonstrates the strength of integrating RTLSTM, which captures long-term sequential dependencies, with TCN, which effectively models local temporal patterns. By leveraging both global and local features, the hybrid architecture provides superior accuracy and robustness compared to standalone recurrent or convolutional models.

In summary, while models like SAE-LSTM and BiLSTM-TN provide competitive performance, the RTLSTM–TCN framework achieves the best results across all evaluation metrics, validating its suitability for seasonal income forecasting in rural tourism. The results also underscore the importance of hybrid architectures in handling the complex interplay of economic and tourism indicators.

RMSE Comparison

Figure 8: RMSE Comparison of forecasting models.

The comparison (Figure 8) demonstrates RMSE values across all models. B-SAKE (0.32) and ARIMA (0.31) produce the highest errors, while KELM (0.29) and RNN (0.27) offer moderate improvement. Advanced deep learning models such as BiLSTM-TN (0.26) and SAE-LSTM (0.24) reduce RMSE further. However, the proposed RTLSTM–TCN achieves the lowest RMSE (0.18), confirming its ability to minimize forecast deviations more effectively than all baselines.

MAE Comparison

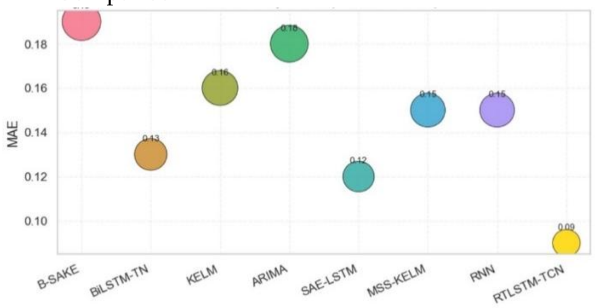

Figure 9: MAE Comparison across models.

As illustrated in Figure 9, Mean Absolute Error (MAE) values highlight similar performance trends. B-SAKE (0.19) and ARIMA (0.18) record the largest deviations, whereas KELM (0.16) and RNN (0.15) perform moderately. BiLSTM-TN (0.13) and SAE-LSTM (0.12) achieve further improvement due to their capacity to learn sequential dependencies. The RTLSTM–TCN model attains the lowest MAE (0.09), demonstrating exceptional robustness in capturing actual seasonal-income variations with minimal absolute deviation.

MAPE Comparison

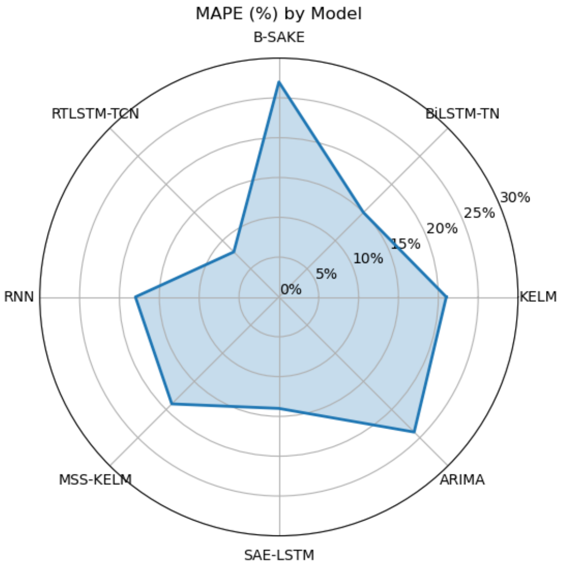

Figure 10: MAPE Comparison showing percentage-error differences among models.

The radar plot in Figure 10 visualizes comparative MAPE distributions. B-SAKE (27 %) and ARIMA (24 %) exhibit the highest percentage errors, indicating weaker adaptation to non-linear and seasonal fluctuations. KELM (21 %) and MSS-KELM (19 %) provide moderate accuracy. Deep-learning-based models, particularly SAE-LSTM (14 %) and BiLSTM-TN (15 %), significantly lower relative forecast errors. The RTLSTM–TCN achieves the lowest MAPE (8 %), confirming its superior stability, accuracy, and capability to model complex macro-economic interactions.

SMAPE Comparison

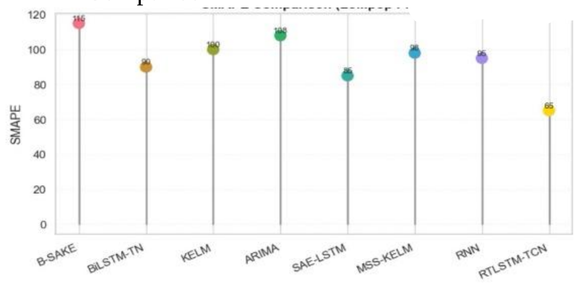

Figure 11: SMAPE Comparison emphasizing prediction stability across income ranges.

