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Daily tourism demand forecasting before and during COVID-19: data predictivity and an improved decomposition-ensemble framework

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ABSTRACT

The global tourism industry is struggling to recover from the COVID-19 pandemic. During the COVID-19 pandemic, daily tourism forecasting is more critical than ever before in supporting decisions and planning. Considering the changes in tourist psyche and behaviour caused by COVID-19, this study attempts to investigate whether the statistical modelling methods can work reliably under the new normal when travel restrictions are eased or lifted. To this end, we first compare the predictivity of daily tourism demand data before and during COVID-19, and observe heterogeneous impacts across different geographical scales. Then an improved multivariate & multiscale decomposition-ensemble framework is proposed to forecast daily tourism demand. The empirical study indicates the superiority and practicability of the proposed framework before and during COVID-19. Finally, we call for more research on the comparability of tourism demand forecasting.

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COVID-19 pandemic; tourism demand forecasting; multivariate decomposition; data predictivity; decomposition-ensemble framework; deep learning

'Never let a good crisis go to waste.'
– Winston Churchill, 1945

Introduction

The coronavirus disease 2019 (COVID-19) pandemic has caused a global medical crisis and economic downturn. To limit the spread of the coronavirus, many governments have imposed a series of lockdown measures, including travel restrictions and social distancing, dealing an unprecedented blow to the tourism industry. According to the United Nations World Tourism Organization (UNWTO), worldwide international tourist arrivals declined 71% in 2020, 69% in 2021, and 37% in 2022, compared with 2019 (UNWTO, 2023). Over the past three years, the emergence of the coronavirus variants and their alarming infection rates have forced intermittent tightening of travel restrictions, resulting in a slow and fragile tourism recovery (Miao et al., 2021; Plzáková & Smeral, 2022).

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Tourism demand forecasting, as the cornerstone of allocating resources and designing policies for tourism recovery, plays an important role as never before during the COVID-19 pandemic (Yang et al., 2022). Tourism recovery forecasting has emerged as a hotspot and frontier in the literature on tourism demand forecasting (Song et al., 2022; Song & Li, 2021). Scholars from all over the world develop various scenarios and judgment adjustments to forecast the path of tourism recovery (Athanasopoulos et al., 2023; Kourentzes et al., 2021; Liu et al., 2021; Qiu et al., 2021; Zhang et al., 2021b). All the aforementioned studies are conducted in the early stages of the pandemic when the extent and duration of the pandemic remain unclear. According to the historical experience in fighting viruses, coexisting with the virus where infections and death are at a tolerable level is the long-term goal for humanity. A *Nature* survey launched in 2021, based on interviews with more than 100 experts working on the coronaviruses, also generally supports the view that the virus will not be eradicated but will coexist with humans as an endemic for the long term (Phillips, 2021). As vaccination campaigns advance and relatively mild variants (i.e. Delta and Omicron) emerge, governments are exploring long-term strategies tailored to their own circumstances, such as living with COVID-19 in Singapore and England, and the past dynamic zero COVID in China. In the context of this new normal, tourists are allowed to travel with compliance to government guidelines and rules on health and safety (Kim & Liu, 2022).

This new normal poses huge challenges and opportunities for tourism demand forecasting. On the one hand, when tourist arrivals data is regenerated, it is worth investigating whether previous statistical modelling methods, which have been recognized by the academic community as unsuitable for tourism recovery forecasting during the pandemic, can work reliably. On the other hand, given the changes in tourist psyche and behaviour caused by the pandemic (Kock et al., 2020; Li et al., 2020b; Li et al., 2021b; Miao et al., 2021; Shin et al., 2022), such as the compensative ‘binge’ travel, the preference for short trips, drive-to destinations, outdoor activities, and small-group or independent tourism, there will be structural changes in tourist arrival patterns during the pandemic (Athanasopoulos et al., 2023; Sun et al., 2023). Therefore, it is urgent to propose more powerful models that can handle data with complex patterns.

Daily tourism demand forecasting greatly supports tourism stakeholders to take more flexible and sophisticated measures to cope with high uncertainty. However, daily tourism demand is more difficult to forecast than monthly and quarterly tourism demand due to more complex and irregular seasonal patterns (Hu et al., 2021; Liu et al., 2022). Fortunately, daily tourism demand has accumulated sufficient data to train deep learning models and to compare data predictivity between normal times (before COVID-19) and crisis times (during COVID-19). The explanatory variables available for daily tourism demand are weather and calendar data, increasing the potential for improving forecasting performance (Bi et al., 2020; Li et al., 2020a). Furthermore, due to the limited availability of datasets, daily tourism demand forecasting instead offers the opportunity to achieve cross-study comparability.

Given the above considerations, we first compare the predictivity of daily tourism demand data of two cases at different geographic scales before and during COVID-19 by referring to the concept and method of predictivity of tourism demand proposed by Zhang et al. (2021d). One is the daily tourist volume at Jiuzhaigou. The other is the daily tourist arrivals to Macao from Mainland China. It is found that the predictivity of tourist volume in Jiuzhaigou during the pandemic is generally higher than that before the pandemic, while the predictivity of tourist arrivals to Macao from Mainland China during the pandemic is generally lower than that before the pandemic. The heterogeneous impacts of the COVID-19 pandemic on different geographic scales may be rooted in changes in tourist psyche and travel behaviour (Kock et al., 2020; Li et al., 2021b).

Then we propose an improved multivariate & multiscale deep learning approach based on the decomposition-ensemble framework for daily tourism forecasting before and during COVID-19. The newly developed multivariate decomposition techniques are introduced to capture the multiscale relationships between daily tourism demand and explanatory variables, which helps to model the complex seasonal patterns of daily tourism demand. We adopt the secondary

decomposition and reconstruction strategy to further process the decomposed intrinsic mode functions (IMFs). Moreover, Bidirectional Gate Recurrent Unit (Bi-GRU) deep learning model, whose hyperparameters are tuned using Bayesian optimization, is adopted to model and forecast multivariable tourism demand series. The above two cases are used to illustrate the superiority and practicability of the proposed model. According to the measures including forecasting indicators, statistical tests, comparisons with existing models, and boxplots, our proposed model outperform all the benchmarks both before the during COVID-19.

This study aims to respond to the tourism research agenda during and after COVID-19 proposed by Assaf et al. (2022), who call for (1) assessing the spatial effects of COVID-19 for various geographic scales, such as country, state/province, city, and sites; and (2) forecasting tourism demand amid major public health crises including COVID-19. Our study also advances the methodology of tourism demand forecasting literature. First, previous tourism demand forecasting studies based on the decomposition-ensemble framework focus on monthly data, and most of them adopt univariate decomposition methods (Xie et al., 2020; Zhang et al., 2022; Zhao et al., 2023), which greatly limits the incorporation of additional explanatory variables. The multivariate decomposition techniques we introduced can align the similar frequency components of multivariate time series and thereby extract the interrelationships between the series more effectively (N. u. Rehman & Aftab, 2019). Second, the classical decomposition-ensemble framework is criticized for its difficulty in modelling the decomposed high-frequency IMFs and the cumulative errors caused by the individual forecasts ensemble of the low-frequency IMFs (Li et al., 2021a; Yu et al., 2015). We combine secondary decomposition strategy and reconstruction strategy to improve this framework to meet the challenge of daily travel demand forecasting. Lastly, and perhaps most importantly, we compare the forecasting accuracy of our proposed model with that of other daily tourism demand forecasting models on the same dataset. We call for follow-up tourism demand forecasting studies to open up research data or adopt public data, as well as state as clearly as possible each step of modelling, which facilitates the comparability of forecasting models (Li et al., 2022).

Literature review

Tourism demand forecasting amid COVID-19

COVID-19 has made a significant negative impact on the tourism market. Accurately forecasting tourism demand has never been more important to decision-making among government officials, tourism practitioners, and other tourism stakeholders (Yang et al., 2022). Back in July 2020, the *Annals of Tourism Research* launched a tourism forecasting competition to forecast the impact of the pandemic on the tourism industry (Song & Li, 2021). Nineteen researchers from around the world take part in the competition by forming three teams of Asia and Pacific, Europe, and Africa (Kourentzes et al., 2021; Liu et al., 2021; Qiu et al., 2021). They perform ex-ante forecasts on quarterly international tourist arrivals for 20 selected destinations by setting up mild, medium, and severe scenarios. They each have their differences in design scenario-based judgmental adjustment.

