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Spatial-temporal forecasting of tourism demand

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ABSTRACT

This study conducts spatial-temporal forecasting to predict inbound tourism demand in 29 Chinese provincial regions. Eight models are estimated among a-spatial models (autoregressive integrated moving average [ARIMA] model and unobserved component model [UCM]) and spatial-temporal models (dynamic spatial panel models and space-time autoregressive moving average [STARMA] models with different specifications of spatial weighting matrices). An ex-ante forecasting exercise is conducted with these models to compare their one-/two-step-ahead predictions. The results indicate that spatial-temporal forecasting outperforms the a-spatial counterpart in terms of average forecasting error. Auxiliary regression finds the relative error of spatial-temporal forecasting to be lower in regions characterized by a stronger level of local spatial association. Lastly, theoretical and practical implications are provided.

Introduction

Successful destination management, tourism facility planning, revenue management, and event operations depend heavily on accurate forecasting of tourism demand (Song & Li, 2008). Various forecasting models have been used to forecast tourism demand in the short- and long-term (Cao, Li, & Song, 2017). Tourism demand, tourist arrivals, or tourism revenue throughout a certain period can be considered time series. Well-developed time-series techniques have been applied to analyze tourism demand, with time-series analysis of tourism flows having achieved notable progress over the last two decades (Hassani, Silva, Antonakakis, Filis, & Gupta, 2017). Prevalent forecasting models include the structural time-series model (Chen, Li, Wu, & Shen, 2017), autoregressive integrated moving average (ARIMA) model (Yang, Pan, & Song, 2014), generalized autoregressive conditional heteroskedasticity (GARCH) model (Balli & Tsui, 2015), long memory model (Hassani et al., 2017), vector autoregressive model (Gunter & Önder, 2016), and artificial intelligence (AI) model (Akın, 2015).

Spatial econometrics have become popular in tourism demand modeling (Liu, Nijkamp, & Lin, 2017; Yang & Fik, 2014). Spatial econometric models embrace terms capturing spatial dependence and spatial heterogeneity effects; such spatial dependence can be contributed by spillover effects in tourism demand (Romão & Nijkamp, 2018). Because of spatial dependence and spillovers, neighboring tourism destinations can demonstrate (dis)similar patterns of tourism demand given the supply interaction between destinations and tourists' multi-destination travel (Yang & Wong, 2012). Therefore, incorporating spatial information such as spatial dependence may be especially advantageous for improving forecasting accuracy. Although many studies have confirmed that spatial-temporal forecasting via spatial econometric models yields superior forecasting results (Angulo & Trívez, 2010; Kholodilin, Siliverstovs, & Kooths, 2008), no studies appear to have applied a spatial-temporal model in tourism demand forecasting.

To fill this research gap, we apply spatial-temporal modeling methods to forecast tourism demand and compare their forecasting

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performance with traditional tourism forecasting methods that do not incorporate spatial information. By doing so, this study makes at least four major contributions to the literature on tourism forecasting and tourism economics in general. First and foremost, the study represents an innovative research effort to apply spatial-temporal models to tourism demand forecasting. After comparing their forecasting performance with a-spatial models (that do not structurally incorporate any spatial terms), we can better evaluate the relative usefulness of integrating spatial information into tourism forecasting. Second, spatial-temporal forecasting is particularly promising for tourism demand analysis in large-size countries like China because of a considerable geographic heterogeneity across different regions in terms of economic, cultural, and political perspectives (Lin, Yang, & Li, 2018). Third, we investigate under which conditions spatial-temporal modeling yields superior forecasting performance. A clearer understanding of the contextual factors that influence forecasting performance can help practitioners select appropriate forecasting models. Last but not least, we detail the specification of a spatial weighting matrix (i.e., how different locations are related to each other) for spatial-temporal modeling. Apart from conventional boundary-, proximity-, and neighbor-based weighting matrices, we also examine flow-based matrices and compare performance among various alternatives. Results facilitate more accurate identification of spatial spillover channels in tourism demand by specifying different spatial weighting matrices.

Literature review

Tourism demand forecasting

As a popular topic in tourism economics, tourism demand forecasting has attracted considerable attention from scholars worldwide (Song, Dwyer, Li, & Cao, 2012). Quantitative forecasting methods fall into three categories: time-series models, econometric models, and AI models (Peng, Song, & Crouch, 2014). First, time-series models extrapolate past patterns of variables of interest to predict future values. Popular examples include the unobserved component model (UCM), which decomposes time series into trends, cycles, or seasonal and irregular components (Kulendran & Shan, 2002); the (seasonal) ARIMA model, which captures autoregressive and moving average terms (Papatheodorou & Song, 2005); the ARCH/GARCH model, which specifies a functional form of error-term variance (Tang, Sriboonchitta, Ramos, & Wong, 2016); the vector autoregressive model, which treats all time series as endogenous in a dynamic process (Hassani et al., 2017); and the long memory model, which applies a fractional order of integration to model the persistence of external shocks (Hassani et al., 2017). An inherent disadvantage of time-series models is that many factors that may profoundly influence tourism flows are largely neglected (Wong, 1997).

Second, the econometric model incorporates powerful explanatory variables to improve forecasting accuracy, such as economic indicators (Song & Witt, 2000), climate/weather indicators (Li, Song, & Li, 2017), big data indicators (Yang et al., 2014), and market sentiment indicators (Guizzardi & Stacchini, 2015). Some cutting-edge econometric techniques applied in econometric tourism demand modeling include models with time-varying parameters (Chen et al., 2017), mixed-data sampling (Hirashima, Jones, Bonham, & Fuleky, 2017), and Bayesian models (Assaf, Li, Song, & Tsionas, 2018). Third, with the development of AI, many relevant methods have been introduced to model and forecast tourism demand. These AI models include the artificial neural network method (Hassani et al., 2017), the Kernel extreme learning machine (Sun, Wei, Tsui, & Wang, 2019), the rough sets model (Goh & Law, 2003), and the support vector regression (Akal, 2004). Although these methods outperform traditional time-series models in some scenarios, the 'black box' nature of AI approaches renders exact economic implications impossible, and theoretical support is weak (Song & Li, 2008).

In a review of tourism demand research, Song and Li (2008) found the ARIMA model to be the most prevailing method, accounting for over two-thirds of entire works. The strict statistical theoretical background, convenience, and ideal forecasting accuracy of this model have made it highly popular. Peng et al. (2014) compared the forecasting accuracy of different models with meta-regression; findings indicated that dynamic econometric (e.g., time-varying parameter model and autoregressive distributed lag model), advanced time-series (e.g., ARIMA and structural time-series model), and AI models can generate more accurate forecasts than basic time-series models (e.g., moving-average and exponential smoothing models). In particular, the dynamic econometric model produces forecasts with the lowest error. In light of the benefits and drawbacks of individual forecasting models, some scholars have examined the efficiency of combining forecasts. Shen, Li, and Song (2011) combined five econometric and two time-series models using different methods. They found that combined forecasting could improve forecasting accuracy compared to individual forecasts. This result is consistent with meta-analytical results from Kim and Schwartz (2013), who found that this integrated forecasting model yields significantly more accurate forecasts than other models (e.g., non-causal econometric, Box-Jenkins, causal econometric, and AI models).

