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Analyzing destination resilience from a spatiotemporal perspective

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Abstract

The tourism industry is vulnerable to external shocks. Various crises inevitably impact the tourism industry and tourist destinations negatively but at the same time bring opportunities to examine destination resilience in response to a real shock that is hard to simulate. To manage a crisis more effectively, two critical issues should be addressed: the duration of the impact of the crisis (i.e., temporal perspective) and the affected geographical scale (i.e., spatial perspective), which have been neglected in previous studies on destination resilience. To address the above gaps, this research develops a comprehensive, multi-stage, dynamic spatiotemporal analytical framework to firstly measure two aspects of tourism resilience (i.e., resistance and recovery), and secondly analyze the influencing factors of tourism resilience. The empirical context of international tourism in Europe during the COVID-19 pandemic is used to demonstrate the applicability of the developed framework and relevant policy implications.

Keywords: Destination resilience, spatial econometrics, resistance, recovery, counterfactual prediction.

Introduction

The rapid development of international tourism during the last decades has brought significant contributions to destination economies. In 2019, the total revenue of the global tourism industry amounted to 8.9 trillion US dollars, which was 10.3% of the global GDP. However, tourism is one of the most sensitive and vulnerable industries due to reasons such as the complex nature of the industry, connected destination governance and management, and the leisure nature of tourism that contributes to a large part of international travel (Nair & Dileep, 2020). Tourism can be viewed as an open network that is sensitive to external events that are usually beyond the control of individuals and even the destination government (Ritchie et al., 2014). The vulnerability of the industry becomes obvious especially when external disturbance and turbulence occur. For example, travel and tourism were among the most affected sectors of the global economy during the prolonged COVID-19 pandemic (Lenzen et al., 2020). Since the global tourism industry faces frequent crises, such as natural disasters, economic recessions, terrorist attacks, and global pandemics, the examination of the tourism system in times of conflict and crisis has gradually become a new sub-field of tourism research over the past two decades (Dahles & Susilowati, 2015).

Many studies have investigated the impact of various crises on the tourism industry, such as climate change (Scott et al., 2019), terrorist attacks (Liu & Pratt, 2017), and the COVID-19 pandemic (Sun et al., 2022). In terms of addressing the impact, the concept of resilience pertains to how the destination responds to external crises and shocks (Dahles & Susilowati, 2015). Broadly, tourism resilience can be understood as a destination's capability to adapt, learn, and self-organize (Della Corte et al., 2021). The resilience of a tourism destination has been viewed as its intrinsic ability to absorb and recover from external stressors, which makes this concept hard to observe and quantify in normal times (Amore et al., 2018). Nevertheless, crises are external shocks that make intrinsic resilience more observable in terms of the actual response to the crisis. Thus, crisis and disaster research has contributed to a better understanding of resilience in the real world (Morsut et al., 2022).

There are many different perspectives on understanding resilience. The process perspective of resilience, which involves multiple stages of resilience building, has been proposed by Ducheck (2020), wherein the dynamic nature of resilience is emphasized. This perspective assumes resilience to be a dynamic evolutionary process, involving vulnerability, shocks, resistance, robustness, and recoverability (Martin & Sunley, 2015). However, previous studies (e.g., Cui et al., 2021; Watson & Deller, 2022) tend to quantify resilience using an aggregated and static indicator over a period of time for relatively short-term shocks. Nonetheless, for longer-term shocks, such as the COVID-19 pandemic, with fluctuations in policies over time, dynamic information at different stages of the recovery path cannot be neglected. Apart from the temporal perspective, the spatial perspective is an important aspect of the regional transmission of shocks. However, spatial connectivity has been neglected in most resilience analyses, largely because socio-spatial interactions between regions are not as obvious, such as in the transportation system. Cross-sectional interactions should be considered when analyzing resilience in response to shocks, as shocks can be transmitted easily, especially in the current global environment (Martin, 2012). Tourism is highly sensitive to geographical locations, and interdependency across destinations has been proven to exist in previous literature (e.g., Jiao et al., 2020). Thus, a thorough understanding of the tourism resilience system requires the incorporation of the spatial perspective.

Although there have been conceptual attempts to develop a systematic framework for destination resilience (Bethune et al., 2022; Sharma et al., 2021), these frameworks have always been developed based on a qualitative approach and face challenges relating to empirical applications and quantification. Existing empirical studies on tourism and destination resilience tend to focus on a single destination or even a single attraction site affected by a relatively short-term and one-off crisis, which is difficult to generalize to other destinations or crises. For a global-scale and long-lasting shock, the tourism system experiences measurable chaotic changes at different points in time.

The COVID-19 pandemic, for example, is a natural experiment to test the post-pandemic resilience of destinations. Thus, learning from this crisis, the present study aims to propose a new, comprehensive, and dynamic multi-stage framework for analyzing destination resilience in crises. Tourism resilience is first quantified at each period across different stages of the pandemic, followed by a cross-sectional comparison and spatial distribution of tourism resilience in the empirical context of European destinations. The whole process of determining destination resilience is divided into two key stages, that is, resistance and recovery following the economic resilience framework proposed by Martin (2012). A spatiotemporal econometric model is employed to understand different influencing mechanisms for destination resilience at different stages so that effective policy recommendations can be made to enhance future destination resilience and competitiveness.

This study makes several important contributions. First, the proposed research is the first attempt to develop a comprehensive and comparable multi-stage tourism resilience framework for tourism destinations and to objectively identify the influencing factors of tourism resilience from a macroeconomic perspective. Therefore, the research findings of this study provide a critical understanding of tourism resilience. Secondly, this research is the first attempt to introduce the temporal perspective of tourism resilience measurement. As such, resilience is regarded as a dynamic rather than a static process. Thirdly, by further considering spatial connectivity in the newly developed tourism resilience framework, our analysis accounts for the interdependency within a tourism system and the transmission of shocks across tourism destinations. Fourthly, from a methodological point of view, this research represents the initial attempt to employ the state-of-the-art spatiotemporal econometric method to analyze resilience and its influencing mechanism beyond the tourism context. Therefore, the contributions of the study extend beyond just the tourism field. Practically, this study contributes to a clear and quantifiable understanding of destination resilience in the context of the pandemic and its influencing factors. For destinations, this study provides a scientific understanding to help develop strategies to enhance long-term destination competitiveness through strengthening resilience when encountering unexpected crises.

Literature review

Theoretical foundations of resilience from different perspectives

Resilience refers to the ability of a system to persist in the presence of change and disturbance, first proposed by Hollings (1973) from an ecological perspective. The notion has been further transferred to and developed for other disciplines, including behavioral psychology, business, and economics (e.g., Holling, 1973; Perrings, 2006). As the contexts are different in different disciplines, no single accepted definition is appropriate and sufficient to interpret resilience in all circumstances (Hall et al., 2018, p33). Resilience in the engineering context originated from the physical sciences, which defines resilience as the ability to bounce back from shocks to the pre-shock state or path. This approach has been frequently used in disaster management literature (e.g., Funfgeld & McEvoy, 2012). The ecological approach originated with a focus on the scale of the shock or disturbance that an ecological system can tolerate before moving to a new state. Adaptive resilience is based on the complex adaptive systems theory, which represents the capacity of a system to gradually reorganize itself to minimize the impact of a destabilizing disturbance while maintaining core performances. As the contexts are different in different disciplines, no single accepted definition is appropriate and sufficient to interpret resilience in all circumstances (Hall et al., 2018, p33).

According to Martin and Sunley (2015), a more comprehensive and integrated view of resilience emphasizes resilience as a process—instead of a characteristic or property—that incorporates multiple stages of adaptation in the field of regional economic resilience. The process view of resilience adopts the theory of complex adaptive systems, stating that complex adaptive systems demonstrate self-organizing behavior from co-evolutionary interactions across their components and adaptive capacity to rearrange their internal structural system gradually, in response to external shocks (Martin & Sunley, 2007). A more generalized and quantifiable resilience framework corresponds to the regional economic resilience framework, whose measures involve quantifying regional responses to a shock by observing the behavior of an economic statistic representing economic activity. Researchers use such economic statistics, such as output, unemployment, and employment, to observe the shock response of a variety of regional units, including countries, regions within countries, metropolitan statistical areas, and counties (Davies, 2011; Fingleton et al., 2012; Martin, 2012). According to chaos theory, even stable systems are 'at the edge of chaos', wherein trivial events may be sufficient to threaten the integrity and coherences of the system (Russell & Faulkner, 2004). Thus, economic systems become complicated in response to external disturbance in the way that regional economic resilience to recessions varies over time in terms of its distinct path dependence, self-organization, and adaptations by economic agents and policymakers.

Building upon the theory of complex adaptive systems, the economic resilience framework emphasizes the four dimensions of regional resilience: resistance, recovery, re-orientation, and renewal (Martin, 2012). The last two stages, re-orientation and renewal, are relatively long-term and hard to observe and quantify. Besides the resilience process itself, structural differences in the determinants of resilience during the whole process of resilience have been identified to emphasize the process view and temporal dynamics of resilience (Martin & Sunley, 2015). From the temporal perspective, resistance reflects the initial impact of the shock on the regional system and thus is more sensitive to the situational or shock conditions. On the other hand, recovery (i.e., recoverability) reflects the extent and nature of the recovery path from the shocks. Moreover, resistance is greatly determined by inherent and inherited characteristics of the system, such as inherent economic dynamism and sectoral structure.

