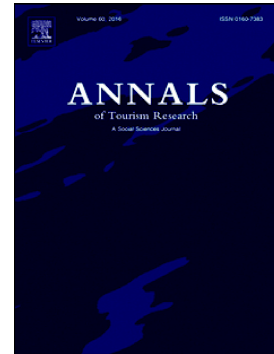


## Journal Pre-proof

The good, the bad and the ugly on COVID-19 tourism recovery

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PII: S0160-7383(20)30261-9

DOI: <https://doi.org/10.1016/j.annals.2020.103117>

Reference: ATR 103117

To appear in: *Annals of Tourism Research*

Received date: 20 August 2020

Revised date: 29 November 2020

Accepted date: 6 December 2020

Please cite this article as: A. Fotiadis, S. Polyzos and T.-C.T.C. Huan, The good, the bad and the ugly on COVID-19 tourism recovery, *Annals of Tourism Research* (2020), <https://doi.org/10.1016/j.annals.2020.103117>

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## THE GOOD, THE BAD AND THE UGLY ON COVID-19 TOURISM RECOVERY

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**Abstract**

This paper is to produce different scenarios in forecasts for international tourism demand, in light of the COVID-19 pandemic. By implementing two distinct methodologies (the Long Short Term Memory neural network and the Generalized Additive Model), based on recent crises, we are able to calculate the expected drop in the international tourist arrivals for the next 12 months. We use a rolling-window testing strategy to calculate accuracy metrics and show that even though all models have comparable accuracy, the forecasts produced vary significantly according to the training data set, a finding that should be alarming to researchers. Our results indicate that the drop in tourist arrivals can range between 30.8% and 76.3% and will persist at least until June 2021.

**Keywords:** Coronavirus; Tourism Demand; Deep Learning; Generalized Additive Model; Pandemia

**Statement of contribution**

100-150 words answering the question: What is the contribution to knowledge, theory, policy or practice offered by the paper?

Our results have important implications both for policymakers and for researchers. In terms of policy, our predictions suggest that the crisis is far from over in the tourism sector.

Without a medical solution to the pandemic, tourists will be reluctant to travel, despite the

protective measures taken by transport and hospitality companies. Our work also illustrates the importance of implementing different methodologies when researchers attempt to produce data forecasts. Additionally, methodologies that utilize training data should be implemented using different data sets for this task, since different results can be generated. This is an important finding and one that is of particular significance in light of the recent development of machine learning methodologies and their increasing adoption by the academic community.

100-150 words answering the question: How does the paper offer a social science perspective / approach?

From a social science perspective and as mentioned in last paragraph, our results have important implications both for policymakers and for researchers. This paper makes three important contributions to the extant literature. First, we add to the discussion on the potential economic costs resulting from the current COVID-19 pandemic. Second, it compares two methodologies that can be used to produce tourist demand forecasts and shows that they have comparable performance. Thirdly and last, we demonstrate the importance of the training set in machine learning modelling, showing how different training sets produce different results that could potentially lead researchers to different conclusions.

## THE GOOD, THE BAD AND THE UGLY ON COVID-19 TOURISM RECOVERY

### Abstract

The aim of this paper is to produce different scenarios in forecasts for international tourism demand, in light of the COVID-19 pandemic. By implementing two distinct methodologies (the Long Short Term Memory neural network and the Generalized Additive Model) and using different training data sets, based on recent crises, we are able to calculate the expected drop in the international tourist arrivals for the next 12 months. We use a rolling-window testing strategy to calculate accuracy metrics and show that even though all models have comparable accuracy, the forecasts produced vary significantly according to the training data set, a finding that should be alarming to researchers. Our results indicate that the drop in tourist arrivals can range between 30.8% and 75.3% and will persist at least until June 2021.

**JEL classification:** H12, P46, Z32

**Keywords:** Coronavirus; Tourism Demand; Deep Learning; Generalized Additive Model; Pandemia

## 1. Introduction

Differently from the recent epidemic outbreaks such as SARS, Ebola, and H1N1, the coronavirus (COVID-19) remain the world's deadliest epidemic outbreak that comes along with a systemic global healthcare crisis, financial crisis, and economic downturn known as COVID-19 recession. To limit the spread of the COVID-19, governments across the globe have taken drastic measures by locking down the entire country or the most affected cities and also by prohibiting entry to their borders, resulting in an immense hit for the global tourism industry, particularly the travel and hospitality sector. The COVID-19 outbreak has forced many tourism destinations to stop their operations following lockdown measures and travel bans, as well as canceled bookings and limited logistics.

According to an estimate of the UNWTO (2020b), international arrivals dropped by 22% in the first quarter of 2020 and are expected to register a decline between 60-80% for the whole year, translating into a loss of between US\$910 billion to 1.2 trillion. Moreover, social distancing has suppressed the hospitality industry where several accommodation facilities were forced to instantly stop their operations and/or significantly downsize them. Among other types of businesses, Hotels and accommodations are considered the preliminary hotspots that transform local epidemic outbreak into a pandemic and the preliminary point for the import of an imminent global pandemic (Hung, Mark, Yeung, Chan, & Graham, 2018). Following this argument, researchers (Chang, McAleer, and Ramos, 2020; Ivanov, Webster, Stoilova, and Slobodskoy, 2020) caution that the COVID-19 pandemic will have a serious impact on travel, tourism, and hospitality worldwide.

Six months after the COVID-19 outbreak it is still uncertain when the global economy and social life will resume as the tourism and hospitality and the supporting sectors are preparing for recovery. Consequently, it is important to forecast the impact of COVID-19 pandemic on the tourism industry and the effect of government policies in supporting the post-recovery of this industry, vaccine advancements notwithstanding. From a business perspective, a good understanding of the effects of the pandemic is likely to provide the actors of the tourism industry substantial insights on how to build and implement effective decision-making frameworks that can, in turn, ensure rapid responses to unanticipated events that threaten the financial sustainability of their businesses. From a policy-making perspective, epidemic outbreaks not only represent a serious public health crisis that challenges governments, but also the underlying economic downturns resulting from the epidemic outbreaks necessitate myriad of fiscal, monetary, and supply-side measures for full recovery (Elgin et al., 2020; International Monetary Fund, 2020b). As such, forecasting

scenarios could provide a better picture of an industry under the best case, worst case, and in-between condition to help the economic actors such as businesses and governments to make the best decisions that capable of mitigating the effect of upcoming epidemic outbreaks on the entire economy.

The study by Williams and Kayaoglu (2020) may be used to illustrate the impact of an epidemic outbreak on the tourism industry and the supporting sectors to the tourism product and service delivery. These authors point out that nearly one-tenth of the European non-financial economic activities were linked to tourism and account for 9.5% of employment among the active population in the EU in 2016. Williams and Kayaoglu (2020) also point out that accommodations and the food and beverage sectors in the EU contributed to 19.7% and 58.7% respectively for the overall employment in the tourism industry. On this basis, it clear that the great lockdown and shutdown of the tourism-related businesses and supporting businesses following the COVID-19 pandemic have resulted in an unprecedented socio-economic impact (Dolnicar & Zare 2020; Qiu, Park, Li and Song, 2020). What is more, Farzanegan et al. (2020), show that international tourism may have contributed to the spread of the virus and the severity of the pandemic.