Spatial spillovers in tourism demand

Spatial spillovers in tourist flows comprise an economic externality associated with tourism industry growth; tourism destinations are likely to generate spillovers unintentionally, which can either help or hinder nearby destinations (Yang & Wong, 2012). Clusters of tourism hotspots are a consequence of this type of economic externality (Majewska, 2015). Yang and Wong (2012) proposed an integrated framework to understand various channels contributing to the spillover effect in tourism demand. From the supply side, productivity spillover, market access spillover, joint promotion, and negative events have been emphasized (Yang & Wong, 2012, p. 770). Chhetri, Arrowsmith, Chhetri, and Corcoran (2013) argued that spillover effects can be triggered through regional collaboration, competition, and sharing of pooled resources between tourism/hospitality firms and destinations. Several studies have recognized spillovers initiated by various terrorism events on tourist flows (Drakos & Kutan, 2003; Neumayer, 2004); whereas a positive spillover effect can be explained by substitution effects across proximate destinations with similar attractions, a negative spillover effect is explained by the contagious effect of tourists' risk-perception adjustment in response to terrorism events (Yaya, 2009). In the context of tourist movement, the spillover effect largely follows from multi-destination travel (Yang, Fik, & Zhang, 2017). Weidenfeld, Butler, and Williams (2010) discovered that spatial proximity is positively related to attraction compatibility on regional and local scales, whereas product dissimilarity is positively associated with compatibility at the local scale. In a micro-economic model of multi-destination travel, de Oliveira Santos, Ramos, and Rey-Maquieira (2011) incorporated the marginal rate of substitution between tourist destinations and found it to be an important determinant of tourists' final choice outcomes in a multi-destination travel setting.

Several empirical studies have highlighted substantial spillover effects in tourism demand (Balli, Curry, & Balli, 2015; Deng & Athanasopoulos, 2011; Yang & Fik, 2014). Multi-equation models have been used to investigate the interdependence of tourism demand (as a type of spatial spillover) between a small number of regions/countries. Balli et al. (2015) utilized a multivariate AR-GARCH model to investigate the spillover effect of tourist flows to regions in New Zealand, revealing highly volatile spillovers. Drakos and Kutan (2003) established a three-equation model to understand the spillover effects of terrorism intensity on three countries: Greece, Israel, and Turkey. Their estimation results suggested that spillover effects in tourism demand across countries were substantial, leading to both positive and negative effects. Gooroochurn and Hanley (2005) proposed a two-equation simultaneous model to examine spillover effects in long-haul tourist flows between the Republic of Ireland and Northern Ireland. Results confirmed significant, albeit asymmetric, spillovers across the two regions. Cao et al. (2017) applied a global vector autoregressive model to examine cross-country co-movements of tourism demand across 24 major countries. *Co-movement* principally refers to interdependence across countries and cross-country spillovers. More recently, Assaf et al. (2018) proposed a Bayesian global vector autoregressive model to forecast tourist flows in nine countries in southeast Asia, and the model captured the spillover effect in international tourism demand.

To incorporate spatial spillover into an empirical model, spatial econometrics provides a rigorous solution to include spatial dependence terms in the conventional econometric model via a spatial weighting matrix, which specifies the interconnectedness patterns of units (LeSage & Pace, 2009). Compared to the multi-equation method, the spatial econometric model can handle a large number of regions/countries under a pre-specified spatial structure. The estimated coefficient terms associated with the spatial weight matrix are termed *spillover coefficients*, which can be further used to gauge the significance and magnitude of spillover effects (Yang & Wong, 2012). Zhou, Yang, Li, and Qu (2016) applied the spatial panel model to understand spillover effects of attractions in eastern Chinese cities, and Deng, Li, and Ma (2017) employed the model to evaluate the spatial impact of air pollution on provincial tourism demand in China. Marrocu and Paci (2013) incorporated spatial dependence terms in their spatial interaction model to understand inter-regional tourism demand in Italy, incorporating origin-specific, destination-specific, and dyad-specific spatial dependence terms. Deng and Athanasopoulos (2011) estimated a dynamic spatial panel model to understand interstate tourist flows in Australia; their results revealed significant spatial and temporal dynamics in tourism demand. However, these models were not used for forecasting. Static spatial panel models have become popular for modeling tourism demand, yet applications of dynamic spatial panel models remain rare. Few studies to this point have applied spatial econometrics models to conduct spatial-temporal forecasting by considering spatial dependence across time series. Long, Liu, and Song (2018) applied a spatial panel model with dynamic terms in an attempt to pool tourism forecasts; however, their study considered yearly time series of only 7 years, which may lead to inconsistent estimates of dynamic terms (Elhorst, 2010).

Spatial-temporal forecasting

Because spatial dependence has been estimated to be empirically significant in past tourism studies (Balli et al., 2015; Li, Chen, Li, & Goh, 2016; Yang & Fik, 2014), a natural question arises: is spatial dependence useful for improving forecasting accuracy? To conduct a spatial-temporal forecasting exercise by leveraging spatial dependence, one possible solution is to extend traditional multivariate time-series models by imposing a spatial structure (e.g., a spatial weighting matrix) on time series associated with different locations. One such model is the space–time autoregressive moving average (STARMA) model (Hepple, 1978). Pfeifer and Deutrch (1980) proposed a three-stage procedure to build a STARMA model and developed relevant diagnostic tools, such as a space–time autocorrelation function and space–time partial autocorrelation function. STARMA models have been applied in traffic flow modeling (Kamarianakis & Prastacos, 2005), timber price modeling (Zhou & Buongiorno, 2006), analysis of regional unemployment (Di Giacinto, 2006), and electricity demand forecasting (Ohtsuka & Kakamu, 2011).

Another intuitive approach to spatial-temporal forecasting involves extending popular spatial econometric models by adding different dynamic terms. Elhorst (2005) proposed an unconditional maximum likelihood estimation for dynamic spatial panel models after first-differencing. To apply dynamic spatial panel models for forecasting, Kholodilin et al. (2008) conducted multi-step forecasts of the GDP growth rate of 16 German Länder and found that forecast accuracy improved substantially compared to the model without spatial dependence terms; this enhancement was particularly sizable for long-term forecasts. Angulo and Trívez (2010) applied the dynamic spatial panel model to forecast regional employment in 50 Spanish provinces, with the resultant forecasting performance as accurate as that from individual seasonal ARIMA models. Girardin and Kholodilin (2010) forecasted the growth of Chinese provinces using dynamic spatial panel models and found that spatial effects in the models were particularly useful in boosting forecasting accuracy, especially for longer forecasting horizons. More recently, Zhao and Burnett (2014) compared the forecasting performance of various dynamic spatial panel models to predict CO_2 emissions in 30 Chinese provinces; the fixed-effects specification outperformed other specifications in dynamic spatial panel models. Apart from dynamic spatial panel models, other spatial econometric models used for forecasting include the spatial vector autoregressive model (Mayor & Patuelli, 2012) and dynamic models after spatial filtering (Griffith & Chun, 2014). To the best of the author's knowledge, dynamic spatial panel models have not been rigorously used to forecast tourism demand.

Methods and data

Data collection

We collected data on annual inbound tourist arrivals to 29 Chinese provincial regions from 1987 to 2016. Mainland China consists of 31 provincial-level administrative divisions, including 22 provinces, four municipalities, and five autonomous regions. The opening-up and economic reform after 1978 has led to two major changes in provincial divisions. In 1988, Hainan, which was previously part of Guangdong, was split into its own province. In 1997, Chongqing, previously administered by Sichuan, became a municipality. Although Chinese tourism statistics from the selected research period could capture tourism statistics in Hainan and Guangdong separately, it was unable to incorporate the division change of Chongqing and Sichuan, which occurred in the middle of the research period. Therefore, we excluded these two areas, resulting in a total dataset of 29 provincial regions. All data were collected from official statistical yearbooks published by the Chinese government, including the China Statistical Yearbook (2012–2017), China Tourism Statistical Yearbook (2012–2017), and China Compendium of Statistics (1949–2013).