Although the recovery stage also shares some determinants, such as sectoral structure, technology profile, and external relations and linkage, recovery tends to reflect the adaptable characteristics of the system compared to the inherency nature of resistance (Martin & Sunley, 2015; Martin, 2012).

Tourism and destination resilience

Although the concept of resilience is not new, the introduction of resilience in tourism research is still nascent (Wang et al., 2022). In the tourism context, tourism destination resilience can be interpreted as the protection of the tourism system from internal and external shocks (Bethune et al., 2022) by focusing on a series of crisis and disaster response management to mitigate risks to the tourism industry (Faulkner, 2001) based on chaos theory stating the vulnerability of even stable systems facing even trivial disturbance.

Different conceptual frameworks have been introduced to tourism resilience, and early works adopted the socio-ecological systems theory to evaluate the environmental sustainability of a destination or an attraction in qualitative case studies, lacking consideration of social and economic components, and external disturbance (Cote & Nightingale, 2012). Ruiz-Ballesteros (2011) applied the socio-ecological resilience (SER) framework to present a case study in Agua Blanca to assess socio-ecological sustainability, specifically in the tourism sector. Similarly, Kutzner (2019) conducted an empirical case study to examine the socio-ecological resilience of tour operators in the Otago Penisula, Dunedin, New Zealand, where the diversity of species, business experience, and local stakeholder networks are key responses to the SER crisis. The SER framework has been further extended into the agency-based livelihood resilience framework to emphasize the importance of the resilience of the local community as a resilient community has a higher chance of survival, adaptation, or, occasionally, transformation in turbulent times (Chen et al., 2020). The conceptual frameworks building upon the SER theories and frameworks are often hard to operationalize and generalize empirically, and the limited empirical application is often qualitative in the form of case studies focusing on one specific destination or even one destination attraction.

Another common resilience perspective in tourism is the focus on the recovery of tourism industries and tourist arrival numbers in a specific destination after a certain crisis, which is more applicable to examining tourism destination resilience in crises. For example, the pandemic disrupted the original socioeconomic system instead of the ecological system, which tends to be more vulnerable to natural disasters. Regarding the recent pandemic crisis, Gaki and Koufodntis (2022) examined regional resilience and recovery in crises using aggregated resistance and a recovery index to indicate descriptive evidence of regional tourism resilience in Greece. McCartney et al. (2021) examined Macao's destination resilience from an economic point of view. Watson and Deller (2022) focused on the destination's economic resilience as well, using an aggregated indicator to quantify resilience and analyze the relationship between tourism and economic resilience. This study contextualizes the analysis of destination resilience regarding the COVID-19 pandemic, which generates unexpected and long-lasting disturbance of the whole tourism industry globally. Considering the real situational indicators can help accurately examine the resilience performance and framework empirically.

The theory of complex adaptive systems is not new in the tourism literature to understand the process of changes in systems in response to fluctuations, to maintain competitiveness in tourism areas (Heylighen, 2002). The pathway to recovery in the tourism industry continues to change in different periods of the aftershock because of its sensitivity to shocks and vulnerability to economic fluctuations. Systematic perspectives have been undertaken to understand the complex characteristics of tourism with interrelated industries, multiple stakeholders, vulnerable and perishable natures, and destination policies (Baggio & Sainaghi, 2011). In particular, given the structural dynamic nature of destinations under emergent shocks, the destination resilience framework should be built upon the complex adaptive systems theory (Hartman, 2020), based on the regional economic resilience framework (Martin, 2012).

Spatial perspective in tourism resilience

In addition to the temporal dimension, the spatial perspective is also important regarding regional transmission of shocks and resilience. Spatial interaction is an important aspect of economic resilience, which emphasizes the need to allow for possible interactions between regions resulting from their differential resilience to shocks (Fingleton et al., 2012). Intuitively, labor or capital flows from less resistant regions into more resistant regions induced by shock may further slow the growth paths of the former and stimulate the growth paths of the latter (Martin & Sunley, 2015). According to the new economic geography theory, shocks may potentially shift the spatial distribution of economic activity from one configuration to another (Redding, 2010). Thus, examining the influencing mechanism of a region's resilience within its own system, in isolation from nearby regions, will neglect the interactions generated from other regions. The same rule applies in the tourism industry, since tourism is a type of economic activity highly related to geographical locations (Jiao et al., 2021). It has been well-documented that tourism in a specific destination is connected to its neighboring destinations (Long et al., 2019; Ma et al., 2015; Yang & Wong, 2012). Supply-side factors such as market access, joint promotion, foreign direct investment (FDI) penetration, and one-off events, and demand-side factors such as multi-destination travel patterns all contribute to spatial interactions of tourism demand and tourism development in neighboring destinations (Yang & Fik, 2014). Therefore, tourism resilience is also subject to spatial interactions from neighboring destinations, corresponding to economic resilience and the spatial characteristics of tourism demand.

The illustration of spatial economic resilience can be further applied to spatial tourism resilience, indicating that tourist flows from a less resilient destination to a more resilient destination will further impede the recovery of the former destination and facilitate the recovery of the latter. Meanwhile, building resilience to a certain scale may contribute to increasing the resilience to other spatial levels (Béné, 2018), which may also diffuse the effect on other destinations within higher spatial levels. Neglecting the spatial spillover of tourism resilience from other destinations will lead to an overestimation of the influence of other explanatory variables. Apart from the destination, the nature of the pandemic shock also suggests strong geographic implications due to its highly contagious nature, which deepens the need to include spatial interactions in the resilience system. Thus, in this study, the spatial perspective cannot be neglected when evaluating tourism resilience in European destinations. Spatial connectivity tends to be neglected because socio-spatial interactions between regions are not as evident as in the transportation system, for example. Fingleton and Palombi (2013) and Fingleton et al. (2012) addressed this connectivity by considering spatial interactions across regions using spatial econometric methods to measure regional economic resilience in the UK.

However, the spatial perspectives have never been conceptually and systematically incorporated into the theoretical and conceptual framework in the tourism and destination resilience literature. The destination resilience framework developed in this study will extend the regional economic resilience framework (Martin, 2010) to advance and operationalize the complex adaptive theory with the integration of the spatial perspective from the new geography theory.

Influencing factors of destination resilience

The drivers of destination resilience, either endogenous to the system or exogenous disturbances, have been examined in many previous studies, mainly using qualitative methods due to the complexity of destination resilience (Wang et al., 2022). As mentioned above, destination resilience is often evaluated for a specific destination or attraction site after it has experienced a regional shock. For example, empirical resilience studies based on the SER framework examined resilience from different dimensions, such as social, ecological, and economic (Bui et al., 2020; King et al., 2021), without explicitly analyzing factors affecting destination or community resilience. Cochrane (2007) identified harnessing market forces, stakeholder cohesion, leadership, and contextual system elements through a qualitative case study of the resilience cycle of Sri Lanka after the tsunami in 2004. McCartney et al. (2021) followed the economic resilience framework and descriptively analyzed determinants of Macau's destination resilience to the COVID-19 pandemic, including tourism industry structure, labor market conditions, financial environment, and governance arrangement, without analyzing the relationship between those factors and destination resilience.

Apart from case studies, efforts have been made to conceptualize a comprehensive framework to address the complexity of tourism resilience as tourism is characterized by the importance of its interconnections with other sectors (Della Corte et al., 2021). Especially when the tourism system experiences external shocks in turbulent times, factors in different domains play roles in shaping destination resilience. In a dynamic model of the tourism system (Tyrrell & Johnston, 2008), resilience is incorporated as an uncertain 'resilience threshold' in destination quality, defined as a combination of ecological–environmental quality, economic–fiscal quality, and social–cultural quality, under which tourism collapses to an unfavorable state. Especially with external shocks, the system becomes volatile and vulnerable to reaching the resiliency threshold. Therefore, the original components within the resiliency threshold, including ecological–environmental quality, economic–fiscal quality, and social–cultural quality, become crucial to determine destinations' adaptability and capability to resist in a relatively stable state. The environmental perspective has also been supported by Espiner et al. (2017), who stated that a sustainable destination implies resilience. From tourists' perspective, environmental quality influences their impression of a tourist destination and further affects their intention to revisit the destination (Sadat & Chang, 2016). During turbulence, such as the pandemic, destination image has proved to mediate the risk perception on revisit intention, which is shaped by environmental quality as an important aspect. Amore et al. (2018) developed a multi-level destination resilience framework with the theoretical foundation from mid-range theories related to attempts to account for changes at multiple scales, such as socioeconomic, environmental, and political (Geels, 2011), in a general resilience framework. This is applicable to a tourism system with regard to constructing a destination resilience framework that incorporates the landscape level, including macro indicators reflecting the macro-level (i.e., socio-ecological, socio-political, socio-economic, and socio-technological) conditions at the destination level, regime level related to the tourism specific actors (such as accommodations and tourism-related employment), and the niche level, including the resident population's characteristics. From the policy perspective, effective government response can positively influence the recovery from tourism decline (Tyrrell & Johnston, 2008).

As Jopp et al. (2010) argued, the socioeconomic resilience of destinations involves capitalizing on opportunities through a holistic approach that is resistant to unexpected disturbance. Potentially, small economic entities might be more vulnerable than larger economic entities due to a lack of diversification, trade dependence, and lower capacity to support the loss of the tourism industry either through fiscal policies or investment. Tourism demand, as an outcome indicator in the tourism resilience system, is also highly dependent on economic conditions (Song & Li, 2008). Thus, the level of resilience in terms of tourism demand cannot ignore the influence of how the economic situation changes during and after the external shocks from the crisis. In disaster management studies (Jaramillo et al., 2016), both the short-term and long-term effects of a natural disaster are determined by a country's income level and population.