In a recent study, Welfens (2020), investigate the macroeconomic and health care aspects of the COVID-19 and concludes that countries that largely depend on the tourism industry in terms of contribution to GDP should expect higher output growth-inhibiting effects. Polyzos et al. (2020) investigate the impact of COVID-19 outbreak on arrivals of Chinese tourists to the USA and Australia using data from the 2003 SARS epidemic outbreak to train a deep learning artificial neural network called Long Short Term Memory (LSTM). By calibrating the neural network to fit the particulars of the current COVID-19 data, they conclude that the recovery of tourist arrivals to pre-crisis levels can take from 6 to 12 months. Furthermore, they caution that the current situation may have significant adverse effects on other sectors that interact with the tourism industry.

In this paper, we build on the approach proposed by Polyzos et al. (2020) to build a 12-month forecast of international tourist arrivals. Polyzos et al. (2020) only used data from the SARS pandemic to train a single Long Short Term Memory (LSTM) network, in order to derive forecasts. In addition, they focused only on Chinese tourists, thus limiting the scope of the results. We use data for international tourist arrivals, expanding our approach to a more global framework. In addition, as the current crisis is evolving rapidly, we choose to develop several scenarios, using data from different crises of the last 20 years.

We thus enhance the authors' approach, extending the methodologies implemented to include also an extension of the Generalized Additive Model of Hastie and Tibshirani (1990) which includes separate components for trend, seasonality and special events. This model is essentially a linear, auto-regressive model but applies potentially non-linear smoothers to the system regressors. It is based on the Prophet model presented by Taylor and Letham (2017). We build different models for each of the two methodologies, based on training data from three different crises, viz. the SARS (Severe Acute Respiratory Syndrome) epidemic (2003-2004), the MERS (Middle East Respiratory Syndrome) outbreak (2012-2013), and the Great Financial Crisis (GFC). Finally, we propose a "worst-case" scenario training set which trains the model using the lowest available data from each data year.

This paper makes three important contributions to the extant literature. First, we add to the discussion on the potential economic costs resulting from the current COVID-19 pandemic. Second, it compares two methodologies that can be used to produce tourist demand forecasts and shows that they have comparable performance. Thirdly and last, we demonstrate the importance of the training set in machine learning modelling, showing how different training sets produce different results that could potentially lead researchers to different conclusions.

The rest of this paper is structured as follows. Section 2 presents the relevant literature, Section 3 discusses the data and the two methodologies, Section 4 presents the forecasting process and the empirical results and Section 5 concludes with our policy and social implications.

## **2. Literature Review**

Over the last decade, the impact of epidemic outbreaks on the tourism industry has received considerable momentum given its negative multiplier effect on other supporting industries. As in the recent case of the COVID-19, any epidemic outbreaks may promptly reduce the flow of inbound and outbound tourism due to the decision of tourists not visit certain geographic regions or destinations and/or government restrictions to stop the spread of the virus. In such a case, epidemic crises may provoke important shifts in demand for certain destinations as travelers may consciously decide not to get exposed to such crises (Seraphin, 2020). This explains why the perceived risk associated with epidemic outbreaks can affect travelers' behavior and their choices of visiting certain destinations (Zhang, Hou, and Li, 2020; Reichel, Fuchs and Uriely, 2007).



The term “crisis” refers to sudden and unexpected events that can result in major unrest and threats for citizens. In this case, a public health crisis is a difficult circumstance that affects individuals in several geographic regions or a whole country. In the case of a global health crisis, this frequently originates in a particular region before spreading to an entire country and the entire planet as the current COVID-19 crisis. Therefore, the choice of traveling and visit to a destination depends on tourists’ perceptions regarding their safety and security (Taylor & Toohey, 2007) and the imagery formed by how the media or social media report the crisis. As a result, it becomes difficult for the tourism industry to face the challenges posed by health crises as these crises are often subject to negative media coverage (Novelli, Gussing, Burgess, Jones, & Ritchie, 2018).

Following the SARS epidemic crisis, several studies have revealed the adverse effects of the outbreak on the global tourism industry and particularly on the economies of Southeast Asian neighboring countries (Overby et al., 2004; Hai et al., 2004; Pine and McKercher, 2004; Siu and Wong, 2004; Hanna and Hwang, 2004). In their study, Abdullah, Thomas, McGhee, and Morisky (2004) show that the SARS outbreak in 2003 has caused a 2.6 percent decrease in international travel during the first 4 months of 2003. For the Asia-Pacific region, these authors reported a decrease of 10 percent in March and 50 percent in April. As the most affected region, Hong Kong has registered a decline of 64.8 percent in March and 67.9 percent in April following the SARS outbreak during that same year (Abdullah et al., 2004).

One should expect important changes in the behavior of Chinese tourists (Wen, Kozak, Yang, & Liu, 2020) as many tourism destinations globally are waiting for the recovery efforts. Interestingly, one should expect tourists to choose less crowded destinations that facilitate the practice of social distancing (Seraphin & Dosquet, 2020). Therefore, one may expect a limit in the interaction between employee and customer in the provision of accommodation services. Within this vein, Wen et al. (2020) suggest the importance for managers to prepare for hotel development once the COVID-19 pandemic crisis is over and also suggest the need for managers to pay attention to possible experiences stemming from this crisis.

In a recent study, Gössling, Scott, and Hall (2020) analyze the effect of prior epidemics and pandemics and the effect of the COVID-19 pandemic on the global tourism industry, the airline and hospitality industries succeeding the travel restrictions and the great lockdown. Based on the results of their study, Gössling et al. (2020) caution how a pandemic outbreak can change society, national economies, and the tourism industry. Accordingly, they

conclude that the negative impact of epidemic outbreaks will be greater on the tourism industry and supporting sectors in the world's poorest economies. The negative effects may be further aggravated by changing work behavior in hotel workers (Stergiou and Farmaki, 2020).

As mentioned earlier, the negative impact of epidemic outbreaks is not only disastrous for the tourism industry but also for the supporting sectors. The study by Williams and Kayaoglu (2020) illustrates the impact of an epidemic outbreak on the tourism industry and the supporting sectors to the tourism product and service delivery, as well as employment. These authors point out that nearly one-tenth of the European non-financial economic activities were linked to tourism and account for 9.5% of employment among the active population in the EU in 2016. Williams and Kayaoglu (2020) also point out that accommodations and the food and beverage sectors in the EU contributed to 19.7% and 58.7% respectively for the overall employment in the tourism industry. On this basis, it is clear that the great lockdown and shutdown of the tourism-related businesses and supporting businesses following the COVID-19 pandemic have resulted in an unprecedented socio-economic impact.