Since then, tourism demand forecasting literature amid COVID-19 turn to tourism recovery in specific regions, with scenario analysis dominating research methods. For example, Zhang et al. (2021b) forecast the possible paths to the recovery of Hong Kong tourism by integrating econometric and judgmental methods. Gu et al. (2022) focus on the possible tourism recovery strategies in small island developing states and design a system dynamics approach to simulate the possibility, duration, and drivers of recovery. Recently, from a global perspective, Yang et al. (2022) investigate whether online search queries could improve the forecasts of daily tourism demand during the COVID-19 pandemic, and further evaluate the factors affecting the effectiveness of online search queries.

Daily tourism demand forecasting

Due to limited data availability, previous tourism forecasting studies focus more on monthly, quarterly, and annual data than on daily data (Bi et al., 2020; Jiao & Chen, 2019). Daily tourism demand forecasting can help tourism practitioners to implement more flexible measures to respond to the high-frequency variation of tourism demand. Therefore, daily tourism demand forecasting has become a hot topic in tourism research in recent years (Bi et al., 2020; Bi et al., 2021; Hu et al., 2021; Li et al., 2020a). Daily tourism demand forecasting could be grouped into two types in terms of forecasting areas, which are international or domestic tourist arrivals forecasting, and tourist volume forecasting for tourist attractions.

Divino and McAleer (2010) explore the modelling and forecasting of daily international tourist arrival to Peru, which is the earliest known research work on daily tourism demand forecasting. Afterward, given that urban, regional, and national statistical departments rarely release daily tourism data, there are few studies on daily tourism demand forecasting at these levels. Recently, Wu et al. (2021) and Zhang et al. (2022) attempt to forecast daily tourist arrivals to Macao from multiple source countries using data released by the Statistics and Census Service of Macao. They believe that daily forecast results could provide more information than monthly or quarterly forecasts, thus facilitating daily operational decisions such as determining tourism tax rates and making differentiated marketing strategies.

As for tourism volume forecasting for tourist attractions, Jiuzhaigou, Mount Siguniang, Mount Huangshan, Kulangsu, and other Chinese tourist attractions are common cases used to verify and compare the performance of different forecasting approaches (Bi et al., 2020; Bi et al., 2021; Hu et al., 2021; Li et al., 2020a; Tian et al., 2021; Zhang et al., 2020a). In particular, according to the survey of this study, at least 6 daily tourism forecasting studies have adopted the data of tourist volume at Jiuzhaigou. On the one hand, such a research status quo provides the possibility to explore the comparability of tourism demand forecasting, considering the previous international tourism demand forecasting literature focuses on different destinations and sources (Sun et al., 2022). On the other hand, as attempted by Bi et al. (2021), daily tourism demand forecasting can help reveal the impact of COVID-19 on tourism demand and provide insights into the recovery of the tourism industry.

Decomposition methods in tourism demand forecasting

Decomposition methods have been shown to significantly improve tourism demand forecasting performance (Silva et al., 2019; Xie et al., 2020; Zhang et al., 2021c; Zhang et al., 2022). A recent comparative study of tourism decomposition methods classifies existing decomposition methods into three types: filtering, denoising, and multiscaling (Zhang et al., 2022).

In recent years, few studies on tourism demand forecasting have extended univariate decomposition to a multivariate decomposition framework to capture the interrelationships between series. For instance, Saayman and de Klerk (2019) introduce a multivariate singular spectrum analysis (MSSA) to forecast tourist arrivals to South Africa. Their comparative experiments indicate that the MSSA improves the forecasting accuracy compared with the univariate form, especially when forecasting over longer time horizons. To effectively model and forecast seasonal tourism demand, Chen et al. (2019) innovatively propose a multivariate STSM framework by restacking the quarterly components. Zhang et al. (2021a) examine whether mining the connections between major inbound markets could improve the tourism demand forecasting performance of corresponding destinations by employing noise-assisted multivariate empirical mode decomposition (NA-MEMD). However, all of the above studies focus on monthly or quarterly rather than daily tourism demand.

The decomposition-ensemble framework based on the 'divide and conquer' principle improves forecasting performance by mitigating modelling complexity and has demonstrated its forecasting

potential in tourism demand forecasting (Xie et al., 2020; Zhang et al., 2021a; Zhang et al., 2021c; Zhang et al., 2022). Xie et al. (2020) summarize the decomposition-ensemble framework as the following steps: (1) data decomposition, dividing complicated tourism time series into relatively simple components; (2) individual forecasting, forecasting each extracted component; and (3) ensemble forecasting, combining the individual results into the ensemble forecasting. Based on the above considerations, this study attempts to develop an improved multivariate & multiscale decomposition-ensemble framework for forecasting daily tourism demand.

Deep learning in tourism demand forecasting

Mining the potential of tourism-related big data would further improve the forecasting accuracy. Deep learning has proven its effectiveness in dealing with complex nonlinear big data in many fields, including tourism demand forecasting (Law et al., 2019; Sun et al., 2022). According to the application paradigm of deep learning, deep learning in tourism demand forecasting can be divided into the following three categories, namely, improved deep learning models, ensemble deep learning models, and the combination of data pre-processing and deep learning models.

Deep learning models, especially the LSTM network, have been reported to be suitable for processing sequential data (Kulshrestha et al., 2020; Law et al., 2019). To capture the nonlinear relationship between tourism demand sequential attributes and explanatory variables more effectively, various improved LSTM models are developed. For example, Law et al. (2019) propose an LSTM embedded with an attention mechanism to automatically identify a set of appropriate search intensity index indicators and determine their lag order.

Ensemble models improve the generalization and robustness of forecasting using multiple individual learners and suitable combination strategies (B. Huang & Hao, 2021). To our best knowledge, only three tourism demand forecasting studies have developed ensemble deep learning models. Both B. Huang and Hao (2021) and Sun et al. (2022) apply Bagging to generate additional training datasets, and then utilize deep belief network (DBN) and kernel-based extreme learning machine (KELM) respectively to obtain multiple sets of forecasting results. Finally, they obtain the final forecasting values through support vector regression (SVR) and average aggregation respectively. Bi et al. (2022) propose an ensemble of LSTM networks by applying multiple time steps and different numbers of units in LSTM networks.

The combination of data pre-processing and deep learning may be a promising approach, given that too little training data is available for monthly and lower frequency tourism demand forecasting, resulting in overfitting and high complexity. Zhang et al. (2020b) develop a clustering method to identify regions with similar tourism arrival patterns and expand the available data of deep learning by the pooling strategy, which effectively alleviates model overfitting and significantly improves forecasting accuracy. Various decomposition methods developed in previous literature significantly reduce the complexity of original data, demonstrating the potential of these methods in combination with deep learning to further improve performance (Li & Law, 2020; Zhang et al., 2021a; Zhang et al., 2021c).

Research methodology

In this study, we use vector $Y^N = (y^{(1)}, y^{(2)}, \dots, y^{(j)}, \dots, y^{(N)})$ to represent daily tourism demand data with N time steps, and matrix $X_{m-1}^N = \{\bar{X}_{(1)}^N, \bar{X}_{(2)}^N, \dots, \bar{X}_{(j)}^N, \dots, \bar{X}_{(m-1)}^N\}$ to represent the auxiliary data made by $m - 1$ exogenous variables. $\bar{X}_{(j)}^N$ is the j th exogenous variable: $\bar{X}_{(j)}^N = (x_{(j)}^{(1)}, x_{(j)}^{(2)}, \dots, x_{(j)}^{(N)})$. We use the auxiliary data $\{\{\bar{X}_{(j)}^{(i)}\}_{j=1}^{m-1}\}_{i=1}^n$ and the past tourism demand data $(y^{(i)})_{i=1}^n$ to forecast

future tourism demand $(y^{(i)})_{i=n+1}^{n+\delta}$, as follows.

$$(y^{(i)})_{i=n+1}^{n+\delta} = f(\{\{\bar{x}_{(j)}^{(i)}\}_{j=1}^{m-1}\}_{i=1}^n, (y^{(i)})_{i=1}^n), \quad (1)$$

where $f(\cdot)$ represents a predictive model and δ is the length of future time steps.