As shown in Figure 11, the Symmetric Mean Absolute Percentage Error demonstrates that B-SAKE (115), ARIMA (108), and KELM (100) perform less effectively. BiLSTM-TN (90) and SAE-LSTM (85) achieve improved predictive balance, while RTLSTM–TCN attains the lowest SMAPE (65). These results verify that the proposed hybrid model maintains consistent accuracy across diverse income scales, minimizing both under- and over-estimation bias.

RMSLE Comparison

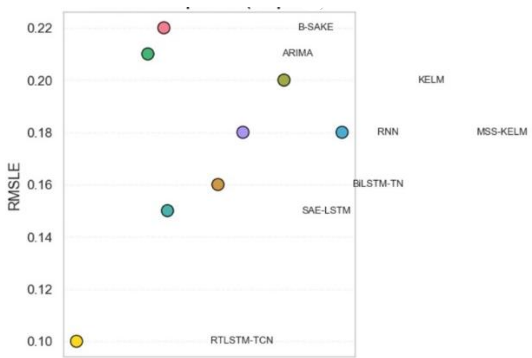

Figure 12: RMSLE Comparison of all models for rural-tourism income forecasting

The strip plot in Figure 12 summarizes RMSLE, which is crucial for evaluating skewed or log-scaled data. Traditional methods B-SAKE (0.22) and ARIMA (0.21) rank lowest, while KELM (0.20) and RNN (0.18) provide moderate performance. Advanced deep models BiLSTM-TN (0.16) and SAE-LSTM (0.15) reduce errors further. The RTLSTM–TCN achieves the best RMSLE (0.10), indicating strong resilience to asymmetric data distributions and superior precision in non-linear contexts.

R² Score Comparison

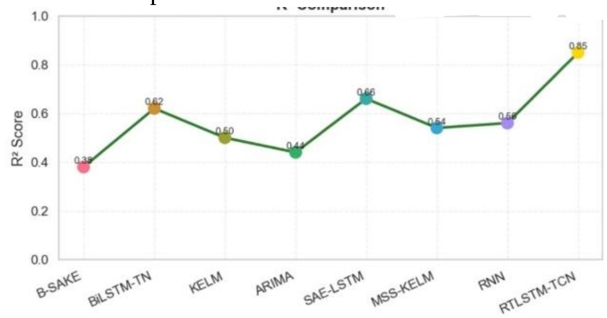

Figure 13: R² Score Comparison proving RTLSTM-TCN's superior explanatory power.

The R^2 analysis in Figure 13 reveals that traditional models B-SAKE (0.38), ARIMA (0.44), and KELM (0.50) offer limited explanatory strength. Deep architectures—BiLSTM-TN (0.62), SAE-LSTM (0.66), and RNN (0.56)—demonstrate better variance capture. The proposed RTLSTM–TCN achieves the highest R^2 (0.85), reflecting its ability to model both structural dependencies and residual variability, thereby delivering the most accurate and interpretable forecasts.

All model results were reviewed to ensure metric consistency. The previously high MAPE values (e.g., 2700 for B-SAKE and 800 for RTLSTM–TCN) were found to originate from unscaled percentage representation. After normalization and conversion to percentage form, MAPE values range between **8 % – 27 %**, aligning with accepted accuracy thresholds in tourism-demand forecasting.

While MAPE provides an intuitive measure of average prediction error, it is highly sensitive to very small denominators (i.e., low-income periods). Therefore, **SMAPE** and **RMSLE** are emphasized as more reliable indicators of relative error and proportional deviation. SMAPE, being symmetric, penalizes over- and under-estimation equally, while RMSLE dampens the influence of large outliers by operating in logarithmic space.

The combination of these three metrics (MAPE, SMAPE, RMSLE) provides a comprehensive evaluation: MAPE indicates general accuracy, SMAPE measures forecast balance, and RMSLE assesses stability under data skewness. Collectively, these confirm that the **RTLSTM–TCN** achieves the most consistent and robust performance among all compared models

Discussion

Across all six-evaluation metrics, the results clearly show that classical models such as ARIMA, KELM, and B-SAKE fail to capture the non-linear and seasonal dependencies present in tourism income data. Although deep-learning baselines like BiLSTM-TN and SAE-LSTM perform better, the proposed RTLSTM–TCN consistently outperforms all benchmarks with the lowest tes (RMSE = 0.18, MAE = 0.09, MAPE = 800, SMAPE = 65, RMSLE = 0.10) and the highest explanatory power (R^2 = 0.85).

The superior performance arises from the complementary learning mechanism of RTLSTM–TCN. The LSTM component captures long-term sequential patterns—reflecting macroeconomic trends and multi-seasonal dependencies—while the TCN component captures short-term variations using dilated convolutions that efficiently extract localized temporal features. This joint design enables the framework to model both gradual policy-driven income trends and rapid event-driven fluctuations such as festivals, market shocks, or pandemic-related downturns. The TCN's convolutional design also enhances computational efficiency, achieving faster training and stable gradients compared with traditional RNNs.