Tsionas (2020) forecasts post-COVID-19 gradual adjustment in the tourism, hospitality, and related industries. The results show that reopening gradually that requires only nonnegative profits is quite feasible, whereas reopening that requires the same profit level as in the pre-COVID-19 period remains significantly more difficult and appears achievable by reopening at capacity neighboring 33%. Based on these results, Tsionas concludes that lower capacities necessitate governmental supports which are likely to differ substantially from hotel to hotel. Within the same vein, Assaf and Scuderi (2020) argue that the tourism industry has been confronted with numerous crises in the past and thus caution that the present crisis resulting from the COVID-19 outbreak remains by far the most damaging one. This argument is also shared by Karabulut, Bilgin, Demir and Doker (2020) and by Dolnicar and Zare (2020). Consequently, the tourism industry and government have an important role to play in the recovery efforts as the tourism industry will look different from post-pandemic (Assaf & Scuderi, 2020). Consistently, it is expected that the consequences of COVID-19 will result in a significant decline in value industries hotels, airlines, cruise lines, and car rentals (Sharma and Nicolau, 2020). The decline is significant enough in each industry to show concerns over the long-term outlook for each of these industries. What is apparent, nevertheless, is that the most critical concerns are largely connected to the cruise industry.

### 3. Methodology & Data

#### 3.1. Generalized Additive Model

Our first approach extends the decomposable time series model of Harvey and Peters (1990) and splits the model into three components, the trend, the seasonality, and the “irregular” component. The latter component is essentially the training set used. This model specification is essentially similar to the GAM methodology of Hastie and Tibshirani (1987) and has been introduced by Taylor and Letham (2017). We build on their model to accommodate the particular needs of our forecasting task.

The general form of the model can be described as follows:

$$y(t) = g(t) + s(t) + k(t) + \varepsilon(t) \quad (1)$$

where  $g$  is the general trend of the time series,  $s$  is the seasonal component and  $k$  represents the effect of the training set, to capture irregular effects on the time series. In this manner, we can model systematic (periodic and non-periodic) changes in the data set, through the seasonality and the trend components respectively, while unsystematic outcomes are modeled by the “special” component. Finally, the error term  $\varepsilon$  will capture the residual, idiosyncratic changes not accommodated by the model. The errors are assumed to be normally distributed and this has been verified in our implementation both visually and by using the Jarque-Bera and the Shapiro Wilk (Shapiro and Wilk, 1965) test for normality. Under this approach, the seasonality component is an additive factor in the modeling approach, in a technique similar to exponential smoothing.

The main advantage of the GAM approach is its ability to incorporate new components with a simply additive transformation. Taylor and Letham (2017) present a “holiday” component that captures the effects of special dates in each calendar year. We choose to replace this component with our training data set, thus decomposing the time series into a different set of predictors. Also, this model has very good performance not only in terms of its predictive accuracy but also in terms of its fitting speed, using different methodologies. Similarly to the original version of the algorithm, we fit the model using the Limited-memory Broyden–Fletcher–Goldfarb–Shanno algorithm (L-BFGS). L-BFGS is a popular algorithm for parameter estimation in machine learning due to its ability to minimize the target function  $f(x)$ , a differentiable scalar function, over an unconstrained set of real

values for the vector  $\mathbf{X}$ . Its fast performance provides us with the flexibility to calculate different models using the four different training sets and a worst-case scenario, as discussed in section 0.

For the trend component of the model, we select the non-linear, saturating growth approach over the linear trend with breakpoints. This is justified since the tourism data series demonstrates non-linear patterns, without specific breakpoints that boost demand on a global level (Hassani et al., 2017). However, demand breakpoints can be captured in our model, as we will see below.

The trend component is as follows:

$$g(t) = \frac{P(t)}{1 + e^{-h(t-m)}} \quad (2)$$

where  $P$  represents the global population at each period,  $h$  is the growth rate and  $m$  is an offset parameter. The growth rate is assumed to be non-constant and exhibits structural breaks. For  $B$  breaks in the data series at points  $b_j$  ( $j = 1$  to  $B$ ), we can define  $\delta$  as a vector of growth rate adjustments, and thus calculate the growth rate,  $h$ , at any given point by

$$h(t) = h + \sum_{j:t > b_j} \delta_j \quad \text{where} \quad \delta \in \mathbb{R}^B \quad (3)$$

At each changepoint  $b_j$ , we can define the growth rate adjustment by

$$\vartheta_j = \left( b_j - m - \sum_{l < j} \vartheta_l \right) \left( 1 - \frac{h - \sum_{l < j} \delta_l}{h - \sum_{l \leq j} \delta_l} \right) \quad (4)$$

We then define a vector  $\alpha(t)$  such that

$$\alpha_j(t) = \begin{cases} 1 & \text{for } t \geq b_j \\ 0 & \text{otherwise} \end{cases} \quad (5)$$

Combining Equations (2), (3), (4), and (5), we get the final growth model as:

$$g(t) = \frac{P(t)}{1 + e^{-(h+a(t)\tau\delta)(t-(m-a(t)\tau\theta))}} \quad (6)$$

For the seasonality component, we follow the flexible model of periodic effects of Harvey and Shephard (1993), which defines a Fourier series as follows:

$$s(t) = \sum_{n=1}^N \left[ \varphi_n \cos \frac{2\pi nt}{12} + \omega_n \sin \frac{2\pi nt}{12} \right] \quad (7)$$

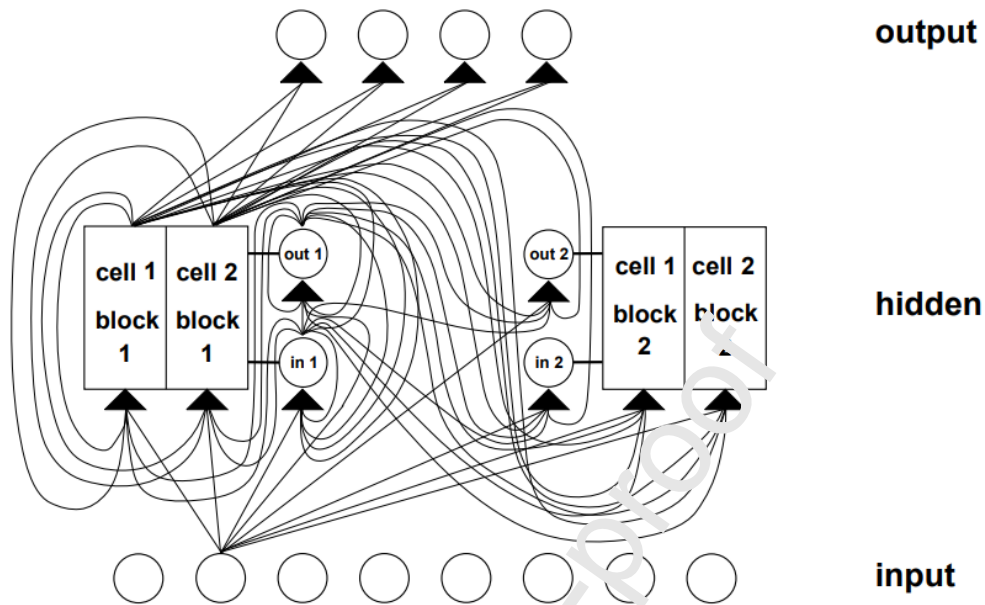
The seasonality parameters vector  $[\varphi_1, \omega_1, \dots, \varphi_n, \omega_n]$  has normal distribution around zero means. The parameters for the estimation are selected using AIC. For yearly seasonality, which is displayed by our data, AIC sets  $N=10$  (Taylor and Letham, 2017).