The multivariate series available in this study includes tourist volume Y^N , exogenous variables $X_{m-1}^N = \{\{x_1^{(i)}\}_{i=1}^N, \{x_2^{(i)}\}_{i=1}^N, \dots, \{x_{m-1}^{(i)}\}_{i=1}^N\}$. The above multivariate data can be expressed as a $(m \times N)$ dimensional matrix, that is

$$MD_m^N = \begin{bmatrix} Y^N \\ X_{m-1}^N \end{bmatrix} = \begin{bmatrix} y^{(1)} & y^{(2)} & \dots & y^{(N)} \\ x_1^{(1)} & x_1^{(2)} & \dots & x_1^{(N)} \\ x_2^{(1)} & x_2^{(2)} & \dots & x_2^{(N)} \\ \vdots & \vdots & \vdots & \vdots \\ x_{m-1}^{(1)} & x_{m-1}^{(2)} & \dots & x_{m-1}^{(N)} \end{bmatrix}.$$

Fast and adaptive multivariate EMD

Starting from the seminal study on EMD by N. E. Huang et al. (1998), various variants of multivariate EMD (e.g. bivariate, trivariate, and general multi-variate EMDs) have been developed and demonstrated to be capable of decomposing multivariate data with cross-channel mode alignment (Rehman & Mandic, 2010). However, early multivariate EMDs are criticized for their high computational cost. And Thirumalaisamy and Ansell (2018) propose a fast and adaptive multivariate EMD (FA-MVEMD), which uses order static filters to replace spline interpolation in the early multivariate EMDs, thus significantly reducing the computational effort. Technically, FA-MVEMD consists of steps (1) extrema detection, (2) envelope estimation, and (3) evaluation of a stoppage criterion (Thirumalaisamy & Ansell, 2018).

FA-MVEMD is employed to capture the multiscale relationship between exogenous variables and tourism demand. The input data MD_m^N is decomposed into K groups of the matched common IMFs and residue at aligned timescales.

$$MD_m^N = \sum_{k=1}^{K-1} C_{(k)}^N + R^N = \sum_{k=1}^{K-1} \{\bar{C}_{(k),y}^N, \bar{C}_{(k),x_1}^N, \bar{C}_{(k),x_2}^N, \dots, \bar{C}_{(k),x_{m-1}}^N\} + \{\bar{R}_y^N, \bar{R}_{x_1}^N, \bar{R}_{x_2}^N, \dots, \bar{R}_{x_{m-1}}^N\}, \quad (2)$$

where the vector $\bar{C}_{(k),y}^N$ and $\bar{R}_y^N$ are the k th IMF and residue of the tourism volume data respectively. The vector $\bar{C}_{(k),x_{ij}}^N$ and $\bar{R}_{x_{ij}}^N$ are the k th IMF and residue of the j th exogenous variables respectively.

The original data (orange) and decomposed FA-MVEMD IMFs and residue (blue) of the Jiuzhaigou case during COVID-19 are shown in Figure 1. The IMFs and residue are jointly, synchronously, and coherently captured to guarantee the timescales are aligned with each other (Yuan et al., 2019). The complexity of decomposed series is generally reduced, but the complexity of high-frequency IMFs such as IMF1 is still very high, indicating that it is still difficult to model and forecast. Therefore, further decomposition or rejection manually is necessary (Li et al., 2020a).

Multivariate adaptive variational mode decomposition

Multivariate variational mode decomposition (MVMD), developed by N. u. Rehman and Aftab (2019), is a multivariate extension of variational mode decomposition. MVMD inherits the advantages of VMD's robustness to noise and has a strong ability for high-frequency decomposition (Gao & Shao, 2022; N. u. Rehman & Aftab, 2019). The goal of MVMD is to decompose multivariate time series into a discrete amount of band-limited IMFs with specific sparsity properties. See N. u. Rehman and Aftab (2019) for the detailed solution process.

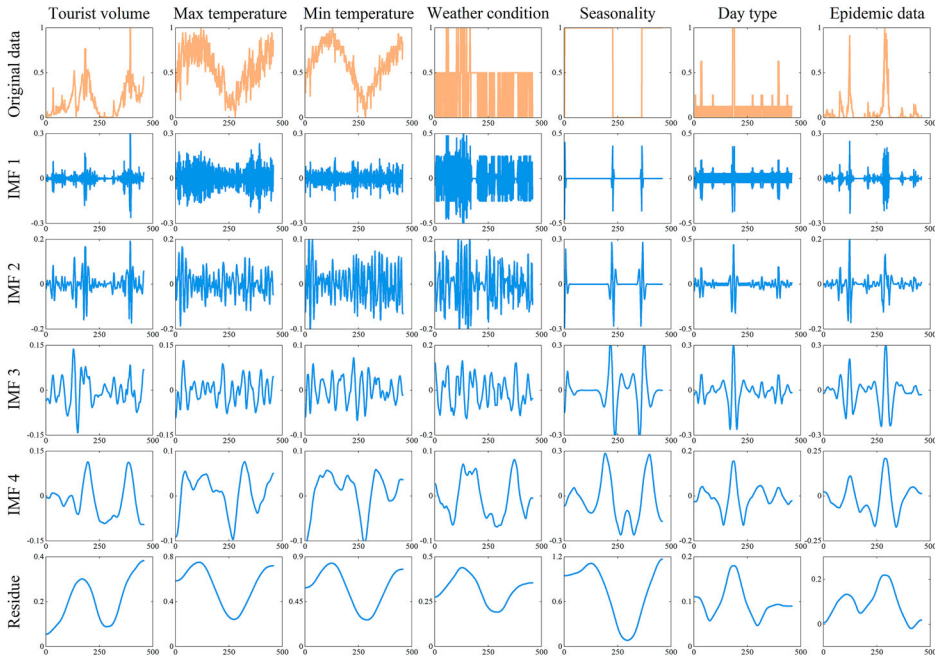


Figure 1. Original data and FA-MVEMD results of Jiuzhaigou case during COVID-19.

The high-frequency component IMF1 $C_{(1)}^N = \{\bar{C}_{(1),y}^N, \bar{C}_{(1),x_1}^N, \bar{C}_{(1),x_2}^N, \dots, \bar{C}_{(1),x_{m-1}}^N\}$ is further decomposed by MVMD into L groups of aligned IMFs.

$$C_{(1)}^N = \sum_{l=1}^L SC_{(l)}^N = \sum_{l=1}^L \{\vec{SC}_{(l),y}^N, \vec{SC}_{(l),x_1}^N, \vec{SC}_{(l),x_2}^N, \dots, \vec{SC}_{(l),x_{m-1}}^N\}, \quad (3)$$

where $\vec{SC}_{(l),y}^N$ and $\vec{SC}_{(l),x_j}^N$ are the l th IMFs of the tourism volume data and j th exogenous variables, respectively.

The flaw of MVMD is the need for a predefined number L of IMFs groups (N. u. Rehman & Aftab, 2019). We follow Sun et al. (2018) to design an adaptive MVMD (MAVMD) by adding a decomposition quality factor (DQF) as the termination condition to automatically determine the suitable L . DQF measures the degree of decomposition under different L values.

The IMF1 $C_{(1)}^N$ and the l th multivariate IMF after re-decomposition are $(m \times N)$ dimensional matrixes as follows:

$$C_{(1)}^N = \begin{bmatrix} C_{(1),y}^{(1)} & C_{(1),y}^{(2)} & \dots & C_{(1),y}^{(N)} \\ C_{(1),x_1}^{(1)} & C_{(1),x_1}^{(2)} & \dots & C_{(1),x_1}^{(N)} \\ C_{(1),x_2}^{(1)} & C_{(1),x_2}^{(2)} & \dots & C_{(1),x_2}^{(N)} \\ \vdots & \vdots & \vdots & \vdots \\ C_{(1),x_{m-1}}^{(1)} & C_{(1),x_{m-1}}^{(2)} & \dots & C_{(1),x_{m-1}}^{(N)} \end{bmatrix} SC_{(l)}^N = \begin{bmatrix} SC_{(l),y}^{(1)} & SC_{(l),y}^{(2)} & \dots & SC_{(l),y}^{(N)} \\ SC_{(l),x_1}^{(1)} & SC_{(l),x_1}^{(2)} & \dots & SC_{(l),x_1}^{(N)} \\ SC_{(l),x_2}^{(1)} & SC_{(l),x_2}^{(2)} & \dots & SC_{(l),x_2}^{(N)} \\ \vdots & \vdots & \vdots & \vdots \\ SC_{(l),x_{m-1}}^{(1)} & SC_{(l),x_{m-1}}^{(2)} & \dots & SC_{(l),x_{m-1}}^{(N)} \end{bmatrix}.$$

The entropy value $MMPE_{(l)}$ of l th IMF can be obtained using the concept of multivariate multiscale permutation entropy (MMPE) introduced in Section 3.3. The variation coefficient VC of $MMPE = \{MMPE_{(l)}\}_{l=1}^L$ can be further calculated to measure the difference between IMFs.