Forecasting models

In specifying the forecasting model, we did not incorporate any explanatory variables. As suggested by Angulo and Trívez (2010), the prediction of these explanatory variables in ex-ante predictions tends to lead to uncontrollable inaccuracy in forecasting; therefore, a clear conclusion cannot be obtained regarding the relative forecasting performance between spatial and a-spatial models. For a-spatial models, we used two popular univariate time-series models: the ARIMA model and the UCM model. It would be technically infeasible to estimate a multi-equation time-series model to forecast 29 time series because the 1-year-lag autoregressive terms require 29 × 29 coefficients to be estimated, which exceeds the size of the estimation sample.

The ARIMA model estimates autoregressive terms in the dependent variable as well as structural models with disturbances. An ARIMA (p, d, q) is specified as follows:

$$\begin{aligned} D^d y_t &= \alpha + \mu_t \\ \mu_t &= \sum_{i=1}^{p} \rho_i \mu_{t-i} + \sum_{j=1}^{q} \theta_j \varepsilon_{t-j} + \varepsilon_t \end{aligned} \tag{1}$$

where y_t is the dependent variable and α is the constant. In the model, p indicates the order of the autoregressive (AR) model, d represents the degree of differencing, and q indicates the order of the moving average (MA) model. D indicates the differencing operation such that $Dy_t = y_t - y_{t-1}$. If d is set to zero, then the model becomes a standard ARMA (p, q) model. Adequate specifications of p, d, and q cause the model residual ε_t to be white noise. Useful tools to determine proper specifications include the unit-root test, autocorrelation function (ACF), partial autocorrelation function (PACF), and extended autocorrelation function (EACF) (Wei, 1990). Also, specifications of p, d, and q can be identified by ad-hoc goodness-of-fit indicators based on the estimation results of different models (Greene, 2007). ARIMA models can be estimated using maximum likelihood estimation (Box, Jenkins, & Reinsel, 2008).

The UCM model is a time-series model that decomposes the dependent variable into four different components: trend, seasonal, cyclical, and idiosyncratic. It is specified as

$$\begin{aligned} y_t &= \tau_t + \gamma_t + \psi_t + \varepsilon_t \\ \tau_t &= \tau_{t-1} + \beta_{t-1} + \eta_t \\ \beta_t &= \beta_{t-1} + \xi_t \end{aligned} \tag{2}$$

where y_t is the dependent variable, τ_t represents the trend component, γ_t represents the seasonal component, ψ_t represents the cyclical component, and ε_t represents the idiosyncratic component (Harvey, 1989). Moreover, β_t is the local slope and η_t and ξ_t are i.i.d. normal error with a mean of zero and a given variance, respectively. Distinct restrictions can be imposed on different components of Equation (2) to derive a family of 11 models (Harvey, 1989). For example, a random walk model indicates $y_t = \tau_t$; $\tau_t = \tau_{t-1} + \eta_t$, a random-walk-with-drift model indicates $y_t = \tau_t$; $\tau_t = \tau_{t-1} + \beta + \eta_t$; $\beta = \beta$, and a deterministic trend model indicates $y_t = \tau_t + \varepsilon_t$; $\tau_t = \tau_{t-1} + \beta + \eta_t$; $\beta = \beta$. Similar to the ARIMA model, UCM can be estimated using maximum likelihood estimation (Harvey, 1993). Therefore, the correct specification of UCM can be gauged by likelihood-based goodness-of-fit indicators, such as the Akaike information criterion (AIC) and the Bayesian information criterion (BIC) (Greene, 2007).

We applied the dynamic spatial panel model for spatial-temporal forecasting. Based on Elhorst (2014), we excluded simultaneous spatial lags in the model for forecasting purposes; the model is specified as

$$y_t = \tau y_{t-1} + \psi \mathbf{W} y_{t-1} + \mu + \varepsilon_t \tag{3}$$

where y_t is a column vector of dependent variable of all regions at year t, $\mathbf{W}$ represents an n by n spatial weighting matrix defining the spatial connection across n regions, μ is a column vector with region-specific effect for each region i, and ε_t is the vector of normal error term. The model can be estimated using bias-corrected quasi-maximum likelihood estimation (Yu, De Jong, & Lee, 2008).

One challenge in estimating any spatial econometric model involves specification of the spatial weighting matrix, $\mathbf{W}$. The matrix specifies how locations are interconnected and how the spillover effect is distributed from generators to receivers; thus, results from spatial econometric models are sensitive to the choice of the spatial weighting matrix. If this matrix is pre-specified, then a proper matrix must be identified based on goodness-of-fit (Seya, Yamagata, & Tsutsumi, 2013). The matrix element w_{ij} indicates the level of connectedness between i and j, with diagonal elements set to zero. In the study, we propose three different spatial weighting matrices: a contingency-based matrix, distance-based matrix, and flow-based matrix. For the contingency-based matrix, $w_{ij} = 1$ if i and j share the same border, and $w_{ij} = 0$ otherwise. To avoid the 'island' problem in the matrix (Anselin, 2005), we imposed a geographic contingency between Hainan and Guangdong. For the distance-based matrix, $w_{ij} = 1/d_{ij}^2$ (Crowder, Hall, & Tolnay, 2011), and d_{ij} indicates the geographic distance (in km) between the capital of province i and j. This inverse quadratic distance matrix captures a quadratic distance decay pattern of cross-regional spillover on tourism demand. For the flow-based matrix, w_{ij} represents the number of inbound tourists moving from province j to i during multi-destination travel within China. We collected these data from the National Inbound Tourist Survey from China in 1996, around the mid-point of the research period. Yang and Wong (2012) indicated that multi-destination travel largely contributes to spatial spillovers in tourism demand. As suggested by LeSage and Fischer (2008), all spatial weighting matrices were row-standardized for model estimation.

The second spatial-temporal forecasting model is STARMA, and it extends the traditional AR(I)MA model by introducing the spatial lags of AR and MA terms into the model. A typical STARMA model (Pfeifer & Deutrch, 1980) is written as

$$y_t = \sum_{k=1}^{p}\sum_{l=0}^{\lambda_k}\varphi_{kl}\mathbf{W}^{(l)}y_{t-k} + \sum_{k=1}^{q}\sum_{l=0}^{m_k}\theta_{kl}\mathbf{W}^{(l)}\varepsilon_{t-k} + \varepsilon_t \tag{4}$$

where p and q indicates the maximum order of AR and MA terms in the model, respectively, and $\mathbf{W}^{(l)}$ indicates lth order of spatial weighting matrix, with $\mathbf{W}^{(0)}$ as an identity matrix and $\mathbf{W}^{(1)} = \mathbf{W}$. In this study, we applied three different types of spatial weighting matrix, and except for the contiguity based matrix, the other two matrices have a less intuitive specification of high-order matrix form. Therefore, we specified both λ_k and m_k to a maximum of 1. In a spatial-temporal forecasting setting, a set of revised ACF and PACF tools can be applied to choose the values of p, q, λ_k and m_k (Pfeifer & Deutsch, 1981), and we centralized the space time-series before estimating the model. To avoid the burdensome optimization problem, we resorted to a Kalman filter algorithm to estimate the STARMA model based on a state space system (Cipra & Motykova, 1987).