### 3.2. Long Short Term Memory neural network

The second approach used is the Long Short Term Memory (LSTM) neural network, as implemented by Polyzos et al. (2020). LSTM networks are very efficient in explaining autoregressive data series and tourist arrivals are a prime candidate for the implementation of this methodology (Athanasopoulos and de Silva, 2012, Law, Li, Fong, and Han, 2019). Similarly to Polyzos et al. (2020), we cross-validate the forecasting network using backtesting, whereby we split the data sample into groups that are used for training and validation and we calculate performance metrics for each window. Under this cross-validation technique, we essentially develop different models on the subsets of our data and test them against a validation data set. This calibrates the logic gates of the model and increases the robustness of our predictions, helping us achieve the desired prediction accuracy level.

The LSTM algorithm is a deep learning algorithm and was first introduced by Hochreiter and Schmidhuber (1997) and it is particularly useful when attempting to model time series with high degrees of autocorrelation, using the fact that it is able to adapt to long-term dependencies (Gers, et al., 2000) and overcome the errors of similar algorithms in the back-propagation of information contained in recent input events (Bengio et al., 1994). In this manner, LSTM networks can utilize the information contained in recent input and this information is used for long periods after the input time. LSTM is essentially a special case in the group of the recurrent neural network, which utilizes sequential information by

selectively passing inputs across time steps during data element processing of data elements (Cho et al., 2014).



Source: Schmidhuber and Hochreiter (1997)

**Figure 1. Example of an LSTM Network**

The LSTM topology (Source: Schmidhuber and Hochreiter (1997))

Figure 1) features a recurrent learning unit inside the network and, also, several decision gates that utilize two important attributes: the longer states from the starting units and the shorter states from the last unit of information. This feature has permitted LSTM networks to achieve great success in solving time series forecasting problems (Law et al., 2019). The general setup follows that of Recurrent Neural Networks (RNN) and includes an input and an output layer, with many hidden layers in between. However, the process involves an attention mechanism that can assign different weights to the various inputs of the model, thus permitting it to learn the importance of new input during data processing. A stateful LSTM methodology suggests that cell states are preserved after each iteration and are simply updated with the new information.

The modeling approach includes building a forecasting network  $\vartheta$  which will predict  $n$  future values based on a vector of  $T$  previous values of the same data series. The model is as follows:

$$\{\hat{y}_t\}_{t=T+1}^{T+n} = \vartheta(\{y_t\}_{t=1}^T) \quad (8)$$

The decision functions at each gate (forget gate  $f$ , include gate  $i$  and output gate  $o$ ) and the hidden layer ( $h$ ) are as follows:

$$f_t = \sigma(W_f \cdot (h_{t-1}, y_t) + b_f) \quad (9)$$

$$i_t = \sigma(W_i \cdot (h_{t-1}, y_t) + b_i) \quad (10)$$

$$o_t = \sigma(W_o \cdot (h_{t-1}, y_t) + b_o) \quad (11)$$

$$h_t = o_t \times \tanh(C_t) \quad (12)$$

where  $\sigma$  represents a sigmoid function,  $W_{f,i,o}$  represents the weight vector of inputs,  $h_{t-1}$  is the hidden layer from previous periods,  $y_t$  is the new input vector and  $b_{f,i,o}$  is the bias of each gate. The bias coefficient is a common feature of all machine learning functions and can either be set beforehand or calculated during the training phase. The sigmoid function is implemented as the gating function for the three gates of the LSTM network because it outputs a value between 0 and 1. Thus, the gate can either let no flow or complete flow of information pass through the gates. However, to overcome the vanishing gradient problem, we implement the tanh function in the hidden layer. The tanh function is commonly used in LSTM networks to determine which candidate values will be added to the internal state since its output can be either positive or negative, allowing for increases and decreases in the cell state.

To determine the new candidate values (vector  $\tilde{C}_t$ ) that can be added to the neural cell's state, LSTM uses the following equations. These are determined as follows:

$$\tilde{C}_t = \tanh(W_C \cdot (h_{t-1}, y_t) + b_C) \quad (13)$$

$$C_t = f_t \times C_{t-1} + i_t \times \tilde{C}_t \quad (14)$$

Thus, the new cell state,  $C_t$ , is as follows:

$$C_t = \sigma(W_f \cdot (h_{t-1}, x_t) + b_f) \times C_{t-1} + \sigma(W_i \cdot (h_{t-1}, x_t) + b_i) \times \tanh(W_c \cdot (h_{t-1}, x_t) + b_c)_t \quad (15)$$

We implement early stopping on the LSTM models in order to prevent overfitting. This is an important addition to deep learning models, as too many training epochs may result to overfitting but too few can yield an underfit model. Early stopping is considered a robust algorithm that prevents overfitting (Li, Soltanolkotabi, and Oymak, 2020) and we make sure that each epoch results in an improvement of the evaluation metrics of the model.

Our implementation includes two LSTM layers and a dropout layer. The dropout layer helps prevent overfitting by reducing the sensitivity of the model to the specific weights of individual neurons. This is performed by discarding randomly selected neurons during training. It is important to remember that we have implemented a stateful LSTM, which means that all cells “remember” their previous state with each iteration. We have chosen to add two layers as this has been shown to be able to handle most complex problems, while more layers can be difficult to train, with little gain in terms of accuracy. The same is true for the process of selecting the number of neurons where we find that nine neurons are adequate since adding more does not further improve accuracy. Also, by limiting our layers to two, we can implement sigmoid activation function, as discussed earlier. The model is optimized using the Adam optimization algorithm, which is a stochastic gradient-descent method. This methodology is computationally efficient and yields robust results with low memory requirements (Kingma and Ba, 2014), which is an appropriate choice given the number of variations in our methodology.