We assume that $\bar{C}_{(1)}^{(n)} = (c_{(1),y}^{(n)}, c_{(1),x_1}^{(n)}, c_{(1),x_2}^{(n)}, \dots, c_{(1),x_{m-1}}^{(n)})^T$, $\vec{SC}_{(l)}^{(n)} = (sc_{(l),y}^{(n)}, sc_{(l),x_1}^{(n)}, sc_{(l),x_2}^{(n)}, \dots, sc_{(l),x_{m-1}}^{(n)})^T$. The error between the original series before decomposition and the reconstructed series (the sum

of the IMFs) is given by

$$Rs = \sum_{n=1}^N \left| \vec{C}_{(1)}^{(n)} - \sum_{l=1}^L \vec{SC}_{(l)}^{(n)} \right|. \quad (4)$$

The ratio of the variation coefficient VC to the error Rs is DQF as follows:

$$DQF = \frac{VC}{R_s}. \quad (5)$$

A Higher DQF value means that the resulting IMFs reconstruct the original series better and are well differentiated from each other. Therefore, the highest DQF value and the corresponding optimal number of IMFs L can be found through traversal.

Multivariate multiscale permutation entropy

The concept of entropy has been an indicator of the complexity of time series data (Morabito et al., 2012; Zhang et al., 2021d). Sample entropy, permutation entropy, and multi-scale entropy are introduced into tourism demand forecasting literature (Xie et al., 2020; Zhang et al., 2021d). Considering that multiple explanatory variables are involved in this study, we adopt Multivariate multiscale permutation entropy (MMPE) to evaluate the complexity of multivariate data. The MMPE techniques are described as follows.

Step 1: Coarse-graining the multivariate time series. For a multivariate time series $SC_{(1)}^N$ of dimension m and length N , the k th column of corresponding m -dimensional coarse-grained time series $\vec{CG}_k^s = ((cg_{j,k}^s)_{j=1}^m)^T$ can be calculated as follows:

$$cg_{j,k}^s = \frac{1}{s} \sum_{n=s(k-1)+1}^{ks} sc_{(1),j}^{(n)}, \text{ for } j = 1, 2, \dots, m \text{ and } 1 \leq k \leq M = \frac{N}{s}, \quad (6)$$

where s refers to the scale factor and $cg_{j,k}^s$ represents the value of the j th variable of the k th column of this coarse-grained time series.

Step 2: Phase space reconstruction. Reconstruct the j th row of this coarse-grained time series with embedded dimension d and delay time τ as $Z_{j,i}^{d,\tau,s}$ using the following formula:

$$Z_{j,i}^{d,\tau,s} = (cg_{j,i}^s, cg_{j,i+\tau}^s, \dots, cg_{j,i+(d-1)\tau}^s), i = 1, 2, \dots, M - (d-1)\tau. \quad (7)$$

Step 3: Ordinal patterns counting. The result of arranging all the elements of $Z_{j,i}^{d,\tau,s}$ in incremental order is given as follows:

$$[cg_{j,i+(n_1-1)\tau}^s \leq cg_{j,i+(n_2-1)\tau}^s \leq \dots \leq cg_{j,i+(n_d-1)\tau}^s]. \quad (8)$$

If there are elements with the same value, they are arranged in the order they appear in the reconstructed time series. In this way, we get the ordinal pattern $\pi_{j,h}$ of all the elements in $Z_{j,i}^{d,\tau,s}$:

$$\pi_{j,h} = [n_1, n_2, \dots, n_d], 1 \leq h \leq d!. \quad (9)$$

For a phase space with an embedded dimension d , there will be $d!$ possible permutations. Let $f(\pi_{j,h})$ represent the frequency of the ordinal pattern $\pi_{j,h}$ occurrence in the coarse-grained series. The frequency of $\pi_{i,j}$ is

$$p(\pi_{j,h}) = \frac{f(\pi_{j,h})}{M - (d-1)\tau}, \quad (10)$$

where $p(\pi_{j,h})$ satisfies $\sum_{j=1}^m \sum_{h=1}^{d!} p(\pi_{j,h}) = 1$.

Lastly, MMPE is represented in the form of Shannon entropy:

$$MMPE = - \sum_h^{d!} p(\pi_h) \log_2 p(\pi_h), \quad (11)$$

where $p(\pi_h) = \sum_{j=1}^m p(\pi_{j,h})$.

Bidirectional gate recurrent unit

To mitigate gradient vanishing and exploding of traditional RNN structures, Cho et al. (2014) propose the GRU architecture that introduces the gating mechanism to control information. GRU is a simple variant of LSTM, with excellent performance and cheaper computation.

As shown in Figure 2 (a), the update gate controls how much information the current hidden state h_t retains from the previous state h_{t-1} and how much information it receives from the candidate state $\tilde{h}_t$, while the reset gate decides whether the candidate state is dependent on the previous state. The corresponding equations are as follows:

$$\begin{cases} h_t = (1 - z_t) \odot h_{t-1} + z_t \odot \tilde{h}_t, \\ z_t = \sigma(W_z x_t + U_z h_{t-1} + b_z), \\ \tilde{h}_t = \tanh(W_h x_t + U_h (r_t \odot h_{t-1}) + b_h), \\ r_t = \sigma(W_r x_t + U_r h_{t-1} + b_r), \end{cases} \quad (12)$$

where $\odot$ represents the pointwise multiplication, σ is the sigmoid function, $\tanh$ is the activation function. W and U are weight matrixes, and b is the bias vector.

Compared with GRU, Bi-GRU can utilize both backward and forward information, as shown in Figure 2 (b). A Bi-GRU consists of two layers of GRUs with the same input but different information transmission directions. The output h_t is then computed by

$$\vec{h}_t = \vec{h}_t \oplus \overleftarrow{h}_t, \quad (13)$$

where $\vec{h}_t$ and $\overleftarrow{h}_t$ denote the forward and backward hidden states, respectively, and $\oplus$ represents the element-wise sum.

The improved decomposition-ensemble framework

In this section, we describe in detail the improved decomposition-ensemble framework for daily tourism demand forecasting proposed in this study. The forecasting framework is shown in Figure 3 and consists

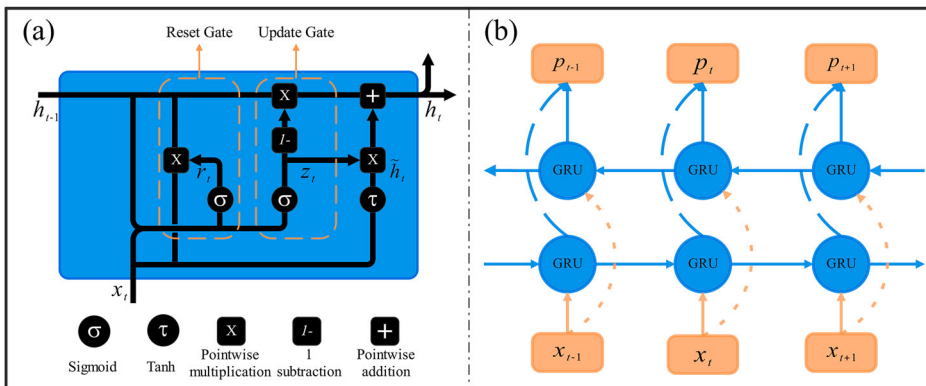


Figure 2. A GRU Memory Cell and the architecture of Bi-GRU.