We collected annual data on inbound tourist arrivals to 29 Chinese provincial regions from 1987 to 2016. This sample was split into two sub-samples. The first was intended for model estimation, and it includes data from 1987 to 2014. The second was used for forecast validation, covering data in 2015 and 2016. After obtaining the estimation results of the a-spatial and spatial models, we conducted an ex-ante forecasting exercise for one-and two-step-ahead prediction. We were especially interested in any improvement in accuracy obtained by leveraging spatial dependence through spatial-temporal forecasting. The forecasting error of a single forecast is specified as

$$\text{error} = \left(\frac{|\hat{y}_t - y_t|}{y_t}\right) \times 100\% \tag{5}$$

where $\hat{y}$ indicates the forecast, and y is the actual value. Note that all predicted values, either log-transformed or centralized, will be converted back to the original scale to calculated the forecasting error.

Lastly, it is of particular interest to identify the geographic units for which spatial-temporal forecasting is superior in reducing forecasting error. Therefore, we ran an auxiliary regression to investigate the relationship between the degree of forecasting improvement and the geographic structure of provinces. In this study, geographic structure is measured by the absolute value of a local indicator of spatial association (LISA): the local Moran's I (Anselin, 1995). This statistic is specified as

$$I_i = \frac{(y_i - \bar{y})}{m_0}\sum_j w_{ij}(y_j - \bar{y}) \quad \text{with } m_0 = \sum_i (y_i - \bar{y})^2/n \tag{6}$$

where $\bar{y} = \sum_i y_i/n$, denoting the average over n spatial units. Although the local Moran's I can be either positive or negative (Anselin, 1995), its absolute value indicates the strength of a region's local spatial association with nearby regions, defined by the spatial weighting matrix $\mathbf{W}$. A higher degree of local spatial association indicates greater similarity/dissimilarity between nearby regions (Yang & Wong, 2013); accordingly, information on neighbors can be more useful for forecasting future values of the focal region in a time series.

Data description

In the sample for model estimation (1987–2014), the average number of inbound tourist arrivals (in 10,000) was 154.680 with a standard deviation of 358.776. After a preliminary check, we found that time series of tourist arrivals exhibited a pattern of exponential growth. Therefore, a logarithmic transformation of each series was taken for modeling and forecasting purposes. After logarithmic transformation, the mean value became 3.742 with a standard deviation of 1.771. Fig. 1 presents the time-series plot of inbound tourist arrivals (in log) to 29 Chinese provincial regions in 1987–2014, the period for model estimation. Several outliers were noted in 1989, 2003, and 2008, presumably due to the Tiananmen Square protests of 1989 (Roehl, 1990), the SARS outbreak in 2003 (Yang & Wong, 2012), and visa regulation in 2008 (Song, Gartner, & Tasci, 2012), respectively. In subsequent modeling efforts, we introduced three dummy variables to capture these effects: D89 (=1 if year = 1989), D03 (=1 if year = 2003), and D08 (=1 if year = 2008).

Before conducting a spatial-temporal forecasting exercise, it was necessary to develop a better understanding of the spatial pattern

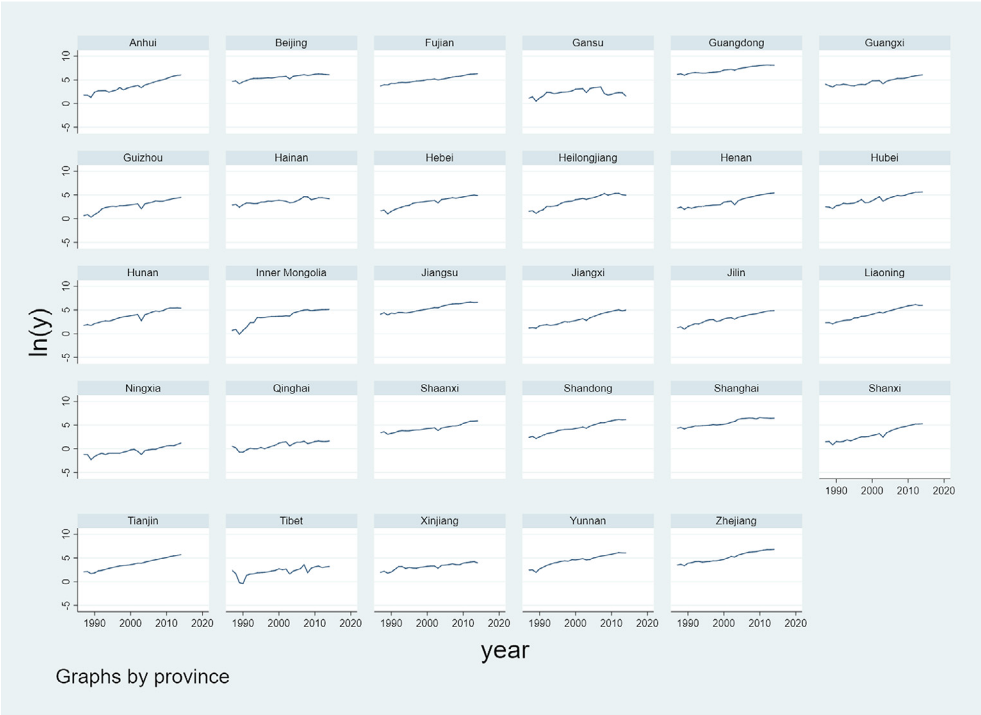

Fig. 1. Time-series plot of provincial regions' inbound tourist arrivals (in log) in 1987–2014.

in the dataset. Fig. 2 displays the spatial distribution of inbound tourist arrivals in the sampled provincial region in 1987, the start of the study period, and 2014, the end of the modeling period. Different regions are colored based on quadrants of the tourist arrival value. As illustrated in Fig. 2, the pattern demonstrated some similarities in 1987 and 2014. For example, the southeast of China (e.g., Guangdong, Fujian, Zhejiang, Shanghai, and Jiangsu) was a consistent hotspot for inbound tourists, corroborating findings from Yang and Wong (2013). However, the lowest quadrant moved from the northern part in 1987 to the western part in 2014, reflecting the lowest number of inbound tourists to this area. Although regions like Qinghai, Gansu, and Ningxia remained in the lowest quadrant in 2014, neighboring regions such as Xinjiang and Tibet joined in 2014 and caused this cold spot to cluster over a large geographic area in western China. Interestingly, the pattern of inbound tourism demand across different provincial regions is highly consistent with

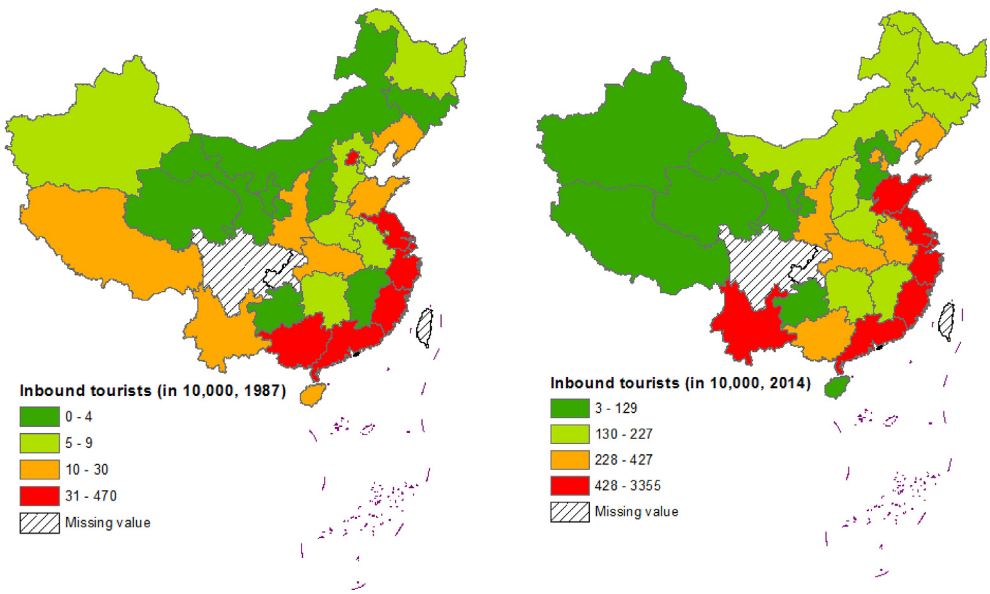

Fig. 2. Spatial pattern of inbound tourist arrivals to Chinese provincial regions in 1987 and 2014.