### 3.3. Evaluation Metrics

The literature defines three principal metrics for the evaluation of prediction accuracy. These are the Mean Absolute Percentage Error (MAPE), the Mean Absolute Error (MAE), and the Rooted Mean Square Error (RMSE). We implement these measurements to evaluate the accuracy of the different models designed. The formulae for the metrics are given below:

$$MAPE = \frac{1}{N} \sum_{t=1}^N \frac{|y_t - \hat{y}_t|}{y_t} \quad (16)$$



$$MAE = \frac{1}{N} \sum_{t=1}^N |y_t - \hat{y}_t| \quad (17)$$

$$RMSE = \sqrt{\frac{1}{N} \sum_{t=1}^N (y_t - \hat{y}_t)^2} \quad (18)$$

where  $y_t$  and  $\hat{y}_t$  are the observed and fitted values of the variable at time  $t$ , respectively.

### 3.4. Data & Training Periods

We use monthly data regarding international tourist arrivals sourced from the UNWTO Tourism Data Dashboard (UNWTO, 2020a), starting from January 1998 up to May 2020. For reference purposes, we extended the value of May 2020 to June 2020, due to lack of available data. Thus, our forecasts begin from July 2020, where borders around the world started to gradually open up.

The figures retrieved relate to the number of international tourist arrivals worldwide, in millions of tourists. The period is long enough to include all the necessary events to perform the rolling-window training, as well as training on the three specific events that interest us. Since both methodological approaches consider the autoregressive patterns, we choose not to deseasonalize the data series, as the seasonality component is captured by both methodologies.

The descriptive statistics for the data are presented in

Table 1, while the data is demonstrated graphically in Note: This figure demonstrates the international tourism flows from January 1999 to May 2020. We zoom in on the three period of interest for training reasons, namely the period of SARS epidemic, that of the MERS outbreak and on the GFC period.

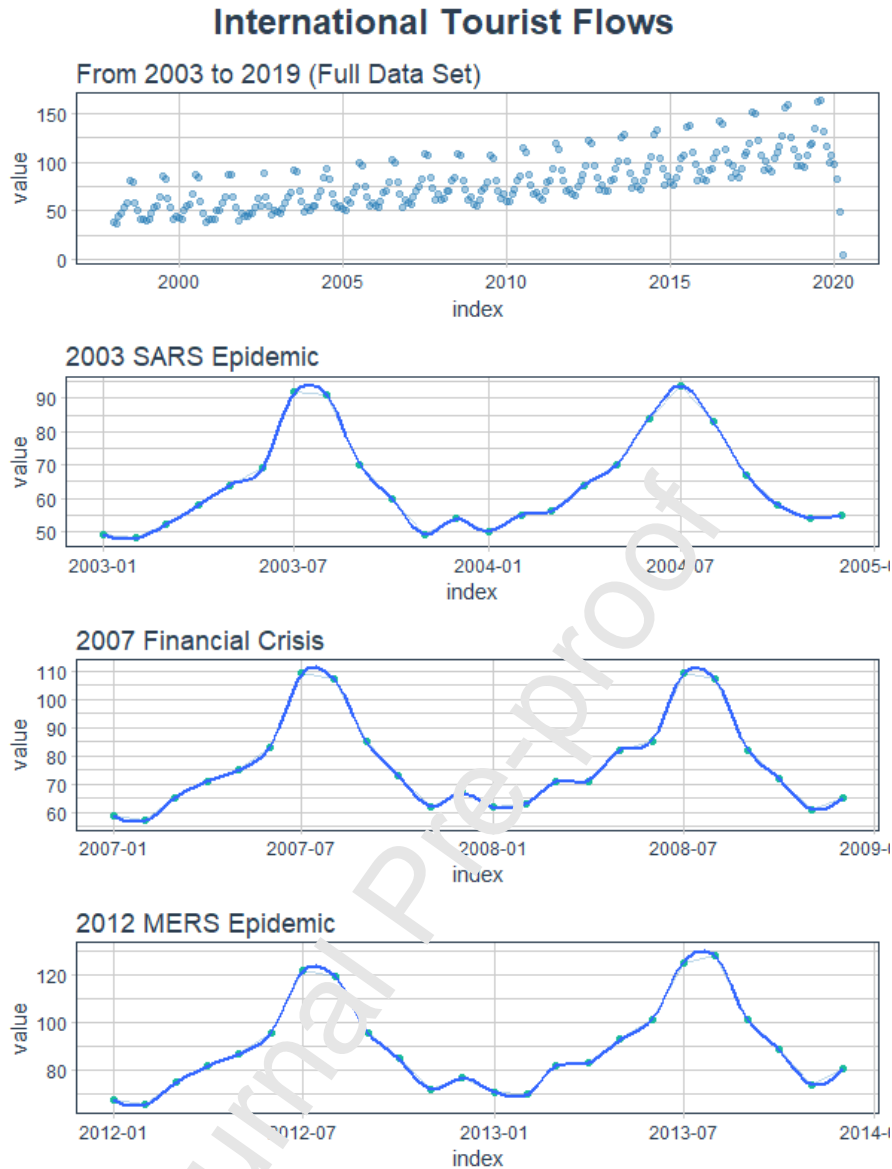
Figure 2, where we also zoom in on the three periods of interest (SARS epidemic, MERS outbreak and the GFC period). We choose to discuss these periods since all three represent points of interest in the tourist demand bibliography. The literature suggests the SARS epidemic one of the most important crises in tourism (Overby and al., 2004). However, despite widespread fears, the results of the SARS epidemic were limited to the

countries with a larger number of cases. In addition, the MERS outbreak has also had detrimental effects on tourism flows, particularly due to the fact the many middle eastern countries are global tourism destinations (Choe, Wang and Song, 2020). Finally, the GFC of 2007-2009 is often discussed as the biggest crisis in the tourism sector of the recent years (Sheldon and Dwyer, 2010). The periods have been included as training periods in order to produce forecasts for the results of the current pandemic.

**Table 1. Descriptive Statistics of the Arrivals Data Series**

Metric	Date	International Tourist Arrivals
Minimum.	01/01/1998	3
1st Quarter	24/07/2003	59
Median	15/02/2009	76.5
Mean	14/02/2009	79.74
3rd Quarter	08/09/2014	96
Maximum	01/05/2020	163.6

*Note: The two columns are not synched, but rather they demonstrate the values of the metrics for each data series separately. This means that, for example, the minimum number of tourist arrivals, which is 3 million, did not occur in January 1998 (in fact it was in April 2020). January 1998 is simply the minimum value in the Date column.*



*Note: This figure demonstrates the international tourism flows from January 1999 to May 2020. We zoom in on the three period of interest for training reasons, namely the period of SARS epidemic, that of the MERS outbreak and on the GFC period.*

**Figure 2. International Tourist Flows**

#### 4. Empirical Results

Figure 3 demonstrates the results of the Autocorrelation Function (ACF), which reveals the correlation between a given time series and lagged versions of itself, in the international tourist arrivals time series. LSTM models require data with a high degree of autocorrelation (Gers et al., 2000) and thus this is the first step of the LSTM modelling approach. The optimal lag is set according to Akaike Information Criterion (AIC) at 12 months, where it is evident that autocorrelation is maximized. This is unsurprising as the data

is highly seasonal. At the 12-month lag, the calculated autocorrelation exceeds the threshold value of 0.5, suggesting that this lag can be considered as for the optimal lag setting and thus help to build the forecasts that are needed employing the LSTM approach. After the 12-month lag, autocorrelation decreases again and thus this value is the optimal value.