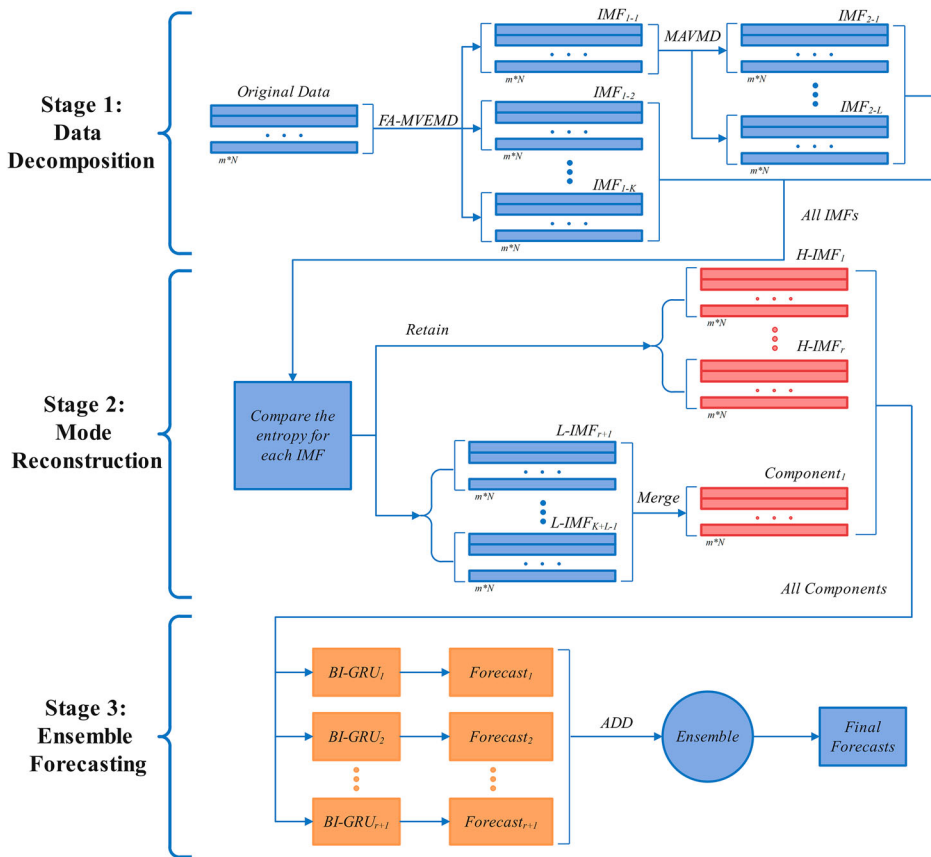


Figure 3. The improved decomposition-ensemble framework for daily tourism demand forecasting.

of the following three stages: data decomposition, mode reconstruction, and ensemble forecasting. The relevant descriptions are described below.

Stage 1: data decomposition

The decomposition methods are criticized for failing to eliminate the high-frequency IMFs that affect the forecasting performance. Two strategies for this deficiency are denoising and re-decomposition (Li et al., 2020a). Specifically, the denoising strategy treats high-frequency IMFs (IMF1 in most cases) as chaotic and unsystematic noise and removes them directly. While the re-decomposition strategy emphasizes the potential beneficial information contained in the high-frequency IMFs and believes that the complex patterns of the high-frequency IMFs can be further reduced by re-decomposition. We adopt the re-decomposition strategy, which is also called the secondary decomposition strategy.

First, the multivariable original data MD_m^N is decomposed by FA-MVEMD into K groups of the matched common IMFs $\sum_{k=1}^{K-1} C_{(k)}^N + R^N$ at aligned timescales. Second, MAVMD is employed to further decompose the most irregular and unsystematic high-frequency IMF (namely IMF1) $C_{(1)}^N$ into L sparse IMFs $\sum_{l=1}^L SC_{(l)}^N$. Using the above secondary decomposition strategy, we obtain $K + L - 1$ IMFs with lower complexity and stronger regularity. Detailed decomposition procedures are described in **Subsections 3.1** and **3.2**.

Stage 2: mode reconstruction

Although the decomposition techniques can effectively deal with nonlinear and non-stationary tourism complex data, modelling each IMFs is a time-consuming process in individual forecasting, especially considering that the re-decomposition also brings a series of new IMFs. More importantly, modelling each IMFs may lead to a poor forecasting result because the cumulative errors of all individual forecasts accumulate in the ensemble forecasting (Yu et al., 2015). It may be promising to combine low-complexity IMFs to reduce the number of individual predictions.

We use MMPE detailed in Subsection 3.3 to measure the complexity of the multivariable IMFs obtained by decompositions. If the complexity of an IMF is relatively low, this indicates that the IMF can be captured and modelled well, and it should be merged with other IMFs of similar complexity to reduce computational costs and cumulative errors. Conversely, if the complexity of an IMF is relatively high, the IMF is retained as a separate component. To avoid introducing the ad-hoc criteria for IMFs complexity recognition, we set the MMPE threshold ranges {0.3, 0.4, 0.5, 0.6, 0.7, 0.8} and optimize it automatically.

Stage 3: ensemble forecasting

In this stage, we output the final forecasts by ensemble forecasting. The Bi-GRU model introduced in Subsection 3.4 is established for each reconstructed component. And the final result is obtained by aggregating the forecasting results of all components. Considering the reduced difficulty of forecasting each reconstructed component individually, ensemble forecasting is expected to improve the forecasting performance.

Empirical study

Data description

We choose two datasets publicly available as empirical cases, namely, tourist volume at Jiuzhaigou, a famous attraction in China (hereinafter referred to as Jiuzhaigou case), and tourist arrivals to Macao

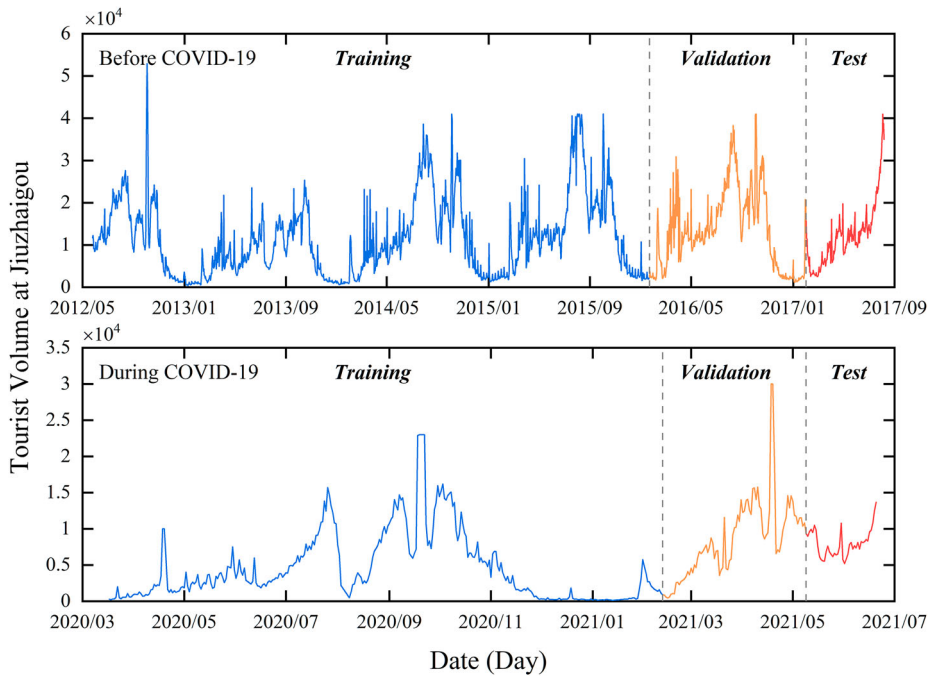


Figure 4. Daily tourist volume at Jiuzhaigou before and during COVID-19.

from Mainland China (hereinafter referred to as Macao case). In addition, auxiliary data including calendar, weather, and epidemic data are considered in each case. The collection and pre-processing of the above data are described as follows.

Jiuzhaigou case

The historical data of daily tourist volume at Jiuzhaigou is obtained from the official website of Jiuzhaigou (<https://www.jiuzhai.com>), and its coverage timespan is from May. 25, 2012 to Jul. 4, 2021, as shown in Figure 4. Within that time, Jiuzhaigou was briefly closed due to the earthquake near the attraction on Aug. 8, 2017, and the COVID-19 outbreak in late 2019. Therefore, the tourist volume data before Aug. 8, 2017, and after the reopening of the attraction on Mar. 31, 2021, are considered as the sub-datasets before and during COVID-19, respectively. Considering the optimization of hyperparameters, the validation set needs to be set, so we follow the general laws of machine learning and divide each sub-dataset into the training, validation, and test sets in a ratio of 7:2:1.