From the social perspective, Biggs et al. (2012) suggested that the concept of destination resilience reinforces the call for networked destination development, emphasizing the development of social capital; that is, resilience is related not only to tourists but also to the wider population that host the tourists in aspects such as health, education, and housing of the residents (Amore et al., 2018). The examination of the impact of natural disasters also corresponds to the socio-economic perspective. Oxley (2013) and Toya and Skidmore (2007) drew similar conclusions that nations with a higher GDP, a more educated population, and a more comprehensive financial system with more social and political freedom experience fewer losses in disasters. Noys and Vu (2010) also suggested that higher levels of literacy and better financial conditions contribute to macroeconomic resilience after natural disasters.

The socio-technological dimension of destination resilience can be viewed through innovations at different levels when facing external shocks. As an intersected industry, tourism has become the experimental ground for many new technologies (such as innovative logistics and humanoid robotics) to reinvent tourist products and experiences (Della Corte et al., 2021). Tourism products, as a result of the co-creation approach, can create attractiveness and added value for tourists and mitigate the negative impact of shocks with the adoption of open innovation (Della Corte et al., 2021). At both the destination and firm level, innovation results in the flexibility to adapt to new situations when facing undesirable shocks, such as the pandemic, including flexible adaptation to customers' changing needs and repositioning and anticipating market trends. As Hall et al. (2020) stated, technology represents a major force in strengthening flexibility in the tourism industry when facing crises and disasters. From the supply side, the ability to recover rests heavily on a community's resources in terms of capital (Cochrane, 2010). Destination resilience is also expected to be dependent on tourism resources, in terms of both human and physical capital, which can be translated as more resources the destination has from which to draw for recovery (Kahsai et al., 2015).

The literature review above reveals several gaps. Firstly, tourism resilience studies are often case studies focusing on the impact of a certain crisis on a specific destination, and a generalizable and quantifiable framework of tourism resilience has not yet been developed. Secondly, the existing measures of tourism resilience are aggregated indicators of resistance and recovery, without temporal dynamics. Thirdly, previous studies have not gone further to identify influencing factors of tourism resilience from a quantitative perspective. Finally, the spatiotemporal dynamics have not been considered in any tourism resilience literature. Building upon the CAS theory and the adaptive resilience perspective, the complexity of the tourism system as part of the socio-economic system in a destination, and the spatial interactions of destination resilience from different perspectives, this study intends to fill the above gaps by developing a multi-stage framework to firstly quantify tourism resilience at different stages, followed by developing a dynamic spatial framework to examine the influencing factors of tourism resilience with empirical evidence. Compared with previous resilience studies, the development of resilience at different stages, the spatial interactions, and the influencing mechanisms are all incorporated in the comprehensive framework as shown in Figure 1.

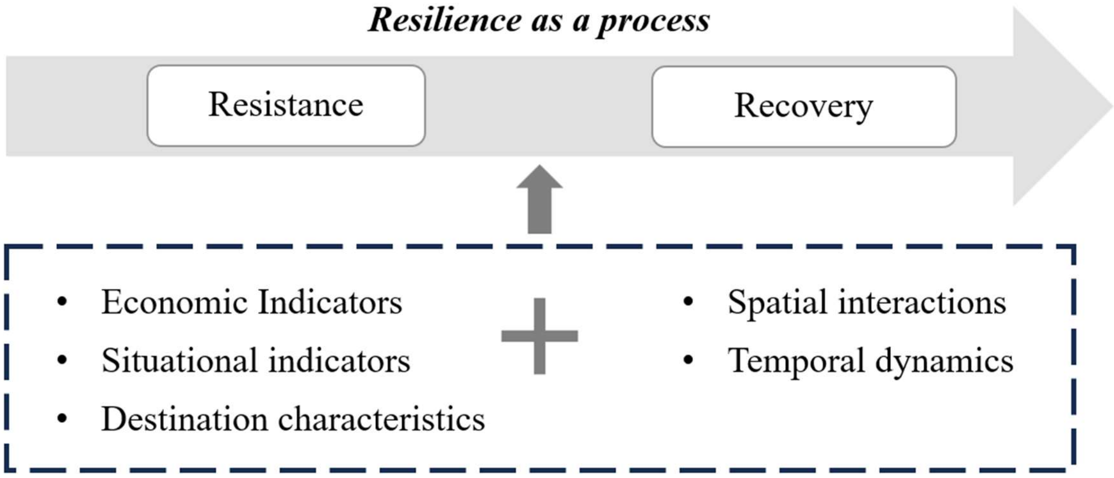

Figure 1. Conceptual framework

Methods

This study uses a multi-stage approach to evaluate tourism resilience and reveal the mechanism influencing tourism resilience from a spatiotemporal perspective in the empirical context of European destinations. Figure 2 summarizes the objectives, required data, and methods at each stage. The whole analytical framework starts with counterfactual predictions of tourism demand to examine how tourism demand would have developed based on historical trends assuming the pandemic had never happened. Resilience patterns are retrieved by comparing the differences between counterfactual predictions and actual observations at different points in time. Finally, the influencing mechanism of the whole resilience process is analyzed from a spatiotemporal perspective. A detailed explanation of each stage with different methods is provided in the following section.

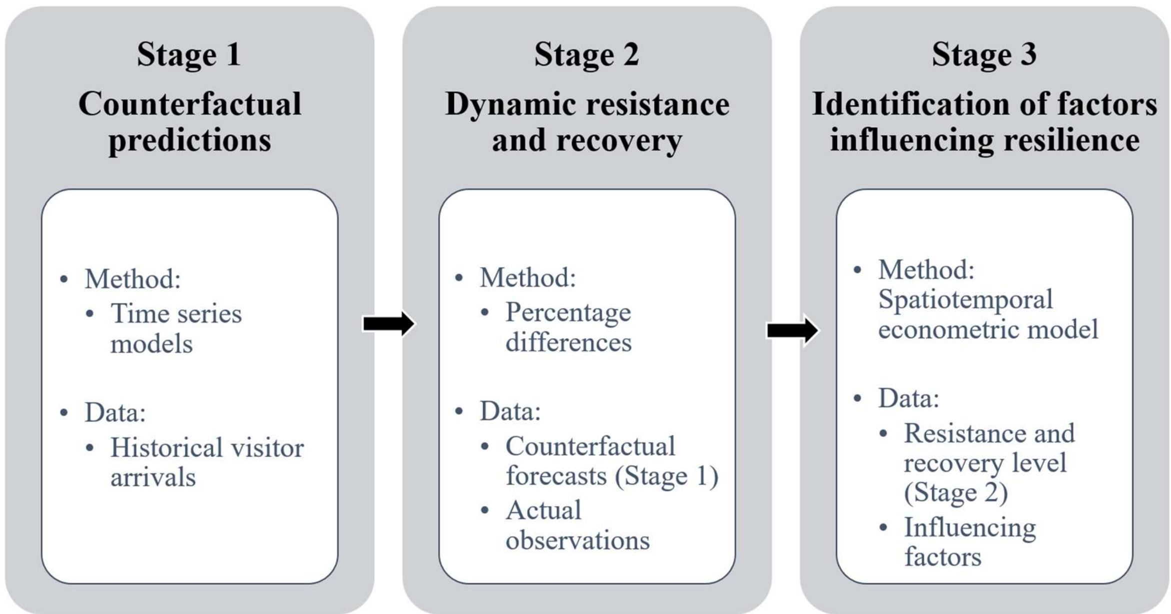

Figure 2. Research objectives and methods

Counterfactual prediction

This study starts with counterfactual predictions of the tourism demand in European destinations since the beginning of the COVID-19 pandemic. Following Fingleton and Palombi (2013), these counterfactual predictions reflect the expected trend of tourism demand, assuming the destinations are completely unaffected by the pandemic. As He et al. (2022) suggested, to restrain the virtual world which is unaffected or without the pandemic from being too complicated, external indicators influencing tourism demand, such as income and price (Li et al., 2005), are excluded in the counterfactual predictions to avoid additional disturbance generated by the prediction error of the external factors. Four time series models and the combination forecasts of the four time series models, by taking their simple average, are applied to generate ex-post forecasts before the pandemic in order to select the model that generates the most accurate forecasting results of the tourism demand historically. Similar to He et al. (2022), this study divided the monthly data of tourist arrival from 2005M1 to 2022M7 into three groups: training set (2005M1 to 2017M12), validation set (2018M1 to 2020M2), and test set (2020M3 to 2022M7). The training set and validation set are used to select the forecasting model to generate ex-ante forecasts of tourism demand after the pandemic. The ex-ante counterfactual predictions are further compared with real tourism demand in the test set to define resilience at different time. The forecasts are generated in multiple horizons for robustness and the forecasting performance of different models was compared using mean absolute percentage error (MAPE), root mean squared error (RMSE), and mean absolute scaled error (MASE) as in most tourism forecasting studies (Song et al., 2019). The forecasting performance and model selection results are presented in the next section.