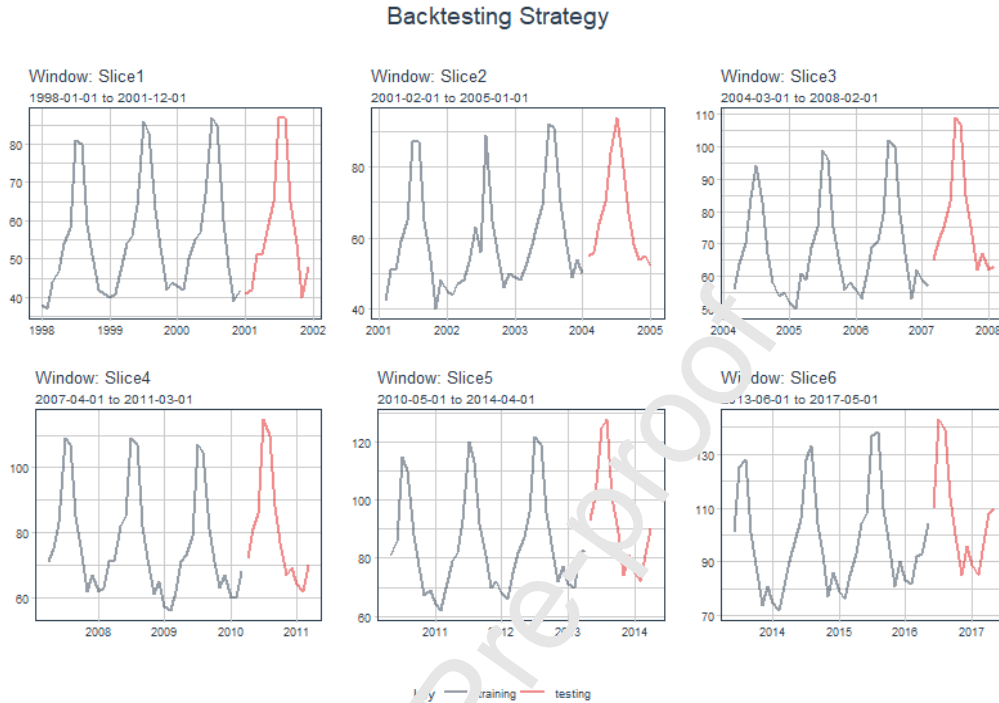


**Figure 3. Autocorrelation Function (ACF) for international tourist arrivals**

We construct ten different models (five for each methodology) as follows. The first model uses the entire sample as a training data source. The next three models are constructed using training data from major crises of the recent past, namely the SARS epidemic, the GFC and the MERS outbreak. The last model in each methodology is a “worst case” scenario approach, which uses the minimum values for each data point (month) in the data series. By training the models with this data, we are able to present a pessimistic scenario for international tourist arrivals forecasts. We duplicate these training periods once in the GAM model and once in the LSTM model, resulting in ten different forecasting models.

After constructing the models, we perform the rolling-window sampling plan (Figure 4) in order to compute accuracy metrics and determine the optimal modelling approach. Using the setup of Polyzos et al. (2020), which splits the data into slices with a three-year training period (36 data points) and a one-year testing period (12 data points), we create six subsamples that allow us to test our prediction model. The sampling window is shifted with each subsample in order to create more datasets (the data subsamples) and to permit us to

compute metrics on the accuracy of each model's predictions. Figure 4 shows the six data slices with forecasts created using the LSTM model.



Note: This figure demonstrates the rolling window backtesting strategy. Training data is shown in blue and validation data is shown in red.

**Figure 4. Rolling window backtesting strategy with LSTM forecasts (entire sample)**

We calculate three accuracy metrics for each model. We also include a simple ARIMA (Auto Regressive Integrated Moving Average) model, trained only over the entire data sample, which is a popular methodology, as a baseline model, for comparison purposes. The reported metrics helps us determine the relative performance of each methodological approach and of each training set. The results are displayed in Table 2, which also includes the average value that the model produces for each metric.

**Table 2. Accuracy Evaluation Metrics**

		MAPE	MAE	RMSE	
<b>ARIMA</b>	Entire Sample	11.2%	12.791	18.969	
	Entire Sample	9.6%	10.846	16.049	
<b>GAM</b>	SARS	9.9%	11.595	16.999	
	GFC	10.1%	12.169	17.634	
	MERS	10.5%	11.752	17.160	
	Worst Case	11.0%	11.591	16.623	
	<b>Average</b>	<b>10.2%</b>	<b>11.710</b>	<b>16.893</b>	
	Entire Sample	8.6%	10.596	14.322	*
<b>LSTM</b>	SARS	9.2%	11.095	15.617	
	GFC	9.0%	10.763	14.972	
	MERS	9.2%	10.835	15.847	
	Worst Case	9.7%	11.220	15.060	
	<b>Average</b>	<b>9.17%</b>	<b>10.902</b>	<b>15.163</b>	