Table 1
Specification and estimation results of ARIMA and UCM models.

Province	ARIMA				UCM			
	Specification (p,d,q)	Dummies	AIC	BIC	Specification	Dummies	AIC	BIC
Anhui	0,1,0	D89, D03	−4.870	0.313	random-walk-with-drift model	D89, D03	1.559	5.556
Fujian	0,1,0	D89, D03	−56.22	−51.04	random-walk-with-drift model	D89, D03	−47.89	−43.90
Gansu	1,1,0	D89, D03, D08	29.06	36.83	random-walk model	D89, D03, D08	29.68	35.01
Guizhou	1,1,0	D89, D03	−15.26	−8.776	random-walk-with-drift model	D89, D03	−7.240	−3.244
Hainan	0,1,1	D89	1.084	6.267	random-walk model	D89	2.464	5.128
Beijing	0,1,1	D89, D03	−38.54	−32.06	random-walk model	D89, D03	−31.73	−27.74
Hebei	0,1,1	D89	−1.082	4.102	random-walk-with-drift model	D89, D03	−19.08	−15.09
Tianjin	0,1,0	D89	−37.46	−33.57	random-walk-with-drift model	D89, D03	−30.96	−26.96
Henan	0,1,0	D89, D03	−25.03	−19.85	random-walk-with-drift model	D89, D03	−17.86	−13.86
Heilongjiang	0,1,0	D89	0.0817	3.969	random-walk-with-drift model	D89, D08	2.757	6.754
Hubei	0,1,0	D03	14.47	18.36	deterministic-trend model	D89, D03	11.13	15.12
Hunan	0,1,0	D03	−22.24	−18.36	random-walk-with-drift model	D89, D03	−24.23	−20.23
Jilin	0,1,1	D89, D03	−16.45	−9.968	random-walk-with-drift model	D89, D03	−10.82	−6.826
Jiangsu	0,1,0	D89	−33.39	−29.50	random-walk-with-drift model	D89, D03	−28.74	−24.75
Jiangxi	0,1,1		−6.345	−2.457	random-walk-with-drift model	D89, D03	−18.68	−14.69
Liaoning	0,1,0	D89, D03	−35.14	−29.95	random-walk-with-drift model	D89, D03	−27.59	−23.59
Inner Mongolia	0,1,0	D89	19.44	23.33	random-walk-with-drift model	D89, D03	24.19	28.19
Ningxia	0,1,0	D89	14.79	18.68	random-walk model	D89, D03	0.824	4.820
Qinghai	0,1,0	D89, D03	14.28	19.46	random-walk model	D89, D03, D08	13.31	18.64
Shandong	0,1,1	D89, D03	−34.81	−28.33	random-walk-with-drift model	D89, D03	−27.13	−23.14
Shanxi	0,1,0	D89, D03	−22.77	−17.59	random-walk-with-drift model	D89, D03	−15.68	−11.68
Shaanxi	0,1,0	D89, D03	−28.35	−23.17	random-walk-with-drift model	D89, D03	−21.05	−17.06
Shanghai	0,1,0	D89, D03	−26.57	−21.39	random-walk-with-drift model	D89	−19.27	−16.60
Tibet	0,1,0	D89, D08	54.59	59.77	random-walk model	D89, D03, D08	52.01	57.34
Xinjiang	0,1,1	D89, D03	0.585	7.065	random-walk model	D89, D03	2.042	6.038
Yunnan	0,1,0	D89, D03	−25.62	−20.44	random-walk-with-drift model	D89, D03	−18.43	−14.43
Zhejiang	0,1,1	D89, D03	−45.49	−39.01	random-walk-with-drift model	D89, D03	−35.36	−31.36
Guangdong	1,1,0	D89, D03	−55.31	−48.83	random-walk-with-drift model	D89, D03	−46.68	−42.68
Guangxi	0,1,1	D89, D03	−10.90	−4.417	random-walk model	D89, D03	−7.150	−3.154

the geographic pattern of economic development. A significant "east-west" division characterizes Chinese regional economy, and eastern provinces are more developed than their central and western counterparts (Yang & Wong, 2012). Also, a larger number of top-branded tourist attractions can be found in more developed regions because they are able to make more investment on developing and promoting these attractions, such as 5A and 4A scenic spots that are officially evaluated and endorsed by the government.

Empirical results

Estimation results of a-spatial models

Table 1 presents the estimation specification and goodness-of-fit measures for univariate forecasting of two a-spatial models: the ARIMA and UCM models. For ARIMA models, we specified the autoregression order *p* and moving average order *q* based on ACF, PACF, and EACF plots. In addition, the inclusion of dummies was guided by the statistical significance of D89, D03, and D08 to capture irregular shocks from 1989, 2003, and 2008, respectively. The yearly data used in this paper did not include any seasonality patterns, and out of 29 provincial time series, 17 could be captured using an ARIMA (0,1,0) model. Regarding the UCM specification, 20 time series resulted in a random-walk-with-drift model, eight in a random walk model, and one in a deterministic trend model. The selection of the appropriate UCM specification among 11 alternatives was determined by AIC and BIC values of alternatives for different series after maximum likelihood estimation. Likewise, three dummies were tested in each UCM model to see if they were statistically significant, and those that were retained to capture substantial and irregular year-specific effects. Note that although an ARIMA (0,1,0) is statistically equivalent to a random-walk-with-drift UCM, the AIC and BIC values differed for the same dataset because of the number of observations in these models; the ARIMA model contained one fewer observation than the UCM counterpart after first-differencing, leading to different AIC and BIC values.

Estimation results of spatial-temporal models

Table 2 lists the detailed estimation results from the spatial-temporal forecasting models. The dependent variable is the first-differenced inbound tourist arrivals to different regions (in log). Unlike a-spatial modeling in which 29 single models needed to be estimated, only one model needed to be estimated in spatial-temporal modeling to generate forecasts for all 29 regions (Angulo & Trívez, 2010). Models 1–3 presents the results of three different dynamic spatial panel models based on the spatial weighting matrices discussed in the Methods and data section. More specifically, Model 1 used a contingency matrix; Model 2 applied an inverse

Table 2
Estimation results of dynamic spatial panel model.