Measuring Resistance and Recovery

Following Martin (2012), this study evaluates the level of resilience based on two perspectives—namely, resistance and recovery—by measuring the differences between the counterfactual predictions calculated in the first stage, assuming that the tourism destination is completely unaffected by the pandemic shock, and real tourist arrival in the resistance and recovery periods, where the former describes the level that a destination resists the destructive impact of the shock and the latter describes the level that a destination recovers from a destructive shock. In our context, the two periods are determined and distinguished by a turning point (T^l), separating the COVID-affected period. The major outbreak of the pandemic in Europe is considered to be in March 2020 (t_0) for most European destinations, looking at the data of real visitor arrivals. The recovery period starts from July 2021, where data from most European destinations' arrivals shows a relatively stable recovery from the pandemic. In addition to descriptive evidence, a structural break test (i.e., Chow test) for individual destinations and a panel structural break test are conducted to confirm the breakpoint dividing the resistance and recovery period statistically. To make the panel comparable, only one universal cut-off point, June 2021, was determined based on the statistical results, which is consistent with the initial observation. After defining the resistance and recovery periods in the temporal dimension, the resistance and recovery levels will be calculated by the differences between counterfactual predictions and real visitor arrivals in the two periods, respectively, as shown in Equations (1) and (2):

$$Resistance_{it} = \frac{(Y_{it} - Y_{it}^{c})}{Y_{it}^{c}} \; for \; t \; in \; |t_0, T^l| \tag{1}$$

$$Recovery_{it} = \frac{(Y_{it} - Y_{it}^{c})}{Y_{it}^{c}} \; for \; t \; in \; |T^l + 1, T| \tag{2}$$

where Y_{it}^{c} and Y_{it} represent the counterfactual predictions and real visitor arrivals at destination i at time t, respectively. The dynamic resistance and recovery series are calculated using Equations 3 and 4.

Influencing factors for tourism resilience: A spatiotemporal econometric model

The next stage of this study is identifying the factors that influence tourism resilience from a spatiotemporal perspective. To consider the multiple theoretical frameworks mentioned above and the quantifiability and availability of data, this study includes the following influencing factors in different dimensions: economic indicators, social indicators, situational or impact factors, and tourism industry factors (human and physical capital in the industry). The proposed factors are consistent with disaster management frameworks as well, which state that a disaster's effects are determined by pre-impact conditions (destination conditions in different aspects), hazard magnitude and intensity (situational indicator) as well as by post-impact conditions (response) (Lindell 2013).

Economic indicators include real GDP as a proxy of income, harmonized index of consumer price (HICP), published in Eurostat, which enables cross-sectional comparison of price across European destinations, and real exchange rate. Social indicators reflect the society or community information, which is reflected in this study by population and human development index (HDI). HDI is a composite index measuring average achievement in basic dimensions of human development, including a long and healthy life, knowledge, and a decent standard of living (UNDP, 2022) at the national level (Banica, 2020). Sustainability or the environmental condition is reflected through carbon emissions in tonnes (CE). As this study evaluates tourism resilience in response to the COVID-19 pandemic specifically, the situational index related to the shock and government response cannot be neglected, as it affects tourism resistance and recovery. This study used the stringency index (SI) in the Oxford COVID-19 Government Response Tracker (OxCGRT) developed by Hale et al. (2021) as a situational indicator, which considered school and workplace closures, cancellation of public events, gathering restrictions, public transport closure, staying at home requirements, internal movement restrictions, international travel restrictions, and public information campaigns at different times (Olsen et al., 2022).

Finally, supply-side indicators relate to the tourism industry, including tourism employment and accommodation establishments, which were included to reflect the tourism destinations' capacity to recover from external shocks. To capture the impact of innovation investment, the overall gross domestic expenditure on research and development (GRED) was incorporated when analyzing the influencing factors for tourism resilience. The complex nature of tourism makes the industry closely associated with many other industries (e.g., transportation and logistics, service, and hospitality). Thus, the overall GRED can be considered as a proxy to reflect the learning capability at the destination level, which will be projected onto the tourism industry to some extent.

By taking into account the spatial interactions from neighboring destinations and the temporal effects, a dynamic spatiotemporal autoregressive (SAR) can be specified as follows (Jiao et al., 2021):

$$Y_t = \lambda W Y_t + \rho Y_{t-1} + \beta X_t + \mu + \alpha + \varepsilon_{it} \quad (3)$$

where Y_t represents the vector of dependent variable at time t. In this study, the dependent variable is the resilience index (i.e., resistance and recovery). W is the spatial weight matrix that captures the relationship across destinations. WY_t considers the spatial interactions across different geographical units, and Y_{t-1} accounts for the temporal dynamics. X_t represents the matrix of independent variables. To account for spatial heterogeneity that reflects destination uniqueness, μ represents a vector of destination-specific fixed effects. α is the intercept, and ε_{it} is the unobserved disturbance. λ, ρ, and β are parameters to be estimated.

The specification of the spatial weight matrix is important as it reflects the spatial relationship across different units and influences the estimation results (Li et al., 2016). This study follows most spatial econometric studies to use the K-nearest-neighbor method to specify the spatial weight matrix. For each destination, K neighbors are identified according to the great circle distance between the capital cities, and the value of K is calibrated based on the model fitness reflected by residual variance using different spatial weight matrices with different number of neighbors.

Data and variables

This study uses Europe's response to the pandemic to demonstrate the measurement and the exploration of influencing factors affecting destination resilience in terms of resistance and recovery. European destinations have shown significant spatial spillovers across destinations (Jiao et al., 2021; Romão & Nijkamp, 2019). In this study, based on data availability, 31 European destinations were included to compare destination-level resilience, and 29 destinations were included to explore factors affecting tourism resilience. According to Jiao et al. (2020), tourism demand in Europe shows significant spatial spillovers across destinations. During the pandemic, many European countries have undertaken similar precautions and border control policies as well. Thus, to analyze the spatial interactions of tourism resilience, Europe is a representative region to start with. Monthly tourist arrivals in 31 European destinations were used for the counterfactual predictions and the quantification of resilience levels, obtained from Eurostat. Economic indicators, including monthly HCIP and real exchange rate, and situational indicators, including the SI (aggregated from daily frequency), were incorporated as explanatory variables of tourism resilience. Other factors, including real GDP, tourism employment, accommodation establishments, population, and GRED, were also obtained from Eurostat, while HDI data was obtained from the United Nations Development Programme (UNDP). The variables used in this study are summarized in Table 1.

Table 1. Variables used in the study

Variable	**Index**	**Data source**
Dependent variable		
Resilience	Percentage differences	Authors' own calculation
Independent variables		
Economic Indicators	GDP	Eurostat
	HICP	Eurostat
	Exchange rate (ER)	Eurostat
Situational Indicator	Stringency index (SI)	OxCGRT
Tourism Destination Development Indicators	Accommodation establishments (AE)	Eurostat

	Tourism employment (TE)	Eurostat
Destination Quality Indicator	Carbon emission (CE)	Eurostat
Innovation	Gross expenditure on research and development (GRED)	Eurostat
Social development	Human development Index (HDI)	UNDP
	Population (POP)	Eurostat

Empirical results

Following the proposed three-stage analytical framework (Figure 2), the empirical results of each stage will be discussed below.

Stage 1: Counterfactual prediction

In the first stage, a set of counterfactual predictions of tourism demand of various destinations are generated to represent the state that the tourism market would have achieved without the impact of the COVID-19 pandemic. To determine the most accurate forecasting model for tourism demand based on historical data, three most commonly used time-series models are utilized: seasonal autoregressive integrated moving average (SARIMA), exponential smoothing (ETS), and seasonal naïve and trigonometric Box-Cox transformation model with autoregressive moving average errors and trend and seasonal components (TBATS) model. These models are employed to generate forecasts. Both short-term (i.e., one-, three- and six-step-ahead) and long-term (i.e., 12-, 18-, and 24-step-ahead) forecasts were generated to select the model that can fit the series most accurately in both the short term and the long term. The forecasting performance was evaluated using three criteria that have been most frequently used in forecasting studies—MAPE, RMSE, and MASE. The forecasting evaluation results are presented in Table 1 below. As revealed by the forecasting evaluation results across different horizons (Table 2), the most accurate model varies across different time horizons according to different measurement criteria. Consequently, a combination forecasting approach was used, wherein the forecasts generated by four time series methods (SNaïve, SARIMA, ETS, and TBATS) are averaged to improve accuracy, as using a single method alone is unsuitable for generating counterfactual forecasts. Results in Table 2 show that combination forecasts consistently outperform the other time-series models across different horizons. Thus, in the following procedures, this study uses combination forecasts.

Table 2. Model selection

Measure	Model	Forecasting horizon					
		H1	H3	H6	H12	H18	H24
MAPE	SARIMA	5.365	6.646	7.275	7.600	10.548	9.683
	ETS	5.147	6.832	7.428	6.850	10.165	8.368
	SNAIVE	7.336	7.287	7.030	7.313	12.938	10.737
	TBATS	5.840	7.544	7.885	8.067	12.181	10.304
	Combination	**4.824**	**5.864**	**6.044**	**6.601**	**9.617**	**6.773**
RMSE	SARIMA	150817	168421	173605	175808	239199	95634
	ETS	147246	162665	179763	166511	245332	99162
	SNAIVE	192308	197652	188675	193312	303464	132542

	TBATS	163114	187264	201314	193172	289148	117120
	Combination	**141255**	**155099**	**162623**	**165657**	**236186**	**75407**
MASE	SARIMA	0.856	1.059	1.136	1.073	1.681	1.068
	ETS	0.852	1.116	1.241	1.009	1.733	0.968
	SNAIVE	1.241	1.273	1.235	1.143	2.383	1.354
	TBATS	0.985	1.267	1.403	1.223	2.143	1.191
	Combination	**0.795**	**0.972**	**1.047**	**0.953**	**1.650**	**0.734**

The forecasts were designed to start when European destinations started experiencing significant influence from the pandemic, which was in March 2020 based on the actual tourist arrivals data. Monthly data from January 2005 to February 2020 was used as historical data for training the model to forecast monthly arrivals in European destinations from March 2020 to July 2022. Figure 3 presents both the destination-level counterfactual predictions (dotted lines) and actual tourist arrival (solid lines). The solid lines represent actual tourist arrivals and the dotted lines represent the counterfactual predictions. It is evident that for all destinations, the forecasts show similar patterns compared to the pre-COVID period, suggesting that as the counterfactual, the trends and patterns of tourism demand before COVID-19 would have continued in the pandemic period; such trends and patterns deviate from the actual tourist arrivals during the pandemic period, indicating the significant impact of the pandemic on tourism.