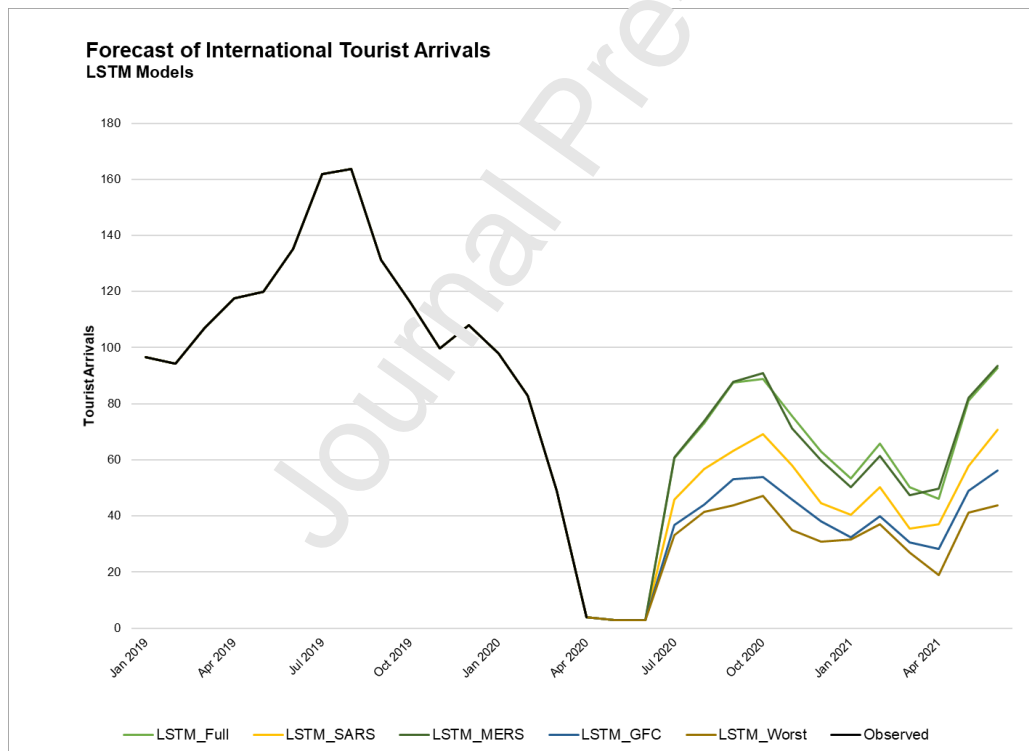
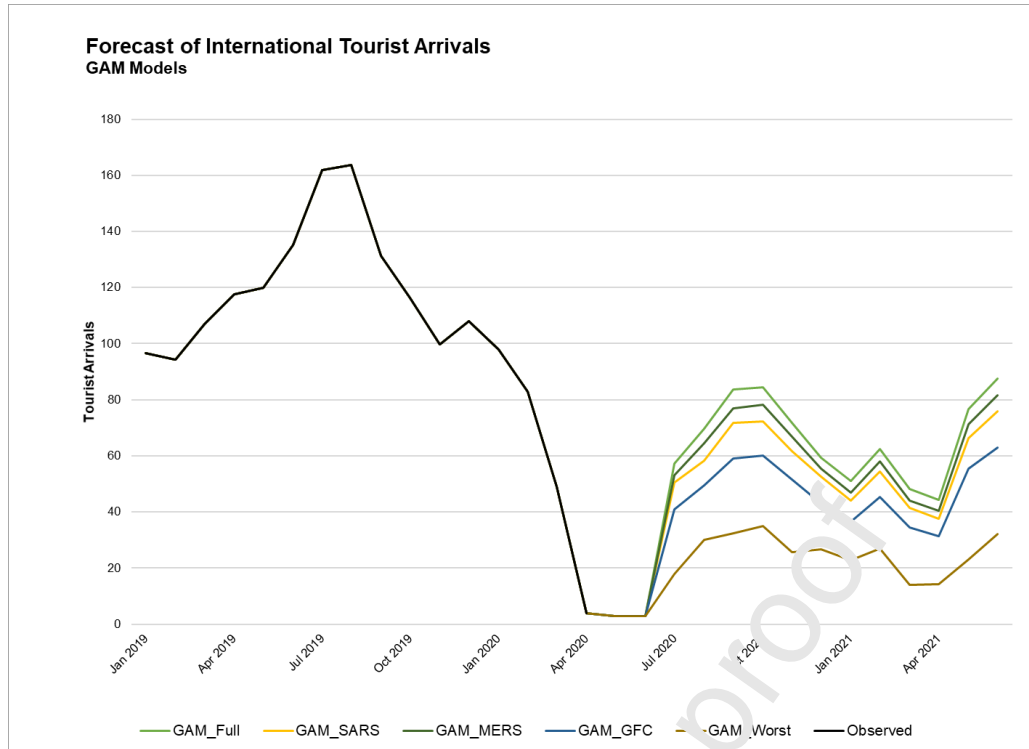
*Note: This table demonstrates accuracy metrics for each methodological approach and each training set. The metrics shown are the Mean Absolute Percentage Error (MAPE), the Mean Absolute Error (MAE), and the Rooted Mean Square Error (RMSE). The table also includes the average value that the two approaches produce for each metric. The best value, obtained by implementing an LSTM over the entire data sample, is marked with an asterisk (\*).*

The table shows that both methodologies outperform the ARIMA model and produce forecasts with comparable accuracy, with the LSTM model being somewhat more efficient for the specific data series. Also, we see that using the entire data sample as a training set yields lower prediction errors, which confirms the efficiency of our metrics, as this is an intuitively expected result. In addition, in both cases, the worst-case scenario will produce the highest errors, regardless of the approach or the metric uses, which is also an anticipated result. It is important to note that we do not use raw error values in any of our metrics (as would be used for example in the Mean Percentage Error metric).

Figure 5 demonstrates our forecasts on international tourist arrivals from July 2020 onwards, using our two methodological approaches and the five different training sets. The graph clearly shows the significant losses of the tourism sector due to the pandemic, which seems to have detrimental effect on tourist flows. In terms of the current situation, the peak in the summer of 2019 is followed by the current trough with the reduction in tourist arrivals

being as high as 97.6% (Year-to-year change from May 2019 to May 2020, actual data). This effectively means that the current tourist season should be counted as an almost total loss for the industry. The two graphs in the figure also depict the different nature of the forecasting models. The GAM model, as a linear model, produces similar forecasts, shifted according to the particulars of each training set used. On the other hand, the forecasts of the (non-linear) LSTM model do not appear to be shifted versions of the same series.

Moving on to our forecast summaries (Table 3), we can see that all models predict that the significant losses are persistent even up to the next tourist period. Firstly, the yearly drop in December 2020, as compared to December 2019, is calculated to be around 56.1% (the averages of both methodologies coincide), with the best scenario predicting a drop of 41.7% and the worst scenario suggesting a drop as steep as 75.2%. In the two-year change (June 2019 to June 2021), our predictions average a 48.5% drop, with different scenarios ranging from 30.8% to 76.3%.



*Note: This graph includes our forecast for the international tourist flows, under the different GAM and LSTM training samples.*

**Figure 5. GAM and LSTM modelling forecasts for international tourist arrivals**



**Table 3. Prediction summaries of different models**

		Average	Yearly Change <i>Dec 19-Dec 20</i>	Two-Year Change <i>June 19-June 21</i>
<b>GAM</b>	Entire Sample	66.37	-45.0%	-35.3%
	SARS	57.25	-51.3%	-43.8%
	GFC	47.52	-60.2%	-53.4%
	MERS	61.48	-48.7%	-39.7%
	Worst Case	25.13	-75.2%	-76.3%
	<b>Average</b>	<b>51.55</b>	<b>-56.1%</b>	<b>-49.7%</b>
<b>LSTM</b>	Entire Sample	69.85	-41.7%	-31.5%
	SARS	52.47	-58.6%	-47.6%
	GFC	42.36	-64.6%	-58.5%
	MERS	69.10	-44.5%	-30.8%
	Worst Case	35.96	-71.3%	-67.7%
	<b>Average</b>	<b>53.95</b>	<b>-55.1%</b>	<b>-47.2%</b>

*Note: This table demonstrates a summary of the empirical findings of our prediction algorithms. The column “Average” demonstrates the average values of our 12-month predictions. The yearly drop columns calculate the percentage drop of international tourist arrivals according to our predictions over one year (December 2019 to December 2020) and two years (June 2019 to June 2021).*

Both the values and ranges of our predictions suggest that recovery of the tourism sector is hardly nigh. The next year holds difficult predictions for the industry and our average forecast for June 2021 suggest that the loss of tourism demand takes the sector back to the tourist flows of 2005, which means that 15 years of growth will be lost due to this pandemic. In addition, the ranges of the prediction values show that the drop will not necessarily be smoother as the months progress. The worst-case for June 2021 is worse than that of December 2020 in percentage, year-to-year terms, despite the fact that the average predictions seems to be better.