	Model 1 Dynamic spatial panel W = cont.	Model 2 Dynamic spatial panel W = inv.dist	Model 3 Dynamic spatial panel W = flow	Model 4 STARMA W = cont.	Model 5 STARMA W = inv.dist	Model 6 STARMA W = flow
τ	−0.0726**	−0.0618	−0.0697*			
	(0.0360)	(0.0387)	(0.0404)			
ψ	−0.131***	−0.167***	−0.181***			
	(0.0506)	(0.0612)	(0.0645)			
d89	−0.723***	−0.722***	−0.712***			
	(0.0744)	(0.0742)	(0.0760)			
d03	−0.643***	−0.641***	−0.635***			
	(0.0733)	(0.0735)	(0.0741)			
d08	−0.211**	−0.210**	−0.213**			
	(0.0837)	(0.0842)	(0.0838)			
φ_{10}						−0.118**
						(0.0457)
φ_{11}				0.109**	0.209***	0.572***
				(0.0478)	(0.0594)	(0.0914)
Variance (ε)	0.0578***	0.0577***	0.0578***	0.969	0.970	1.185
	(0.0122)	(0.0122)	(0.0122)			
N	754	754	754	754	754	754
BIC	1.021	−0.234	1.604	2222.861	2215.752	2205.545

(Notes: *** indicates significance at the 0.01 level, ** indicates significance at the 0.05 level, * indicates significance at the 0.10 level. Robust standard errors are presented in parentheses.)

quadratic distance matrix ($w_{ij} = 1/d_{ij}^2$); and Model 3 employed a flow matrix capturing multi-destination travel flows across different provincial regions based on a nationwide intercept survey of inbound tourists. As indicated by Eq. (3), τ denoted the coefficient of the time lag of the dependent variable, whereas ψ denoted the coefficient of the spatial-temporal lag of the dependent variable.

In Models 1 and 3, τ and ψ were each estimated to be statistically significant and negative; only ψ was estimated to be significant in Model 2. In all three models, dummy variables (D89, D03, and D08) were estimated to be statistically significant and negative. Judging from the magnitudes of their estimated coefficients, the political events in 1989 appeared to have exerted the largest impacts on provincial inbound tourism in China, followed by the SARS outbreak in 2003. Lastly, as suggested by the smallest BIC value in Model 2, an inverse quadratic distance matrix was found to fit the data better than the other two spatial weighting matrices.

Models 3–6 presents the estimation results of STARMA models. Note that the results are based the data set that was centralized (Pfeifer & Deutrch, 1980). We specified the model based on the results from space-time ACF and PACF plots (Pfeifer & Deutsch, 1981), and alternative specifications were screened to make sure the correct specification based on post-estimation statistics, goodness-of-fit, and residual diagnostics. Since the estimation algorithm cannot accommodate any exogenous variables, like the year-specific dummy variables, we adjusted the data first based on the dummy estimates from pooled regression models. In Models 4–6, only AR terms were specified without any MA term. More specifically, Models 4 and 5 include a spatial lag of AR(1) term, while Model 6 includes both spatial-lagged and own AR(1) terms. In terms of goodness-of-fit, Model 6 has the smallest BIC value among three STARMA models.

Ex-ante forecasting comparison

Based on the estimation results of the a-spatial time-series models (ARIMA and UCM models) and spatial-temporal models (dynamic spatial panel and STARMA models), we conducted ex-ante forecasting starting from 2015 to predict the number of inbound tourist arrivals in each provincial region in 2015 (one-step-ahead forecast) and 2016 (two-step-ahead forecast). Benchmarking the focal model against several alternatives prevalent in the literature is common practice in tourism forecasting analysis to facilitate evaluation of relative forecasting performance (Song & Li, 2008). Table 3 presents the forecasting error (Eq. (5)) in different years for each provincial region based on the eight selected models: ARIMA; UCM; dynamic panel data models with different weighting matrices (Models 1–3 in Table 2); and STARMA models with difference weighting matrices (Models 4–6 in Table 2). In Table 3, the smallest forecasting error value among the eight models is in bold for each region in each year.

In general, spatial-temporal forecasting errors were lower than their a-spatial counterparts in most of the 29 provincial regions in one-step-ahead (2015) and two-step-ahead (2016) forecasts. The ARIMA model generated the best one-step-ahead forecasts in four regions, whereas the UCM model predicted the best one-step-ahead forecasts in six regions. Regarding the two-step-ahead forecast, the ARIMA model resulted in the best forecasts in four regions, and the UCM model was best in nine regions. Superior spatial-temporal forecasts were found in the vast majority of Chinese provinces as indicated by a smaller forecasting error. The STARMA model outperforms the dynamic spatial panel model, and its forecasting error was found to be the smallest in 17 regions for one-step-ahead forecasts and in 15 regions for two-step-ahead ones. Average forecasting errors among the eight models in 2015 and 2016 are calculated in the last rows of Table 3. The STARMA model with a distance-based weighting matrix has the lowest average forecasting error for a one-step-ahead forecast, while that with a contingency matrix has the lowest for a two-step-ahead forecast. Interestingly,

Table 3
Forecasting error of different models.