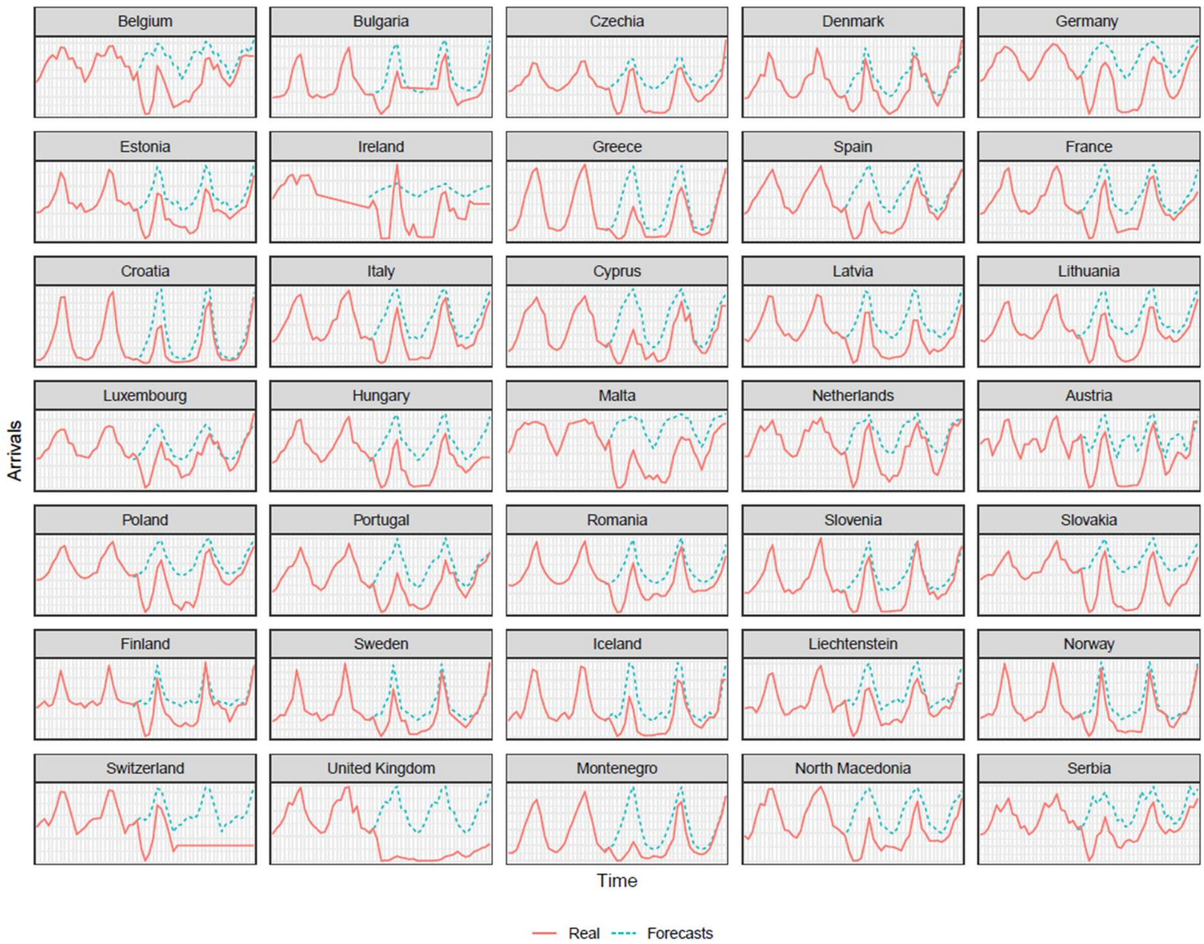

Figure 3. Counterfactual prediction and actual tourist arrivals

Stage 2: Resistance level and recovery level

After generating counterfactual predictions of tourist arrivals in the destinations, the next step is to measure comparable resistance and recovery levels over time to reflect the temporal dynamics of tourism resilience during the pandemic period. A positive resilience indicator at a specific time represents a full recovery to the pre-pandemic level of tourist arrivals over time, whereas a negative resilience represents that the current tourist arrivals pattern has not recovered to the counterfactual level before the pandemic. Figure 4 illustrates the difference between actual tourist arrivals and counterfactual forecasts from March 2020 to July 2022, providing insights into the resilience level from the pandemic in different destinations. The horizontal red line is positioned at 0, which serves as a threshold to determine whether a destination has fully recovered (i.e., the actual observation is greater than the counterfactual forecast) to the original tourism demand level without the impact from the COVID-19 pandemic or not (i.e., the actual observation is lower than the counterfactual forecast). The vertical black line separates the series into resistance and recovery periods. Notably, all destinations exhibited negative resistance levels below 0, revealing the severe impact of the pandemic on the European tourism industry. Nevertheless, a majority of destinations unveiled a stable recovery trend since the beginning of 2022. Most of the destinations did not fully recover until July 2022, with the exceptions of some destinations, such as Denmark, Greece, and Austria. Bulgaria, Netherlands, and Luxembourg recovered relatively quickly to their pre-COVID levels compared to other destinations.

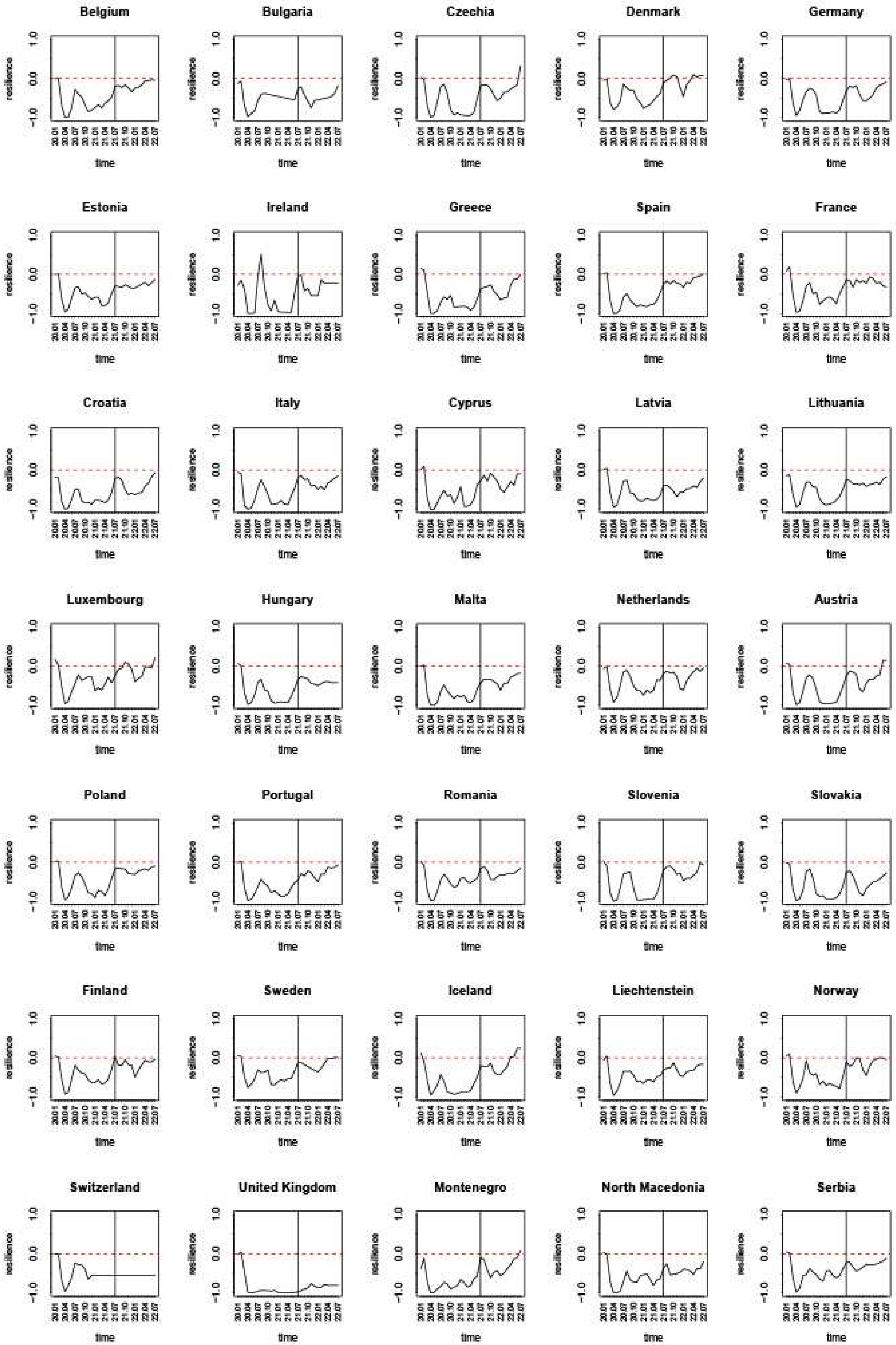

Figure 4. Resilience levels at different times

Figure 5 demonstrates the spatial pattern of destination resilience, with the left panel displaying the average resilience index throughout the sample period, the middle panel displaying the average resistance levels, and the right panel displaying the average recovery levels. In terms of overall resilience, Northern European destinations (such as Denmark, Norway, Sweden, and Finland) and Western European destinations (such as France, Luxembourg, and the Netherlands) show relatively better resilience levels than other regions, whereas the Eastern and Southern European destinations suffered hugely from the pandemic. The heterogeneity in tourism resistance is more pronounced between Northern European destinations, and France with Central European destinations, and the differences become less during tourism recovery. In terms of the resilience level in the latest period of data collection (July 2022), the disparities in tourism resilience have significantly reduced.