The calendar data of the Jiuzhaigou case consists of day type and attraction seasonality, of which day type includes weekdays/weekends and national statutory holidays, and attraction seasonality includes off seasons and peak seasons designated by the attraction. The weather data used in this study include temperature and weather conditions, which are collected from a professional weather website named Tianqi (<https://lishi.tianqi.com>). Given that calendar data and weather conditions are qualitative data, they need to be converted according to certain rules before being incorporated into the quantitative forecasting model. As shown in Table 1, we follow Bi et al. (2021) and Li et al. (2020a) to design the mapping rules to achieve this conversion. Additionally, the epidemic data used to forecast the tourist volume during COVID-19 is the number of newly confirmed local cases in mainland China per day, which has been confirmed in recent empirical studies (Li et al., 2021b). Although the Mainland China has contained the rampant spread of the coronavirus during this time, scattered cases have led to the dynamic tightening of anti-epidemic measures in provinces and cities across the country, affecting travel plans for tourists.

Macao case

The database of Macao Statistic and Census Service (<https://www.dsec.gov.mo>) records daily tourist arrivals to Macao from Mainland China since January 2017. As shown in Figure 5, due to the COVID-19 outbreak in late 2019, the sub-dataset before COVID-19 covers a time range from Jan. 1, 2017 to Dec. 31, 2019. After the outbreak of COVID-19, the number of tourists from Mainland China to Macao dropped sharply and only gradually recovered since Aug 2020. Therefore, the tourist arrivals after Aug. 1, 2020, are considered as the sub-dataset during COVID-19. Consistent with Case 1, the sub-datasets before and during COVID-19 are also divided into the training, validation, and test sets in a ratio of 7:2:1.

The calendar data of the Macao case only includes day types and no seasonality. Since we focus on tourist arrivals from Mainland China, the mapping rules of day types are the same as those in the

Table 1. Mapping rules for the qualitative auxiliary data.

Auxiliary factors		Mapping for Jiuzhaigou	Mapping for Macao
Weather condition	Sunny, cloudy, and overcast	1	1
	Light rain/snow, shower, and snow shower	5	5
	Heavy/moderate rain/snow	9	9
Day type	Weekdays	1	1
	Weekends	2	2
	New Year, Spring Festival, Ching-Ming Festival, Dragon Boat Festival, and Mid-autumn Festival	3	3
	May day	6	6
	National Day	9	9
	Off seasons	1	\
Seasonality	Peak seasons	2	\

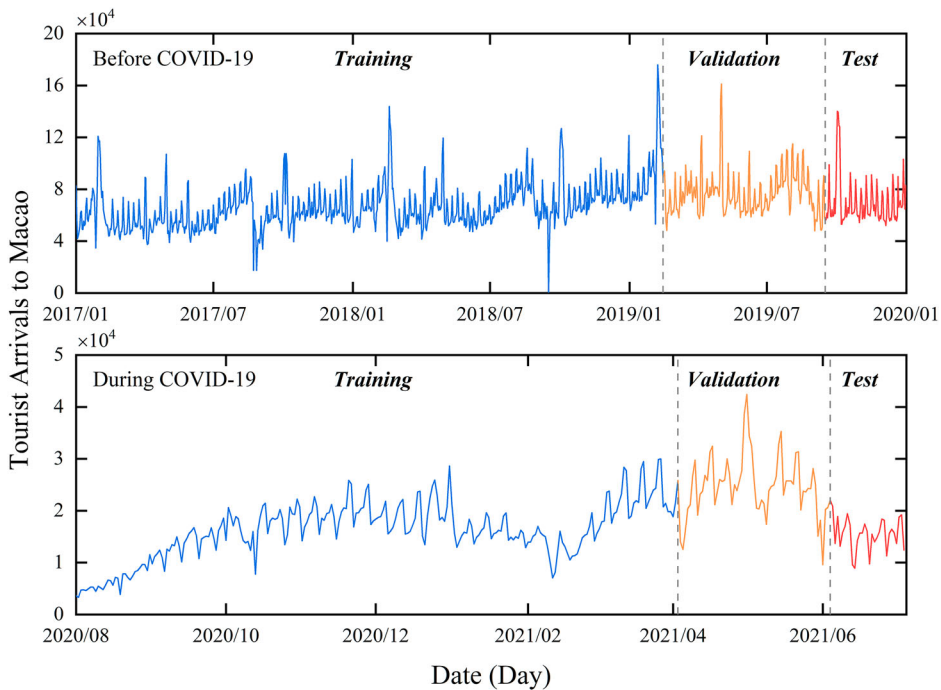


Figure 5. Daily tourist arrivals to Macao from Mainland China before and during COVID-19.

Jiuzhaigou case. In addition, the collection of weather data and mapping of weather conditions follow the practice of the Jiuzhaigou case.

Predictivity analysis

Before the formal forecasting experiment, we follow Song et al. (2010) and Zhang et al. (2021d) quantitatively evaluate the predictivity of daily tourism demand data in Jiuzhaigou and Macao cases, and highlight the differences between before and during COVID-19. A two-step calculation procedure is described as follows: sample entropy is first introduced to measure data complexity, and then the maximum predictivity of the given daily tourism demand data could be obtained through Fano's Inequality transformation.

To compare the maximum predictivity before and during COVID-19, the corresponding time series are sampled consecutively and repeatedly with a data length of 30 days (consistent with the later forecasting input setting). Next, the sample entropy and maximum predictivity values of the sub-series samples are calculated. Finally, we plot the probability density distributions of entropy and maximum predictivity of the above two cases respectively, as shown in Figure 6. We observe two opposite patterns in Jiuzhaigou and Macao cases. Specifically, in the Jiuzhaigou case, the maximum predictivity of tourism demand data before COVID-19 is generally lower than that during COVID-19. In other words, daily tourist volume data at Jiuzhaigou before COVID-19 are more complex and harder to forecast than that during COVID-19. However, these above comparisons are exactly the opposite in the Macao case.

Recent researches on the impact of COVID-19 on tourist psyche and travel behaviour offer clues to explain this finding. Based on the analysis of attractions in seven provinces of China, Li et al. (2021b) find that tourists prefer short-distance and local trips after experiencing COVID-19. For the Jiuzhaigou case, the vast majority of tourists come from proximity areas. Therefore, the complexity of tourist arrival mode is greatly reduced and the corresponding predictivity will be improved. As for the relatively long-distance trip case of Chinese mainland tourists to Macao, this tourism demand is relatively fragile

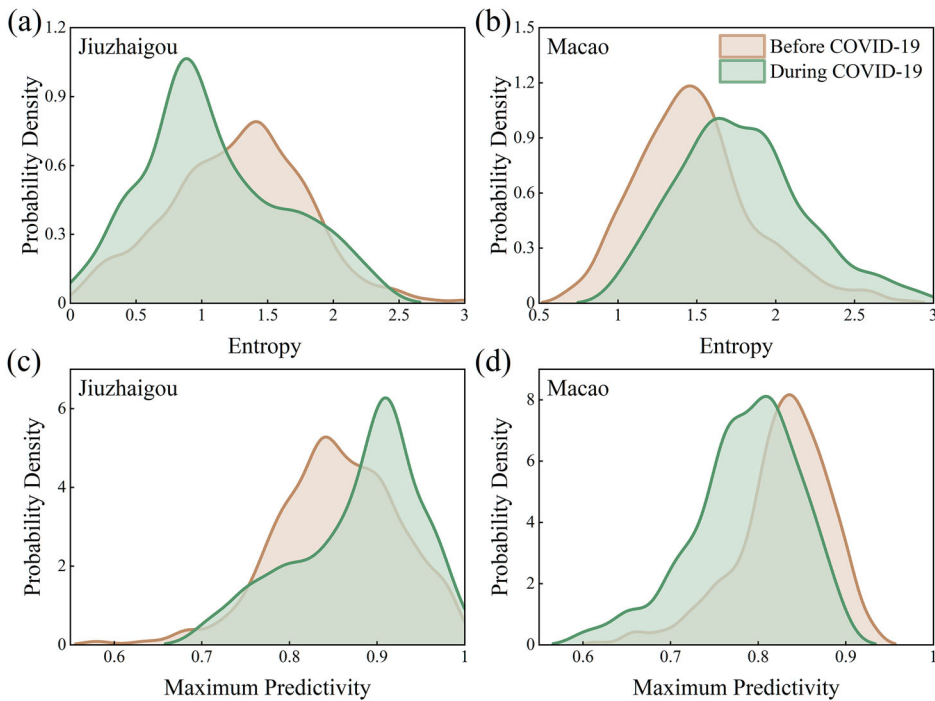


Figure 6. Comparison of entropy and maximum predictivity of tourism demand data before and during COVID-19.

and vulnerable to external shocks. As a result, the tourism demand data patterns during COVID-19 are more irregular than that before COVID-19. We will further confirm this finding in empirical tests.