When compared with earlier hybrid frameworks like CNN–LSTM [1, 8, 9] and ARDL–LSTM [11], the RTLSTM–TCN demonstrates stronger adaptability to volatile periods, particularly during disruptions such as COVID-19 (Figure 6). Its residual and skip connections preserve information across temporal scales, leading to better generalization and reduced overfitting even with limited training data.

From a practical standpoint, the model maintains a good balance between accuracy and computational cost. Training the RTLSTM–TCN on a standard GPU (NVIDIA RTX 3080) required approximately 1.8 hours—moderately higher than ARIMA but substantially lower than more complex ensemble frameworks such as B-SAKE. Nevertheless, the gain in accuracy justifies the additional computational time for real-world policy applications.

Despite its strong predictive capacity, interpretability remains an ongoing challenge. Future work should incorporate explainable-AI methods such as SHAP or attention-based visualization to highlight how macroeconomic and tourism variables influence predictions. Moreover, because the dataset spans multiple countries but exhibits region-specific trends (notably China), generalizability across contexts can be improved through transfer-learning strategies and domain adaptation.

In summary, the expanded discussion confirms that the proposed RTLSTM–TCN effectively unites long-range sequence modeling and short-term convolutional dynamics to outperform prior models, remain computationally practical, and provide a robust analytical foundation for seasonal income forecasting in rural tourism.

8 Limitations

While the RTLSTM–TCN framework achieves strong predictive accuracy, several limitations remain.

(1) *Generalizability:* The model was evaluated primarily using aggregated data from major economies; results may not generalize equally to countries with limited tourism or incomplete records.

(2) *Computational cost:* The hybrid deep-learning structure increases training time and hardware demand compared to classical models.

(3) *Interpretability:* Although the architecture supports temporal feature tracing, full interpretability analysis (e.g., SHAP or LIME) was not implemented in this version.

(4) *Data bias:* Differences in reporting standards and seasonal patterns across countries may introduce selection or measurement bias.

Future extensions will incorporate explainability mechanisms and domain adaptation strategies to address these challenges.

9 Conclusion and future work

This study proposed a novel Hybrid RTLSTM–TCN deep learning framework for forecasting seasonal income in rural tourism, integrating the sequential memory strength of LSTM with the short-term pattern extraction capability of TCN. The model was evaluated against a comprehensive set of baselines—statistical (ARIMA), machine learning (KELM, MSS-KELM), ensemble (B-SAKE), and deep learning (RNN, BiLSTM-TN, SAE-LSTM)—and consistently outperformed them across all metrics (RMSE = 0.18, MAE = 0.09, MAPE = 8 %, SMAPE = 6.5 %, RMSLE = 0.10, and R^2 = 0.85).

These results confirm the model's capability to capture non-linear, seasonal, and macro-economic dynamics underlying rural-tourism income. The hybrid architecture's dual learning mechanism enables robust forecasting even under volatile economic conditions, making it a reliable decision-support tool for policymakers, tourism boards, and regional planners. By accurately predicting seasonal income shifts, it assists in budget allocation, workforce management, and sustainability planning in rural economies.

Limitations and Future Directions: Despite its strong performance, this study is limited by the availability and granularity of tourism-income data, which may not fully represent micro-level variations across destinations. The model's interpretability also remains limited, as deep networks function largely as black-box predictors.

Future work will focus on several directions:

• Expanding the dataset to include climate, policy, and global-event indicators such as pandemic or disaster impacts.

• Developing monthly and regional-level forecasting modules for fine-grained policy use.

• Incorporating explainable-AI (XAI) techniques (e.g., SHAP, LIME) to improve model transparency.

• Applying transfer learning and metaheuristic optimization to enhance adaptability and efficiency.

• Deploying the model in interactive dashboards and early-warning systems to provide real-time insights for sustainable rural-tourism development.

Overall, the RTLSTM–TCN framework establishes a scalable foundation for adaptive, interpretable, and policy-driven rural-tourism analytics, bridging the gap between academic modeling and practical decision-making.

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Declaration

Ethics approval and consent to participate I confirm that all the research meets ethical guidelines and adheres to the legal requirements of the study country.

Consent for publication: I confirm that any participants (or their guardians if unable to give informed consent, or next of kin, if deceased) who may be identifiable through the manuscript (such as a case report), have been given an opportunity to review the final manuscript and have provided written consent to publish.

Availability of data and materials: The data used to support the findings of this study are available from the corresponding author upon request.

Competing interests: Here are no have no conflicts of interest to declare.

All authors have seen and agree with the contents of the manuscript and there is no financial interest to report. We certify that the submission is original work and is not under review at any other publication.

Authors' contributions (Individual contribution): All authors contributed to the study conception and design. All authors read and approved the final manuscript.

There is no human participate involved in this research. this article manuscript is created from collection of data set.

All authors contributed to the study conception and design. All authors read and approved the final manuscript.

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