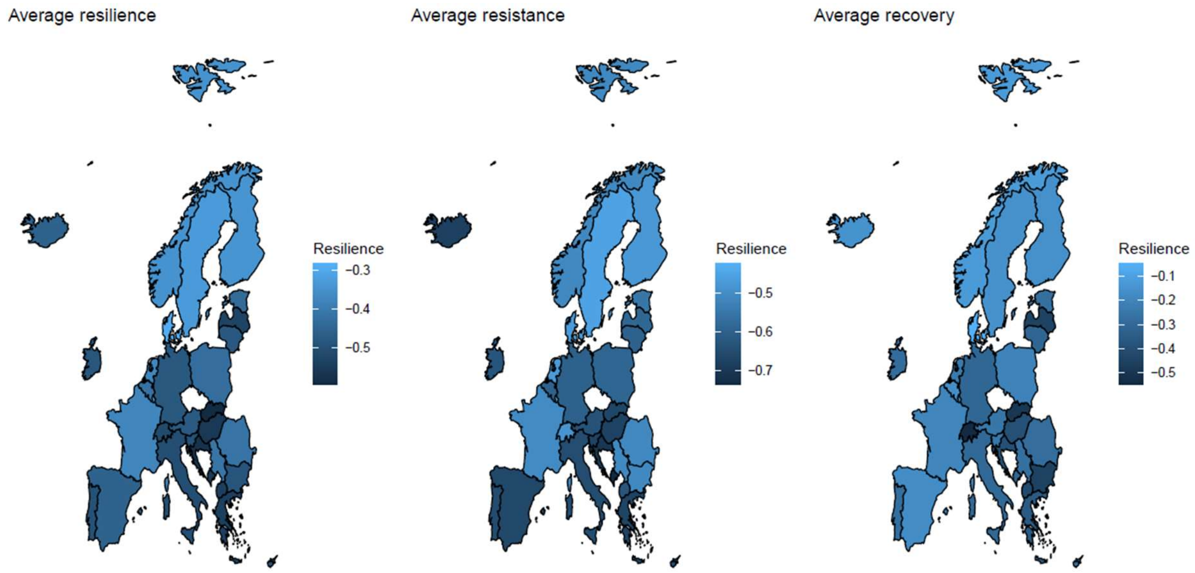

Figure 5. Spatial distribution of resilience at different periods in Europe

Furthermore, by partitioning resistance and recovery levels into quadrants, the overall tourism resilience condition cross-sectionally across different European destinations can be clearly shown in Figure 6. In the quadrant plot, the resistance and resilience levels of each destination are aggregated into single indicators to allow for an overall cross-sectional comparison across destinations in Europe. The vertical and horizontal baselines in the plot, representing the average resistance and recovery levels, respectively, aid in dividing the destinations into four quadrants. Destinations positioned at the top-right quadrant are the relatively more resilient destinations in terms of both resistance and recovery levels, and the destinations positioned at the bottom-left quadrant are relatively less resilient. Northern European destinations such as Norway, Sweden, and Finland, and Western Europe destinations such as France, Belgium, and Netherlands, are resilient in terms of both resistance and recovery levels. Destinations such as Spain, Slovenia, and Cyprus (in the top left quadrant) were largely affected in the early periods of the pandemic but recovered relatively quickly above average in Europe. Destinations such as Romania displayed resistance initially and recovered at an average speed. Nearly no destination shows relatively high resistance and low recovery patterns (in the bottom-left quadrant). Slovakia and Latvia, however, experienced a slower recovery from the pandemic, with their resistance levels initially hovering around the average mark. From the cross-sectional comparison of resistance and recovery, destinations can gain insights into their relative position at different stages of the resilience process. The necessity of examining resistance and recovery is evident as destinations exhibit different resistance and recovery positions compared to other destinations in Europe.

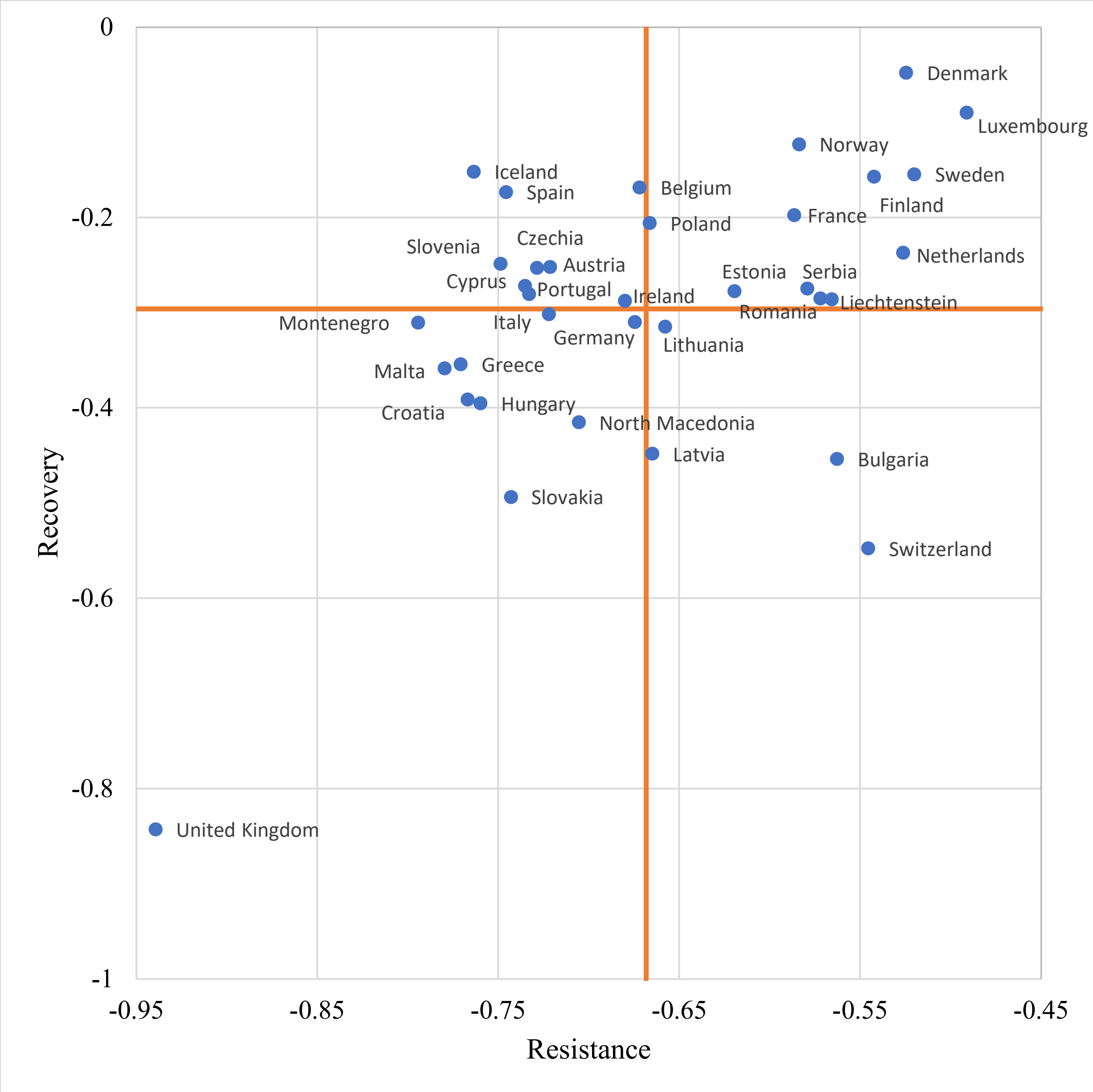

Figure 6. Quadrant plot mapping resistance and recovery

Stage 3: Factors influencing resilience from a spatiotemporal perspective

The previous results depicted the descriptive evidence of resistance and recovery levels across different periods in each of the European destinations. While spatial patterns were observed, further analysis is needed to gain a deeper understanding of the influential factors affecting tourism resilience at different times. To address this, this study pooled destination-level time series of resistance and recovery levels into a panel and applied the dynamic spatiotemporal autoregressive (SAR) model to capture the spatial and temporal dynamics of tourism resilience in European destinations. Several benchmark models, including individual ordinary least square (OLS) models, panel OLS with fixed effects, and other spatiotemporal models, have been also employed for model comparison; the dynamic SAR model with fixed effects shows a better model fit.