Benchmarks and experiment settings

Three categories of benchmark models are considered: traditional time series models, machine learning models, and hybrid models. The traditional time series models include Naïve, autoregressive integrated moving average (ARIMA), and ARIMA with exogenous variables (ARIMAX). The machine learning models include SVR, which has been proven to have excellent performance in small-sample and nonlinear forecasts (Li et al., 2020a; Zhang et al., 2017), and BiGRU, an improved version of LSTM, which is more suitable for modelling time series data. The hybrid models include two subversions of the proposed model, namely decomposition-BiGRU (D-BiGRU) and secondary decomposition-BiGRU (SD-BiGRU), which are designed to progressively demonstrate the contribution of each improvement of the proposed model to the forecasting performance.

Parameter tuning is performed to determine the best performance of all models involved. For ARIMA and ARIMAX, the difference order d is determined first to ensure that the tourism demand time series are stable. Then the best lag order p and the order of the moving average q are identified from the ranges $\{0, 1, 2, 3, 4, 5\}$ based on the Bayesian information criterion. We follow Kulshrestha et al. (2020) to choose Bayesian Optimization to perform hyperparameters tuning for machine learning models. For SVR, the RBF kernel function is adopted. The corresponding hyperparameters, the penalty factor and the kernel parameter, are determined through Bayesian Optimization from the ranges $[1, 300]$ and $[0.0001, 100]$. For Bi-GRU, the hyperparameters are set as follows: epochs = 200, batch size = 512, early stopping patience = 50, optimizer = Adam, dropout rate $\in [0, 0.3]$, size of hidden unit $\in [5, 200]$, and L2 regularization $\in [0, 0.02]$. It is worth noting that the above hyperparameters are set from the range of continuous intervals except for those

given empirically, which is different from those are set with a limited option adopted by Zhang et al. (2021c). The reason behind this is that sufficient daily tourism demand data compared with monthly data provide a larger range for parameter setting, which helps to further improve the forecasting accuracy. We follow Sun et al. (2022) to adopt the dynamic forecasting with rolling windows. For model training and testing, the first 30 observations are used to fit and forecast the next value.

Empirical evaluations

To fully verify the superiority and practicability of the proposed model, a variety of measures including forecasting indicators, statistical tests, comparisons with existing models, and boxplots are performed in this subsection. The detailed description is given as follows.

Forecasting indicators

Three widely used performance indicators are adopted to evaluate our proposed model. These indicators are mean absolute percentage error (MAPE), mean absolute error (MAE), and root mean square error (RMSE), as defined below.

$$MAPE = \frac{1}{N} \sum_{n=1}^N \left| \frac{x_n - \hat{x}_n}{x_n} \right| \times 100\%, \tag{14}$$

$$MAE = \frac{1}{N} \sum_{n=1}^N |x_n - \hat{x}_n|, \tag{15}$$

$$RMSE = \sqrt{\frac{1}{N} \sum_{n=1}^N (x_n - \hat{x}_n)^2}, \tag{16}$$

where N is the number of observations in the test sets, x_n and $\hat{x}_n$ are the actual and forecasted values at the time step n , respectively. Obviously, the smaller the values of MAPE, MAE, and RMSE, the better the forecasting performance of the test model.

The one-step and multi-step forecasting results for Jiuzhaigou and Macao cases before and during COVID-19 are listed in Tables 2 and 3, S1, and S2. All the forecasting indicators indicate that the proposed SDR-BiGRU model outperforms the benchmarks including Naïve, ARIMA, ARIMAX, SVR, BiGRU, D-BiGRU, and SD-BiGRU. Despite the considerable computational resources invested in parameter settings, many benchmark models such as ARIMA, ARIMAX, SVR, and even BiGRU are not as accurate as Naïve, the simplest univariate model, in both one-step and multi-step forecasts. This finding is consistent with previous literature on tourism demand forecasting (Law et al., 2019; Song et al., 2019; Xie et al., 2020). D-BiGRU performs better than Bi-GRU, further demonstrating the effectiveness of FA-MVEMD multivariate decomposition. Moreover, two comparisons, SD-BiGRU and D-BiGRU, SDR-BiGRU and SD-BiGRU, respectively indicate that the secondary

Table 2. Forecasting results of different models for Jiuzhaigou before COVID-19.

Models	One-step			Four-step			Seven-step		
	MAE	RMSE	MAPE	MAE	RMSE	MAPE	MAE	RMSE	MAPE
Naïve	1360.42	2112.11	13.18	2369.04	3349.46	23.05	3171.54	4230.54	32.19
ARIMA	3096.77	5361.45	23.22	3704.88	6018.18	32.29	4022.19	6316.04	38.58
ARIMAX	4522.15	5681.34	38.37	5742.04	7800.86	47.91	6711.60	9134.66	53.75
SVR	2055.09	2625.25	29.35	2674.52	3317.43	37.10	3091.43	3906.47	43.69
BiGRU	1447.53	2082.35	14.78	2396.53	3305.73	25.90	3006.26	4089.74	32.18
D-BiGRU	1027.48	1425.53	10.31	1383.91	1885.65	15.52	1973.32	2628.52	20.65
SD-BiGRU	790.07	1005.24	8.38	1200.48	1647.36	13.78	1658.09	2229.22	18.43
SDR-BiGRU	586.21	810.38	6.06	1020.98	1251.66	11.90	1424.14	1943.84	16.12

Note: D-BiGRU: decomposition-BiGRU; SD-BiGRU: secondary decomposition-BiGRU; SDR-BiGRU: secondary decomposition and reconstruction-BiGRU. Bold font indicates the unique highest forecasting accuracy among the models.

Table 3. Forecasting results of different models for Macao before COVID-19.

Models	One-step			Four-step			Seven-step		
	MAE	RMSE	MAPE	MAE	RMSE	MAPE	MAE	RMSE	MAPE
Naïve	10181.50	14140.30	13.86	18011.20	25288.80	25.24	12407.60	23470.50	16.92
ARIMA	13092.10	17844.50	18.28	13311.20	20019.00	17.86	13095.00	19294.60	17.36
ARIMAX	13187.60	18812.10	17.10	12989.80	18770.60	17.23	14159.00	18183.90	20.19
SVR	10157.10	12962.70	14.18	9992.46	16550.20	13.03	10656.70	16565.30	14.03
BiGRU	6626.39	9642.82	9.37	9467.68	15681.80	11.94	9893.86	16521.30	12.35
D-BiGRU	5837.80	9076.30	7.95	7998.54	10917.20	11.09	9719.53	16511.70	12.05
SD-BiGRU	4703.04	5736.58	6.80	7105.91	9369.21	9.85	8053.80	12090.80	10.76
SDR-BiGRU	2915.24	3971.43	4.14	5868.13	7618.68	8.45	6220.50	8324.72	8.53

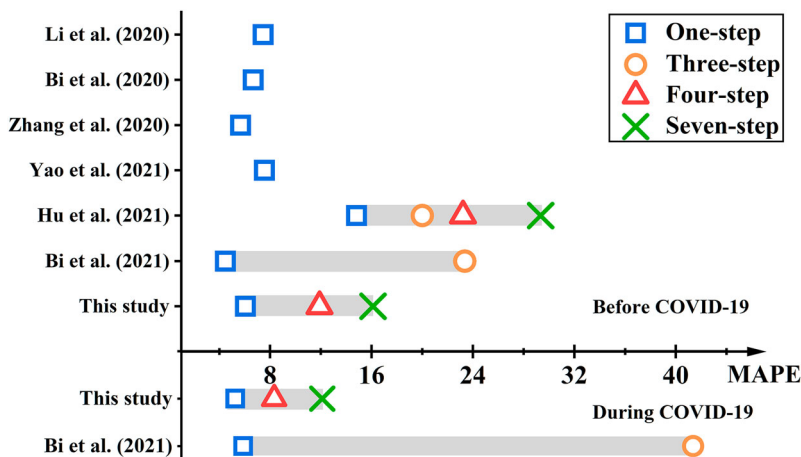
Note: D-BiGRU: decomposition-BiGRU; SD-BiGRU: secondary decomposition-BiGRU; SDR-BiGRU: secondary decomposition and reconstruction-BiGRU. Bold font indicates the unique highest forecasting accuracy among the models.

multivariable decomposition and the reconstruction strategy introduced in this study both contribute to the improvement of forecasting accuracy.