Province	Year	ARIMA	UCM	Dynamic spatial panel W = cont.	Dynamic spatial panel W = inv.dist	Dynamic spatial panel W = flow	STARMA W = cont.	STARMA W = inv.dist	STARMA W = flow
Anhui	**2015**	1.03%	1.03%	2.37%	2.42%	2.46%	0.96%	0.71%	**0.06%**
Fujian	**2015**	0.22%	0.22%	1.19%	1.29%	1.36%	1.11%	0.88%	**0.03%**
Gansu	**2015**	6.52%	19.86%	0.95%	**0.24%**	1.43%	2.29%	2.36%	2.84%
Guizhou	**2015**	1.00%	**0.68%**	2.66%	2.68%	3.03%	1.08%	0.74%	1.55%
Hainan	**2015**	2.03%	**1.83%**	5.23%	5.14%	5.26%	5.52%	5.33%	4.69%
Beijing	**2015**	**0.29%**	0.79%	2.51%	2.38%	2.46%	2.69%	2.66%	2.01%
Hebei	**2015**	2.17%	3.78%	3.96%	3.95%	4.00%	2.78%	2.53%	**1.95%**
Tianjin	**2015**	0.64%	0.64%	2.16%	2.08%	2.06%	0.69%	**0.47%**	0.62%
Henan	**2015**	0.81%	0.81%	0.46%	0.51%	0.46%	**0.35%**	0.61%	1.62%
Heilongjiang	**2015**	14.80%	14.80%	16.85%	16.81%	16.92%	15.33%	15.05%	**14.19%**
Hubei	**2015**	0.16%	**0.04%**	1.41%	1.46%	1.53%	0.58%	0.36%	0.59%
Hunan	**2015**	1.95%	1.95%	3.40%	3.45%	3.57%	2.27%	2.05%	**1.23%**
Jilin	**2015**	0.16%	0.15%	1.88%	1.96%	1.84%	0.36%	**0.04%**	1.12%
Jiangsu	**2015**	**0.99%**	**0.99%**	2.00%	2.05%	2.04%	1.87%	1.70%	1.01%
Jiangxi	**2015**	1.79%	2.35%	3.23%	3.32%	3.27%	1.92%	1.64%	**0.49%**
Liaoning	**2015**	2.06%	2.06%	3.62%	3.54%	3.56%	2.17%	2.00%	**1.14%**
Inner Mongolia	**2015**	4.01%	4.01%	5.78%	5.64%	5.67%	3.51%	3.38%	**2.29%**
Ningxia	**2015**	7.71%	0.90%	5.91%	5.83%	4.77%	1.57%	**0.01%**	5.62%
Qinghai	**2015**	12.65%	10.46%	4.34%	**2.78%**	4.09%	6.60%	9.87%	14.37%
Shandong	**2015**	1.61%	1.50%	2.88%	2.88%	2.95%	1.73%	1.52%	**0.54%**
Shanxi	**2015**	1.72%	1.72%	3.32%	3.43%	3.40%	1.83%	1.46%	**0.22%**
Shaanxi	**2015**	**0.06%**	**0.06%**	1.27%	1.23%	1.30%	0.75%	0.56%	0.62%
Shanghai	**2015**	0.88%	0.88%	1.92%	1.96%	2.06%	1.98%	1.82%	**0.77%**
Tibet	**2015**	5.33%	4.44%	1.47%	1.34%	**1.13%**	1.21%	1.71%	4.77%
Xinjiang	**2015**	**0.41%**	0.54%	4.91%	4.52%	4.91%	3.58%	3.66%	2.19%
Yunnan	**2015**	2.23%	2.23%	1.08%	0.88%	**0.85%**	1.93%	2.25%	2.97%
Zhejiang	**2015**	0.58%	0.57%	1.57%	1.62%	1.69%	0.99%	0.77%	**0.05%**
Guangdong	**2015**	0.55%	**0.24%**	1.48%	1.53%	1.56%	1.46%	1.26%	0.71%
Guangxi	**2015**	1.09%	0.02%	1.60%	1.66%	1.64%	1.29%	0.97%	**0.02%**
Anhui	**2016**	2.15%	2.15%	4.32%	4.35%	4.33%	**0.31%**	0.38%	0.88%
Fujian	**2016**	1.19%	1.19%	2.81%	2.86%	2.88%	0.71%	0.64%	**0.10%**
Gansu	**2016**	19.42%	34.46%	10.54%	11.78%	**10.27%**	11.36%	11.95%	13.34%
Guizhou	**2016**	0.62%	**0.21%**	3.11%	3.07%	3.33%	1.97%	2.09%	2.63%
Hainan	**2016**	2.88%	1.92%	2.27%	2.11%	2.17%	0.84%	0.72%	**0.08%**
Beijing	**2016**	**0.43%**	1.78%	4.19%	4.05%	4.08%	3.08%	2.99%	2.35%
Hebei	**2016**	2.14%	3.78%	4.74%	4.71%	4.70%	0.57%	0.48%	**0.23%**
Tianjin	**2016**	2.44%	2.44%	4.76%	4.70%	4.60%	0.64%	0.59%	**0.08%**
Henan	**2016**	**0.28%**	**0.28%**	1.66%	1.67%	1.58%	1.71%	1.79%	2.38%
Heilongjiang	**2016**	14.11%	14.11%	17.06%	16.98%	17.04%	12.11%	12.00%	**11.27%**
Hubei	**2016**	0.84%	**0.58%**	2.91%	2.91%	2.94%	0.63%	0.71%	1.32%
Hunan	**2016**	3.24%	3.24%	5.47%	5.48%	5.55%	1.24%	1.16%	**0.50%**
Jilin	**2016**	1.02%	**0.72%**	3.54%	3.60%	3.44%	1.08%	1.15%	1.73%
Jiangsu	**2016**	1.18%	1.18%	2.76%	2.75%	2.71%	0.84%	0.78%	**0.20%**
Jiangxi	**2016**	3.36%	3.96%	5.72%	5.75%	5.66%	1.00%	0.92%	**0.25%**
Liaoning	**2016**	3.71%	3.71%	6.05%	5.96%	5.93%	1.84%	1.76%	**1.25%**
Inner Mongolia	**2016**	5.14%	5.14%	7.67%	7.53%	7.51%	1.90%	1.81%	**1.24%**
Ningxia	**2016**	25.61%	14.64%	**6.31%**	6.48%	7.40%	15.81%	16.13%	17.71%
Qinghai	**2016**	15.83%	11.62%	2.89%	**1.39%**	2.82%	7.64%	7.75%	8.58%
Shandong	**2016**	3.00%	2.91%	4.93%	4.90%	4.91%	1.12%	1.04%	**0.52%**
Shanxi	**2016**	3.22%	3.22%	5.68%	5.76%	5.68%	0.97%	0.90%	**0.41%**
Shaanxi	**2016**	**0.89%**	**0.89%**	1.06%	1.00%	1.03%	1.29%	1.37%	1.84%
Shanghai	**2016**	1.23%	1.23%	2.93%	2.94%	2.97%	1.29%	1.23%	**0.76%**
Tibet	**2016**	7.93%	6.21%	1.37%	1.27%	**1.20%**	3.36%	3.49%	4.72%
Xinjiang	**2016**	1.84%	**1.00%**	5.23%	4.86%	5.18%	2.07%	1.95%	1.25%
Yunnan	**2016**	**0.91%**	**0.91%**	0.96%	1.13%	1.12%	2.62%	2.70%	3.24%
Zhejiang	**2016**	0.89%	0.89%	2.50%	2.52%	2.54%	**0.34%**	0.40%	0.89%
Guangdong	**2016**	1.24%	**0.83%**	2.70%	2.72%	2.72%	1.43%	1.37%	0.97%
Guangxi	**2016**	2.20%	**0.07%**	2.61%	2.63%	2.56%	0.40%	0.32%	0.17%
Average	**2015**	2.60%	2.74%	3.15%	3.05%	3.15%	2.43%	**2.36%**	2.42%
Average	**2016**	4.45%	4.32%	4.44%	4.41%	4.44%	**2.77%**	2.78%	2.79%
Average	**2015–16**	3.52%	3.53%	3.80%	3.73%	3.79%	2.60%	**2.57%**	2.61%

(Notes: the smallest value of forecasting error is in bold for each region in each year.)

the average forecasting error of the other type of spatial-temporal model, the dynamic spatial panel model, generated the largest forecasting error, even larger than the a-spatial models like ARIMA and UCM. Among models with three different spatial weighting matrices, their average forecasting errors were quite close to each other, with a moderately smaller error with an inverse quadratic

Table 4
Estimation results of regression on relative error of spatial-temporal forecasting (dynamic spatial panel models).

	Model 7 Year = 2015 W = cont.	Model 8 Year = 2015 W = inv.dist	Model 9 Year = 2015 W = flow	Model 10 Year = 2016 W = cont.	Model 11 Year = 2016 W = inv.dist	Model 12 Year = 2016 W = flow
abs_Moran_I	−0.0167**	−0.0217***	−0.0105	−0.0386***	−0.0371***	−0.0525***
	(0.00781)	(0.00526)	(0.0168)	(0.00636)	(0.00380)	(0.0138)
constant	0.0189***	0.0186***	0.0142*	0.0291***	0.0243***	0.0306***
	(0.00271)	(0.00288)	(0.00698)	(0.00224)	(0.00307)	(0.00766)
N	29	29	29	29	29	29
R-sq	0.285	0.503	0.036	0.658	0.758	0.392
adj. R-sq	0.259	0.485	0.000	0.645	0.749	0.369
W	cont.	inv.dist.	flow	cont.	inv.dist.	flow
Turning point and 95% CI of abs_Moran_I	1.132	0.858	1.352	0.752	0.655	0.582
	[0.212, 2.053]	[0.408, 1.308]	[0, 4.616]	[0.494, 1.010]	[0.457, 0.853]	[0.367, 0.797]

(Notes: *** indicates significance at the 0.01 level, ** indicates significance at the 0.05 level, * indicates significance at the 0.10 level. Robust standard errors are presented in parentheses.)

Table 5
Estimation results of regression on relative error of spatial-temporal forecasting (STARMA models).