Descriptive evidence of influencing factors

A number of influencing factors reflecting the destinations' economic conditions (in terms of GDP, HICP, and ER), environmental conditions (represented by CE), social conditions (measured by POP and HDI), tourism supply (proxied by TE and AE), innovation level (measured by GRED), and situational factors (in terms of SI) are incorporated according to the theoretical foundations and the practical characteristics of the tourism industry. The descriptive statistics of the dependent and independent variables are presented below in Table 3. To avoid the multicollinearity issue, the variance inflation factor (VIF) was calculated, and the population level (POP) was dropped due to the high VIF value in the panel regression model and the spatial econometric model.

Table 3. Descriptive statistics of resilience and influencing factors

Variable	Mean	Standard deviation	Median	Min	Max
resilience	-0.48	0.30	-0.46	-1.00	0.34
GDP	123.23	25.05	117.60	71.30	250.91
HICP	110.64	6.99	109.10	98.41	141.73
ER	104.42	6.36	106.18	81.07	118.35
SI	47.55	21.71	47.22	0.00	96.30
AE	21816	43717	7046	260	226855
CE	33827.90	44688.13	17900.09	488.74	234538.53
TE	8055.76	10500.46	3926.80	258.20	42848.20
GRED	11781.43	21777.18	4501.54	86.21	112850.00
HDI	0.90	0.04	0.90	0.80	0.96
POP	16899046	21544544	8032926	439539	81465344

Model performance and estimations

The dynamic spatiotemporal model was used to assess the impact of proposed influencing factors on tourism resilience. The resilience series of each destination was divided into resistance and recovery periods, resulting in three models: resistance, recovery, and overall resilience. Prior to estimation, model calibration was conducted to determine the spatial weight matrix representing geographical relationships. The spatial models were estimated using the quasi-maximum likelihood approach of Yu et al. (2008). The empirical results of the three models are presented in Table 4.

The calibration results suggest a consistent number of neighbors of each destination, demonstrating the optimal categorization of geographic relationships among European destinations over time. The partitioned series demonstrated a better fit in terms of residual variance and log-likelihood, whereas the full resilience model achieved higher R-squared and adjusted R-squared values. This can be explained by the differences in the number of observations in the respective models. The dynamic spatial Durbin model (SDM) was used to test the direct influence of explanatory variables on neighboring destinations. The results indicated that the spatially lagged explanatory variables are statistically non-significant, suggesting that these variables may only extend their spillover effect through the transmission of the dependent variable (resilience of the destination). Therefore, the SAR models only implemented the spatial lag on the dependent variable.

The estimation results are mostly consistent at different stages after the pandemic shock with some differences identified, which is reasonable since higher resistance indicates the need for less effort to return to the normal path of tourism demand and even further develop in the post-pandemic period. The spatial autoregressive coefficients (WY) are consistently significant in the resistance and recovery periods, which indicates the existence of a positive spatial spillover effect across destinations in terms of destination resilience. This implies that the spatial perspective should not be ignored in tourism resilience research.

The findings of this study align with previous research emphasizing the inclusion of spatial interactions in analyzing regional resilience by Fingleton et al. (2012) and Martin and Sunley (2015). The spatial transmission of the pandemic shock corresponds to the potential shift in the spatial distribution of economic activities, such as tourism. The temporal dynamics were reflected through the positive and significant coefficient of the time lag of the dependent variable (y_{t-1}), confirming the process perspective and dynamic nature of destination resilience, as proposed by Ducheck (2020). For European destinations, the resistance and recovery trend in the temporal dimension is consistently increasing over time, as indicated by the significant and positive coefficient.

Table 4. Estimation results of resistance, recovery and overall resilience models

	Resistance model	Recovery model	Overall_resilience model
Number of destinations	29	29	29
Number of neighbors	11	11	11
WY	0.625***	0.507***	0.612***
y_{t-1}	0.217***	0.413***	0.313***
gdp	-0.097	-0.075	-0.070
hicp	0.114	0.001	-0.051*
er	0.127	0.228***	0.085
si	-0.248***	-0.106***	-0.120***
ae	2.438***	-0.241	1.981***
ce	-0.299***	-0.136	-0.259***
te	-1.702	-0.119	0.058
gred	1.036	-0.226	0.443
hdi	0.898***	0.116	1.382***
Intercept	0.122*	-0.004	0.018
R squared	0.811	0.814	0.878
Corr R squared	0.628	0.504	0.750
Residual variance	0.120	0.084	0.124
Log-likelihood	-165.595	-66.615	-320.329
Time period	2020.03-2021.06	2021.07-2022.07	2020.03-2022.07
No of observations	435	348	783

Note: * p<0.05 ** p<0.01 *** p<0.001

Spatiotemporal effects of resilience

The regression coefficients alone cannot fully represent the influence of the explanatory variables on the dependent variable, given the existence of spatial spillover effects generated by the spatial lags imposed on the dependent variable, independent variables, or the error term based on the model specification. Although spatial lags have not been directly incorporated into the explanatory variables, the indirect effects of the explanatory variables can be extracted by representing the spatial spillovers to neighboring destinations as proposed by Lesage and Pace (2009). Direct effects represent the influence of the explanatory variables on the dependent variable, whereas indirect effects can be explained as either the impact of a certain explanatory variable's change in a destination on another destination's dependent variable or the change of explanatory variables in other neighboring destinations on the focal destination. The direct, indirect, and total effects of the explanatory variables and the time-lagged dependent variable are presented in Table 5. Past tourism resilience (i.e., yt-1) generates significantly positive direct and indirect effects, indicating that, generally, the tourism resilience level gradually increases both timely and spatially, as reflected by the coefficient in Table 4.

Spatiotemporal effects of influencing factors

The situational indicator reflecting the government policy response influences tourism resilience both directly and indirectly through spatial spillovers, indicating that more stringent policies will slow down the resistance and recovery speed both of the focal destination and the neighboring destinations. This is plausible as more stringent policies in a destination lead to more hindrance and reluctance for tourists to visit the destination. The consistently significant influence of the situational indicator at both stages also highlights the situational nature of destination resilience, which is highly dependent on the specificity of external shocks. Comparing the resistance and recovery stages, the government response generated a greater impact during the resistance stage. This aligns with Martin and Sunley's (2015) findings, which suggested heightened sensitivity during the initial resistance period following external shocks. Tyrrell and Johnston (2008) also underscored the importance of government response in recovering from a tourism decline, further supporting these findings.

Traditional economic variables, including GDP and HICP, that influence tourism demand did not significantly influence the resilience level during both resistance and recovery periods. These results indicate that, during turbulent times with severe external shocks affecting demand, the influencing factors become more complicated and different compared to stable periods. As explained by Jaramillo et al. (2016), destinations' economic conditions are likely to play a role in shaping long-term resilience, which was not reflected in this study.

The non-significant influence of the innovation level on tourism resilience can be attributed to the long-term nature of destination innovation and learning abilities, as highlighted by Williams et al. (2020). They argued that the innovation journey is often lengthy and challenging. The complexity of the tourism experience, which involves interactions between tourists and local stakeholders, adds to the complexity and dynamics of knowledge-sharing and innovation. Consequently, the influence of innovation on the tourism industry may only become significant and observable over longer periods (Trunfio & Campana, 2019). The other explanatory variables incorporated in the models show distinct patterns during the resistance and recovery stages.

During the resistance stage, more accommodation establishments indicate a greater scale of the tourism industry and higher tourism development level, which led to higher resistance in the tourism industry to the pandemic shock in the initial periods. However, these effects become non-significant during recovery. The findings correspond to Geels's (2001) general resilience framework, which proposed the role of tourism-specific stakeholders in shaping destination resilience.

Environmental quality contributes to the tourism resistance level of the focal destination and the neighboring destinations, as shown by the negative direct and indirect effects generated by the carbon emission levels. The ecological environment quality of a destination plays a crucial role in determining its 'resilience threshold', and represents the destination's quality, which is an important characteristic for attracting tourists (Tyrrel & Johnston, 2008; Espiner et al., 2017). These findings can be further explained from the tourists' perspective, as the environmental quality of a destination shapes their perceived destination impression and image (Sadat & Chang, 2016) and further affects revisit intention. Particularly during the pandemic, the destination image was shaped predominantly by environmental quality, which mediated the negative influence of risk perception on visit intention. Thus, in the context of this study, a destination's environmental quality positively strengthens its capability to resist the pandemic crisis due to the higher 'resilience threshold' from the destination's perspective and by 'securing' capability to retain tourists from the tourists' perspective.

The society development level, reflected by the human development level, positively contributes to tourism resilience in both the focal destination and neighboring destination through feedback effects. This is consistent with the socio-economic perspective of resilience, suggesting that higher levels of literacy and social development tend to lead to higher macroeconomic resilience after disasters (Noy & Wu, 2010).

However, those effects become insignificant when the destinations' tourism industry starts to recover. During the recovery stages, the exchange rate plays an important role that influences the tourism resilience level spatially through positive and significant direct and indirect effects, which indicates that a weaker position in the exchange market will attract more tourists and enhance tourism resilience in the recovery stage, in both the focal destination and its neighbors through the feedback effect from the dependent variable.

Summary of findings

To sum up, it can be seen that the destination resistance level is mostly influenced by supply factors or destination-specific factors, including tourism development level, society development level, and destination environmental quality. These intrinsic factors determine the capability of European destinations to resist the shocks at earlier stages. However, the recovery of tourism is more dependent on demand-side factors, related to the overall tourism market. These findings further justify the necessity to distinguish between destination resistance and recovery when examining the influencing factors of resilience at different stages.