In terms of methodologies, we see that GAM predictions are somewhat more conservative when compared to LSTM predictions. However, we can see that the events included as training sets affect the prediction outcome in a different manner according to the methodology. For example, despite lower predictions in general, the GAM model yields higher predictions on average when the SARS or the GFC training set is used. This means that, particularly in machine learning algorithms, the training set used is important in determining the final outcome of the prediction model. It is important to note, however, that except for the worst-case scenario, all training sets yield similar accuracy metrics and thus there does not seem to be a consistent pattern of performance in the different training sets.

Finally, it is important to note that, barring the worst-case scenario, the GFC training set produces the lower forecasts in both methodologies, confirming existing literature that the GFC was the deepest crisis faced by the tourist sector before the current pandemic (Sheldon and Dwyer, 2010).

## 5. Conclusions

Using a multi-perspective approach to evaluate the impact of crises has important practical implications for economic actors that still look forward to starting with phase one recovery. Crises are undesirable events that greatly affect the tourism industry. By viewing conflicts as crises, introducing a holistic and multi-perspective framework provides researchers with substantial insights on how tourism-related businesses can develop and manage post-conflict goals (Reddy, Boyd, & Nica, 2020).

In this paper, we produced a 12-month forecast for international tourist arrivals, using two methodologies and five different training sets. Our empirical findings show that the COVID-19 pandemic will result in losses of around 50% for the next year and that these losses will be persistent at least until the next summer and will backtrack the growth of the tourism industry as much as 15 years. In addition, we show that the worst-case scenario predicts that a deterioration of tourist arrivals in the coming months, suggesting that the tourism industry needs to prepare for a potentially worsening crisis. The predicted drop is in line with UNWTO forecasts of a 60%-80% for 2020, but our results do not agree with expectations of recovery in early 2021 (UNWTO, 2020b); recovery should be expected after the summer of 2021. Also, our findings are consistent with Polyzos et al. (2020) who show that it may take up to a year for the trend in tourist arrivals to return to pre-crisis levels.

In addition, our work shows that it is important to compare different training sets when designing machine learning algorithms, since each training set may yield different results. It is noteworthy that the different training sets used produce forecasts with comparable accuracy across both methodologies. However, the predictions of each model vary to a great extent and this is an important conclusion and one that is often overlooked by the literature. Machine-learning research tends to compare different methodologies across the same training set, whilst our work suggests that different training sets should also be explored.

Our results have important implications both for policymakers and for researchers. In terms of policy, our predictions suggest that the crisis is far from over in the tourism sector.

Without a medical solution to the pandemic, tourists will be reluctant to travel, despite the protective measures taken by transport and hospitality companies. The current tourist season should be counted as an almost total loss for the industry, since the drop for the current year currently exceeds 98%. Our forecasts for the coming months show a drop of around 50% in December 2020, compared to the previous December, while predictions in some of our scenarios for June 2021 are even graver.

In addition to being faced with reduced revenue, the industry is also facing increased costs when implementing the protective measures put in place by authorities. The persistence of this crisis, as signified by our predictions, suggests that firms in the tourism sector will need to re-evaluate their business models to incorporate for the reduced demand and increased costs. The new status quo, which will linger for at least a year based on our predictions, suggests that profitability in the industry needs to be re-evaluated and new tourist products may need to emerge, reshaping the sector. These changes may be temporary or may persist even after the crisis has passed.

As a response, authorities will need to subsidize the protective measures they propose in order to support tourism, especially in countries where tourism revenue contributes highly to GDP. Government subsidies on these measures will also help confirm that the measures will be implemented as they are planned by medical professionals, since poor or scanty implementation can have the same detrimental effects as no implementation, with the added cost of false security. It is important that the tourist sector embraces medical guidelines as they represent the shortest path out of the current crisis.

Finally, our work illustrates the importance of implementing different methodologies when researchers attempt to reduce data forecasts. Additionally, methodologies that utilize training data should be implemented using many different data sets, from different periods, for this task, since we have shown that the results generated can differ significantly. This is an important finding and one that is of particular significance in light of the recent development of machine learning methodologies and their increasing adoption by the academic community. Researchers should cross-validate their findings with different data sets, in order to compare the outcomes and add further substance to the results.

Our conclusions and suggestions are built on the outcomes of the particular methodologies employed, given the specific training sets. We acknowledge that research incorporating different methodologies and different variables could yield different results. As Kock et al. (2020) note, previous research assumptions on tourism may need to be revised during the COVID-19 era. Our findings depend heavily on post-COVID-19 travel behavior

(Li, Nguyen and Coca-Stefaniak, 2020) and also, on the discovery and distribution of a safe and effective vaccine that can be made widely available worldwide. On the other hand, if a vaccine is available only in certain regions, vaccine tourism can be a prime candidate for tourism revenue recovery. Similarly, proliferation of travel insurance packages could also alter travel patterns (Uğur and Akbıyık, 2020). The results of the current research would need to be revised when there is a foreseeable end to the pandemic.

An appealing methodological addition would be to prepare the data for multi-step forecasting, which is a useful extension of LSTM models that uses each forecast as a new data point and retrains the model using it as an observation. What is more, the COVID-19 pandemic is still evolving and the numbers worldwide are still rising rapidly. As the crisis is developing, the outcomes of our predictions may need to be adjusted. A particular issue comes from data availability. Safer predictions could be postulated after the summer of 2020, since the summer months of July and August have typically been the yearly peaks of tourist traffic. We believe that it would be interesting to explore similar predictions once data up to September 2020 become available. Furthermore, our forecasts do not consider the potential changes in tourist behavior and choices, following the pandemic (Nguyen and Coca-Stefaniak, 2020). The differences in transportation choices or vacation duration could have a significant effect on our projections. Finally, our work is focused solely on international tourism flows, meaning that our results do not account for regional particulars which affect tourism flows in the coming months. In addition, we cannot take into account domestic tourism flows. We believe that the numbers in staycation tourism will increase as a response to border closures and this may alleviate the negative effects of the pandemic, at least in part.

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Journal Pre-proof

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**Declaration of interests**

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

## THE GOOD, THE BAD AND THE UGLY ON COVID-19 TOURISM RECOVERY

### Highlights

- We forecast international tourist arrivals from July 2020 to June 2021
- We use a GAM model and an LSTM network
- The training sets include three recent crises and a worst-case scenario
- The drop in tourist flows ranges from 30.8% to 75.2%
- Different training sets yield different forecasts