In terms of the comparison of forecasting performance before and during COVID-19, the results of the forecasting indicators in the Jiuzhaigou and Macao cases confirm the above findings of predictivity analysis. Take the proposed SDR-BiGRU as an example. For the Jiuzhaigou case, the MAPE values of one-step, four-step, and seven-step forecasts before COVID-19 are 6.06, 11.90, and 16.12, which are generally higher than those of corresponding steps forecasts during COVID-19. For the Macao case, the MAPE values before COVID-19 are all lower than those during COVID-19 (i.e. 4.14 VS 10.25, 8.45 VS 14.11, 8.53 VS 13.46 for one-step, four-step, and seven-step forecasts, respectively). This comparison is true for other models as well.

Comparisons with existing models

As described in the data description, Jiuzhaigou was temporarily closed for some time due to the earthquake on Aug. 8, 2017, resulting in the interruption of the tourism demand time series. Therefore, daily tourism demand forecasting literature taking Jiuzhaigou as an empirical case generally adopts the tourism volume data before Aug. 8, 2017. This provides an opportunity to achieve comparability of tourism demand forecasting. We thoroughly search all the tourism demand forecasting studies using daily tourist volume at Jiuzhaigou and extract their one-step and multi-step MAPE values, as shown in Figure 7.

**Figure 7.** The comparison of MAPE with existing models in Jiuzhaigou case.

It could be found that only Bi et al. (2021) conduct forecasts before and during COVID-19, while other studies focus on before Aug. 8, 2017, that is, before COVID-19 defined in this study. Since Bi et al. (2021) only use data up to Oct. 31, 2020, while we update it to July. 4, 2021, the comparison of forecasting experiments during COVID-19 is meaningless. Let us refocus on the comparison of forecasts before COVID-19. Figure 7 demonstrates that the forecasting performance of our proposed improved decomposition-ensemble framework is similar to or better than that of most existing models, especially over longer time horizons.

DM tests

To verify whether the proposed SDR-BiGRU model significantly outperforms the benchmark models, we perform the Diebold-Mariano (DM) tests on the one-step and multi-step forecasting results in Jiuzhaigou and Macao before and during COVID-19. The null hypothesis of the DM test is that there is no significant difference in the forecasting performance between the two comparison models (Bi et al., 2022). DM statistics and corresponding p values are shown in Tables S3-S4.

Table S3 indicates that in the cases of Jiuzhaigou and Macao before COVID-19, the forecasting results of SDR-BiGRU are significantly different from those of all benchmark models at 1% level or 5% level, regardless of one-step or multi-step forecasts. Therefore, SDR-BiGRU outperforms all the benchmark models at a 99% confidence level. Similarly, Table S4 presents the forecasting results of SDR-BiGRU that are significantly different from those of all benchmark models during COVID-19 at 1% or 5% levels, which once again proves the powerful forecasting performance and robustness of SDR-BiGRU model before and during COVID-19.

Boxplots

To further verify the effectiveness of the proposed improved decomposition-ensemble framework, we compare the forecasting performance of Bi-GRU, D-BiGRU, SD-BiGRU, and SDR-BiGRU in the form of boxplot, as shown in Figure 8.

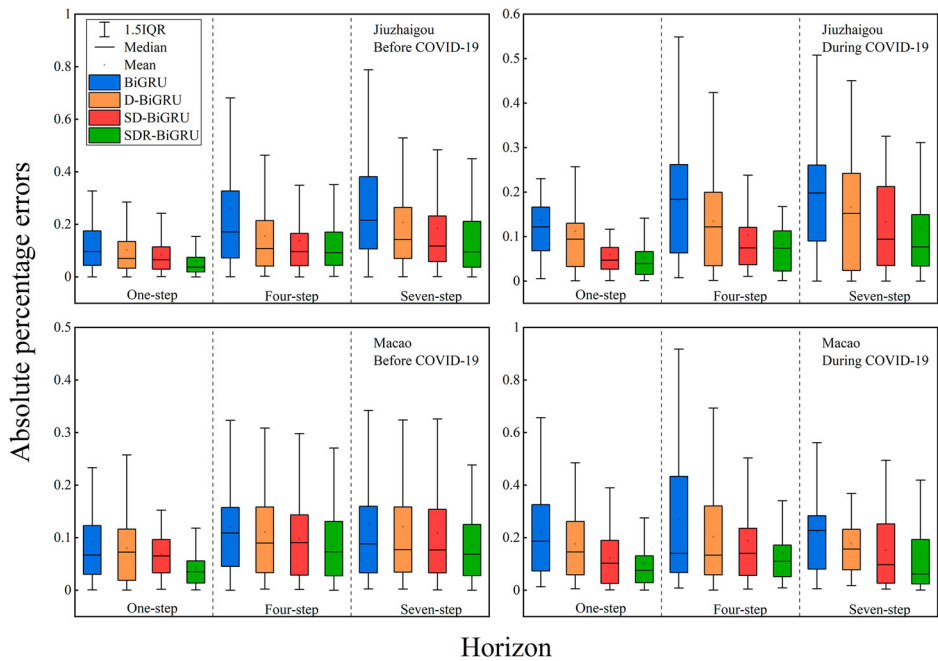


Figure 8. Absolute percentage errors of main models in Jiuzhaigou and Macao cases before and during COVID-19.

Figure 8 reflects the mean and distribution of absolute percentage errors of each model for one-step and multi-step forecasts in Jiuzhaigou and Macao cases before and during COVID-19. Concretely, the whisker lengths are 1.5 times the interquartile range (IQR); the boxes represent the upper and lower quartiles; and the bars and dots represent the median and mean, respectively. It can be seen from **Figure 8** that in most cases, Bi-GRU, D-BiGRU, SD-BiGRU, and SDR-BiGRU generate more concentrated forecasting distribution in turn, indicating that decomposition technique, secondary decomposition strategy, and reconstruction strategy all contribute to improving forecasting performance.

Conclusions

Accurately forecasting daily tourism demand is critical for government officials, tourism practitioners, and other tourism stakeholders during the COVID-19 pandemic (Yang et al., 2022). As more countries and regions approach herd immunity through vaccination, tourists will be allowed to travel with compliance to government guidelines and rules on health and safety. Considering the shift in policies to respond to the COVID-19 pandemic, we concentrate on tourism demand forecasting under the new normal when travel restrictions are eased or lifted, instead of forecasting tourism recovery from the pandemic. However, the current pandemic may lead to shifts in tourist psyche and travel behaviour, resulting in structural variability in tourism demand. This study analyzes and forecasts the daily tourism demand under the new normal, and provides important contributions advancing research in tourism demand forecasting.

First, we systematically assess the predictivity of daily tourism data for Jiuzhaigou and Macao cases before and during COVID-19, which helps promote understanding of the impact of the COVID-19 pandemic on different geographic scales. Second, this study develops an improved multi-variate & multiscale deep learning framework for daily tourism forecasting and confirms its applicability both before and during COVID-19. We also combine the secondary decomposition strategy with the reconstruction strategy to further deal with the complex high-frequency components and the cumulative errors caused by individual forecasts of multiple low-frequency IMFs. Third, we preliminarily compare the performance of our proposed model with that of other models proposed by other studies. Jiuzhaigou was once closed due to an earthquake near the attraction, resulting in a period of cut-off tourism demand data, which provides an opportunity to achieve the comparability of tourism demand forecasting.

Our study indicates that previous statistical modelling and forecasting may also be applicable during the pandemic, provided that travel behaviour is allowed. This finding is encouraging given that researchers have devoted considerable effort to the study of statistical methods of tourism demand, even if more evidence is needed for further evaluation. Given the actionable insights that daily tourism demand forecasting can provide, relevant government officials and tourism practitioners will benefit from our research. For example, during the COVID-19 pandemic, managers can deploy additional staff to guide tourists to ensure social distancing and orderly travel when the forecasted tourist volume is large (Park et al., 2021). Accurate tourist arrival forecasts also help tourism authorities determine the best times to hold activities.

This study is not free of limitations. Although the secondary decomposition strategy has been demonstrated to improve forecasting performance, it has to be admitted that this strategy is an inexhaustive treatment of high-frequency components. In other words, the secondary decomposition strategy relies on experience to determine which components need to be re-decomposed in an ad-hoc fashion, but fails to provide a complete and adaptive solution. Additionally, only the number of newly confirmed local cases is considered to measure the severity of the epidemic in this study. New variables could also be quantified and incorporated into the proposed model to further improve the performance. We leave these extensions and challenges for future research.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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