Table 5. Spatial spillover effects of the temporal lag and explanatory variables

	Resistance			Recovery		
	Direct	Indirect	Total	Direct	Indirect	Total
Yt-1	0.228***	0.351***	0.579***	0.426***	0.417***	0.843***
gdp	-0.107	-0.168	-0.275	-0.078	-0.078	-0.156
hicp	0.121	0.190	0.311	0.007	0.006	0.013
er	0.128	0.198	0.327	0.237***	0.233***	0.470***
si	-0.260***	-0.404***	-0.664***	-0.111***	-0.107***	-0.217***
ae	2.548***	4.014***	6.562***	-0.263	-0.239	-0.501
ce	-0.309***	-0.484*	-0.793*	-0.142	-0.140	-0.281

te	-1.803	-2.860	-4.663	-0.117	-0.129	-0.246
gred	1.097	1.716	2.813	-0.262	-0.259	-0.520
hdi	0.945***	1.500***	2.446***	0.110	0.116	0.225

Note: * p<0.05 ** p<0.01 *** p<0.001

Conclusion

To conclude, this study developed a comprehensive and dynamic framework to examine tourism resilience and its influencing factors from a spatiotemporal perspective. The developed framework is illustrated through an empirical study on tourism resilience in Europe during the COVID-19 pandemic. In the context of this study, both the descriptive evidence and the influencing factors of destination resilience confirm the necessity to distinguish between resistance and recovery. Spatial patterns can be seen from the resilience map and the quadratic plot, where Northern European destinations show relatively stronger resistance and recovery levels. France and the Netherlands were also more resilient. Some destinations also showed different relative positions in terms of tourism resistance and tourism recovery. For example, the recovery levels of Latvia, North Macedonia, and Slovakia were relatively lower than other destinations, but the resistance levels of these destinations were relatively in the middle.

From modeling the influencing factors of tourism resilience in a dynamic spatiotemporal framework, it can be seen that the value and significance of the coefficients are different at the resistance period and the recovery period, which further justifies the necessity to partition the tourism resilience series into tourism resistance and tourism recovery. The spatial spillovers and temporal lag of tourism resilience are consistently positive and significant at different periods, indicating that the spatial interactions and temporal dynamics of tourism resilience in destinations in Europe—which corresponds to the need to take account of both spatial and temporal perspectives when measuring destination resilience in response to an external shock—is also highly subject to the shock itself. The resilience performance reflected in the quadrant plot also generates implications related to spillovers in smaller regions. For example, the resilience level in the UK was relatively low and one of the reasons behind this is the relatively loose connections with other destinations in Europe, contributing to potentially lower levels of interactions in resilience with other destinations, compared to Denmark as a highly resilient destination in Europe. Regionally, northern European destinations such as Denmark, Sweden, and Finland were more resilient where positive spillovers contribute to further enhancements of resilience to the region.

Findings show that more stringent destinations, in terms of government response and containment policy, are less resilient, with a higher influence on resistance at the early stage of the pandemic. Other factors are different in terms of significance and value in determining resistance and recovery, respectively. The findings indicate that resistance is highly dependent on destination-specific characteristics, including tourism development level, society development level, and destination environmental quality level. At the earlier stage of the pandemic shock with unexpected fluctuations and uncertainties, these intrinsic factors determine a destination's capacity to resist external disturbance. Moving towards the tourism recovery stage, where situations become smooth and predictable to some extent, tourism recovery is more related to tourism demand factors, where the level of recovery is more dependent on the tourism market and relatively less dependent on the destinations' intrinsic factors shaped in the long-run prior to the pandemic. This pattern is consistent with the regional economic resilience framework suggested by Martin and Sunley (2015) from the process perspective, which confirms the applicability and appropriateness of the economic resilience framework in modeling destination resilience.

Theoretical contributions

This study contributes to a more critical and comprehensive understanding of resilience by developing a quantifiable and generalizable tourism resilience framework, with the identification of key influencing factors. The economic resilience framework is still at the aggregated level which cannot fully reflect the evolutionary feature of resilience. This study extends the economic resilience framework to systematically operationalize the complex adaptive systems theory in the dynamics and structural changes of resilience at different stages. The development of the resilience framework, based on the complex adaptive systems theory, was still at a conceptual stage, whereas this study further advances the theoretical framework of resilience by providing clear guidance to operationalize it in an analysis of resilience in response to a real external shock. As such, this study offers empirical evidence of the applicability of the complex adaptive systems theory in the field of tourism and destination resilience.

Moreover, the complex adaptive systems theory is also advanced and enriched by the integration of the spatial perspective, to account for the dynamic changes of spatial distributions in the adaptive systems in response to external shocks. The co-evolutionary feature of the complex adaptive systems is firstly incorporated in the destination resilience framework through the spatial econometric framework and results show significant spatial connectivity of destination resilience across units, advancing the theory of complex adaptive systems and the resilience literature. With the integration of the spatial perspective, the destination resilience framework contributes to a comprehensive understanding of the mechanism influencing destination resilience from a spatiotemporal perspective, which can also provide foundations for future research on resilience. From a methodological perspective, this study advances the literature on tourism and destination resilience from the econometric perspective in space and time.

In addition, the clarification of the systematic differences in the determinants of resistance and recovery from a spatial perspective enriches the new economic geography theory, emphasizing the changes not only in spatial distribution but also in structural components of resilience in tourism activities. Moreover, the findings of this study enhance the understanding of resistance and recovery as two different stages in the whole resilience process, in which destination resistance is more affected by the destination's long-term and intrinsic characteristics shaped before experiencing shocks, whereas destination recovery is less related to the destination itself but more related to the tourism market.

In summary, the comprehensive dynamic resilience framework integrates the current understanding of resilience with a spatial perspective, taking into account the interdependency of destination resilience regionally. The resilience of a destination cannot be fully understood without considering the interactions with other destinations nearby. Furthermore, this study provides insights into different influencing mechanisms of the resistance and recovery stages during a resilience process.

Practical implications

This study also makes several practical contributions. Firstly, the cross-sectional comparison of the resistance and recovery periods can help destination governments gain an understanding of their relative resilience levels in Europe. The significant and positive spillover effects of destination resilience at the resistance and recovery stages have important practical implications for destinations to monitor the instant response of highly resilient destinations and co-develop recovery plans that benefit multiple destinations more efficiently through transmission and loop effects from spatial interactions of resilience.

Moreover, with a systematic understanding of the influencing factors of tourism resilience, destinations can work to enhance these aspects in order to improve destination resilience at different stages. In cases of future crises, the findings can provide managerial and policy implications for destination governments and local businesses to respond timely and effectively to situational changes during turbulent times. To strengthen tourism resistance in the long run, development strategies should be carefully considered, such as expanding tourism supplies in terms of accommodation establishments and human development index in the long term in long and healthy life, knowledge, and a decent standard of living. For tourism recovery, the positive and significant effects generated by the exchange rate indicate that tourism destinations can consider developing monetary policies to strengthen their position in the exchange market to facilitate tourism recovery. As tourism recovery tends to be more dependent on market factors and demand factors, destinations can also consider putting more effort into constructing promotion and marketing strategies to attract more tourism demand and reinvigorate tourists' confidence in and enthusiasm for traveling to the destination.

As indicated by the positive spatial spillovers in tourism resilience in European destinations, collaborative plans are also efficient in facilitating the recovery pace of regional tourism systems. Increasing tourism resilience even in normal times can help destinations be better prepared for potential future crises, which further enhances destination competitiveness in the long run. In terms of the government response, the conclusion that less stringent policies can contribute to stronger tourism resistance and tourism recovery can also provide insights for destinations to consider the responses in the resistance and recovery stage when facing future crises.

The destination resilience framework developed in this study has broader applicability. The relatively high model fit indicates that the framework can be further extended to predict tourism resilience based on a series of destination-specific factors and neighboring destinations' situations. The universal tourism resilience framework can be applied in any region, such as Asia-Pacific to measure and compare the tourism resistance and resilience level after the pandemic shock. The tourism resilience framework can also be applied when future crises (e.g., natural disasters, pandemics, economic recessions, or terrorist attacks) happen to re-evaluate the framework and the destination resilience through comparisons of the tourism resilience systems under different shocks. The framework is not limited to turbulent times. In normal times without crises too, to monitor long-term destination development, tourism resilience can be evaluated and compared cross-sectionally by integrating the influencing factors of each destination using the current framework.

Limitations and future research directions

This study has several limitations. Firstly, this study demonstrates the tourism resilience system using Europe as an empirical case. Thus, the findings are more applicable in the context of European destinations. Future studies can consider other contexts, such as Asian destinations, to compare if the influencing factors and mechanisms will be different to some extent. Secondly, due to data availability, not all destinations in Europe were taken into account in this study. Switzerland was not included in the last stage for identifying influencing factors of tourism resilience in Europe. Thirdly, this study captured relatively short-term resilience after the pandemic due to limited data availability. Long-term resilience is also worthy of exploring further to determine if the pandemic has shaped the innate structure of the tourism industry and the spatial relationship across destinations in Europe, using the same analytical framework developed in this study. Finally, the current framework focuses on a holistic perspective to view Europe as a tourism system to examine the overall spillovers of destination resilience, whereas differences in the resilience process in different destinations are only reflected through aggregated indexes to demonstrate the relative position in Europe in resistance and recovery. Given that significant spillovers of resilience have been proven, future studies can incorporate local estimations of spatial econometric models to fully reflect the heterogeneity of spatial spillover effects of resilience across individual destinations.

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