	Model 13 Year = 2015 W = cont.	Model 14 Year = 2015 W = inv.dist	Model 15 Year = 2015 W = flow	Model 16 Year = 2016 W = cont.	Model 17 Year = 2016 W = inv.dist	Model 18 Year = 2016 W = flow
abs_Moran_I	−0.00964*	−0.00778*	0.00503	−0.0115*	−0.0125**	0.00366
	(0.00512)	(0.00387)	(0.0147)	(0.00674)	(0.00524)	(0.0166)
constant	0.00777***	0.00528**	0.000164	−0.00271	−0.00327	−0.0105
	(0.00226)	(0.00257)	(0.00544)	(0.00422)	(0.00373)	(0.00704)
N	29	29	29	29	29	29
R-sq	0.188	0.210	0.016	0.165	0.255	0.005
adj. R-sq	0.157	0.180	−0.020	0.134	0.227	−0.032
W	cont.	inv.dist.	flow	cont.	inv.dist.	flow
Turning point and 95% CI of abs_Moran_I	0.806	0.679	N/A	N/A	N/A	2.864
	[0.018, 1.594]	[0, 1.383]				[−19.599, 25.327]

(Notes: *** indicates significance at the 0.01 level, ** indicates significance at the 0.05 level, * indicates significance at the 0.10 level. Robust standard errors are presented in parentheses.)

distance matrix. For the one-step-ahead prediction, the error difference between a-spatial forecasting and spatial-temporal forecasting, more specifically, the STARMA forecasting, was moderate. However, this difference inflated substantially for the two-step-ahead prediction, and the average forecasting errors of the STARMA forecasting were significantly smaller than that of a-spatial forecasting. These results echo findings from Kholodilin et al. (2008) and Girardin and Kholodilin (2010) in which spatial-temporal forecasting performance was better for longer forecasting horizons.

Auxiliary regression

Lastly, it is worthwhile to examine which factor explains the relative forecasting error of spatial-temporal models compared to a-spatial models. Here, we calculated the relative forecasting error as the forecasting error of spatial-temporal forecasting minus the smallest error of a-spatial forecasting (i.e., ARIMA or UCM forecasts). As shown in Table 3, their errors were quite close to each other. After that, we ran several regression models using the relative forecasting error as the dependent variable. The independent variable was the absolute value of the local Moran's I statistic (abs_Moran_I), reflecting the level of local spatial association. Tables 4 and 5 presents the estimation results of these models with three different spatial weighting matrices for one-step-ahead (2015) and two-step-ahead (2016) forecasts.

Table 4 presents the results for the errors from the dynamic spatial panel model. In Models 7–12, the coefficient of abs_Moran_I was estimated to be statistically significant and negative in five out of six models. A negative coefficient indicates that the relative forecasting error of dynamic spatial panel models (compared to a-spatial models) is smaller in a location with a stronger local spatial association. The estimated coefficient of the constant reveals the expected relative error of spatial-temporal forecasting without any local spatial association (abs_Moran_I = 0). A positive and significant constant in all six regression models suggests that in the absence of local spatial association, spatial-temporal forecasting from dynamic spatial panel models led to a significantly higher forecasting error than a-spatial forecasting. As the level of local spatial association increased, the relative forecasting error of these models declined. After a turning point, the relative forecasting error reached a negative value, implying that spatial-temporal forecasting generates smaller errors than a-spatial forecasting. If the turning point is negative, it became unavailable. The last row of Table 4 presents the calculated turning point and its 95% confidence interval. The turning point was found to be lower in the 2016 forecast, indicating that spatial-temporal forecasting may be more useful in two-step-ahead prediction for locations characterized by a strong local spatial association.

Table 5 presents the results for the errors from the STARMA model. The coefficient of abs_Moran_I was estimated to be statistically significant and negative in four out of six models. This result, again, indicates that the spatial-temporal forecasting, like the STARMA in this case, can significantly reduce the forecasting error in locations with a higher level of local spatial association with their neighbors in terms of inbound tourism demand.

Conclusion and implications

In this study, a spatial-temporal forecasting exercise was conducted to forecast annual inbound tourist arrivals to 29 Chinese provincial regions. The spatial-temporal forecasting model was estimated based on dynamic spatial panel models and STARMA models with different spatial weighting matrices. After ex-ante forecasting, the performance of these models was compared with that of a-spatial models, such as the ARIMA model and the UCM model. The forecasts of spatial-temporal models generally yielded a smaller error than their a-spatial counterparts. Furthermore, the auxiliary regression was estimated to understand which regions were associated with a smaller relative forecasting error in the spatial-temporal models. Spatial-temporal forecasting was more effective in regions with a larger absolute value of the local Moran's I statistic, indicating a stronger spatial association with neighbors in terms of inbound tourism demand.

The current study represents a pioneering effort in spatial-temporal forecasting of tourism demand, and the effectiveness of incorporating spatial dependence terms was rigorously evaluated compared to a-spatial forecasting models. This study contributes to the tourism forecasting literature by offering a new perspective that leverages existing information that has been long overlooked. Based on forecasting performance, this new forecasting method was found to lead to more satisfactory results in most regions, and on average, outperformed the a-spatial method. Further, findings of the auxiliary regression may inform a recent debate on the economic theories and practices behind spatial econometrics (Corrado & Fingleton, 2012). As a popular statistic in spatial econometrics, LISA, such as the local Moran's I statistic, can be used to gauge the suitability of spatial-temporal forecasting for future indicators of interest. The spatial-temporal forecasting results suggested that the performance of three spatial weighting matrices, on average, is very close to each other; therefore, the choice of spatial weighting matrix is less critical for global forecasting than model selection (dynamic spatial panel vs. STARMA). However, the forecasting error did vary across different matrices for the same province. Therefore, we recommend LISA with different spatial weighting matrixes to select proper matrixes for local spatial-temporal forecasting.

In this paper, we evaluated the forecasting performance of spatial-temporal models to facilitate model selection for tourism forecasting practitioners. First and foremost, results supported the superior performance of spatial-temporal forecasting of tourism demand, especially in areas exhibiting stronger spatial associations with their neighbors in terms of tourism demand level. Therefore, forecasting practitioners in these regions should strongly consider conducting spatial-temporal forecasting on tourism demand. Second, spatial-temporal forecasting possesses an important advantage over a-spatial forecasting, namely time effectiveness in specifying a single model rather of than several models for individual locations/regions. Third, findings indicated that spatial-temporal forecasting achieved a smaller relative forecasting error over a longer forecasting horizon, highlighting the suitability of this forecasting method for long-run forecasting. Fourth, results revealed a preference toward the inverse quadratic distance matrix as a spatial weighting matrix in the model; as indicated by this matrix, local governments and destination marketing organizations may propose specific strategies for collaborating with other destinations to maximize potential spillovers as spillover receivers. Lastly, our results highlighted the significant spatial spillover effects in tourism demand, and local DMOs and stakeholders should propose and implement more tactic strategies to leverage the beneficial spillovers. Some useful endeavors include inter-regional product bundling and marketing collaboration, performance benchmarking with neighboring destinations, and transport system planning to attract tourists from hub destinations.

Some limitations may temper the generalizability of these major conclusions. First, because annual data contained no seasonality, this characteristic was not incorporated into spatial-temporal modeling and forecasting (Kulendran & Wong, 2005). Second, owing to data unavailability, two provincial regions (Sichuan and Chongqing) in mainland China were not included; this shortcoming can lead to 'spatial leakage' when estimating a spatial econometric model. Third, no long-run forecasts were conducted due to the brief time-series length, yet a comparison of short- and long-run forecasting performance can provide a holistic understanding of the effectiveness of spatial-temporal forecasting (Girardin & Kholodilin, 2010). Therefore, future studies should apply spatial-temporal forecasting on monthly and weekly time series that demonstrate a clear pattern of seasonality, and compare the relative performance of spatial-temporal forecasting on the long-run prediction of tourism demand.

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