“Multi-model tourist forecasting: case study of Kurdistan Region of Iraq”

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# MULTI-MODEL TOURIST FORECASTING: CASE STUDY OF KURDISTAN REGION OF IRAQ

## Abstract

The tourism industry has been one of the leading service industries in the global economy in recent years and the number of international tourism in 2018 reached 1.4 billion. The goal of the research is to evaluate the performance of various methods for forecasting tourism data and predict the number of tourists during 2019 and 2022. Performance of 15 prediction models (i.e. Local linear structural, Naïve, Holt, Random walk, ARIMA) was compared. Based on error measurements matrix (i.e. RMSE, MAE, MAPE, MASE), the most accurate method was selected to forecast the total number of tourists from 2019 to 2022 to Kurdistan Region (KR), then forecasts were performed for each governorate in KR. The results show that among 15 examined models of tourist forecasting in KR, Local linear structural and ARIMA (7,3,0) model performed best. The number of tourists to KR and each governorate in KR is predicted to increase by most experimented models, especially those which demonstrated higher accuracy. Generally, the number of tourist to KR predicted by ARIMA (7,3,0) is a lot bigger than Local linear structure. Linear structural predicted the number increase to 3,137,618 and 3,462,348 in 2020 and 2022, respectively, while ARIMA (7,3,0) predicted the number of tourists to KR to increase rapidly to 3,748,416 and 8,681,398 in 2020 and 2022.

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## INTRODUCTION

The tourism sector is of great importance in the economic balance of a large number of countries in the world that have the characteristics and qualifications of tourism. Tourism has continued to develop as a human activity, achieving many advantages, which led many countries to pay attention to them and increase their revenues. The tourism industry has played an important role in achieving the economic development of the countries. Tourism depends on the human factor in a great way. It aims at achieving many occupation opportunities according to the reports of the World Tourism and Travel Council. Tourism has proved to be a strong sector of economic activity and a major contributor to the state economic recovery through generating billions of dollars, on the one hand, and creating occupation opportunities for the region's population, on the other hand (Petrevska, 2017). The tourism industry has been one of the leading service industries in the global economy in recent years through economic flows resulting from tourism (Ekanayake & Long, 2012; USAID, 2008) For example, the number of international tourism in 2018 reached 1.4 billion, an increase of 6% (Chhorn & Chaiboonsri, 2017; UNWTO, 2019). The prediction of the number of tourists to the Kurdistan Region of Iraq for the next period assists in order to the required services and tourism facilities (Unakıtan & Akdemir, 2015).



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# 1. LITERATURE REVIEW

Being one of the significant fields in tourism studies, tourism request modeling and predicting has involved much consideration from academics and experts (Chhorn & Chaiboonsri, 2017; Song & Li, 2008). There are many models were utilized to forecasting of tourism demands such as ML, linear and nonlinear models, multivariate exponential smoothing model, a MLP ANN, ANN-GARCH model and others. The field of prediction has undergone profound changes. A combination of linear and nonlinear models provides solutions in which models are optimally combined and can be applied to actual situations, for example, predicting economic time series, travel request and exchange rates. ML is founded on the creation of an empirical learning algorithm (Lin et al., 2014). The key ML prediction approaches are support vector regression (SVR) and artificial neural network (ANN) models. Artificial neural network models are used to predict economic development and predict exchange rates through several artificial neural networks. Although for economic modeling and prediction, SVR and ANN models have been used, other ML methods (Gaussian Process Regression (GPR)) are almost unsuitable for prediction purposes (Claveria et al., 2016). More detailed prediction studies and research reviews were given to Song and Li (2008). They reviewed 121 papers on modeling and forecasting of internal and international tourism published after 2001. Of the 121 studies, 72 time series methods were used to simulate travel requests, more than 30 of which utilized both time series and econometrics. Bermudez et al. (2009) generate forecasting periods for hotel occupancy in three provinces of Spain using a multi-variable exponential homogenization model. The first attempt to use ML techniques is to predict demand for tourism in Spain in Palmer, Montano, and Sesé (2006) and Medeiros et al. (2008), designed by MLP ANN to estimate tourism spending in the Balearic Islands.

Petrevska (2017) utilized Box Jenkins Model for forecasting international tourism demands in Macedonia. The researchers used models to predict the number of tourists and relied on the figures for the period between 1956 and 2013. The model ARIMA (1,1,1) was used as a more suitable predictor for the increase in the number of tourists by 13.9%. For forecasting international tourism demand in Malaysia, the researchers utilized Box Jenkins and SARIMA Application (Loganathan & Yahaya, 2010). The research predicts that Malaysia would perceive significant tourism for the next years. For forecasting tourist inflow in Bhutan using Seasonal ARIMA (SARIMA), Singh used the model of (0,1,1) (1,1,1) (Singh, 2013). Ellis used four models, namely, Naïve, Etas, ARMA, THETA, for monthly and yearly data tourism study (Ellis, 2016).

In the Kurdistan Region of Iraq, a number of tourist sites were planned to support local economies and promote employment and growth. In recent years, the number of tourists to tourist areas has increased due to the availability of spare time and holidays for the population. There are a number of aspects that contributed to reviving the tourism sector in the Kurdistan Region of Iraq. The development of the tourism industry has established its position as an attractive destination in the region and secondly the development of strategy and policies in a timely manner. The government has constructed two international airports that are capable of operating direct flights to and from Kurdistan (Altaee et al., 2017). In addition, there are many natural attractions in the study area (topography, climate, water resources and forests, all of these factors have attracted many tourists to tourist site (USAID, 2008). The period of growth between 2007 and 2013 demonstrates a number of problems that interface in the strategy of the Kurdistan Regional Government, in addition to the ongoing budget crisis with the federal government and the threat to the security of the province by the preacher. These problems include failure in investment and planning of basic infrastructure services (health, transportation, hotels and restaurants). These challenges and problems will have to be addressed in order to flourish tourism as a cornerstone of a structured and diversified economy of the state (Rasaiah, 2016; Cura et al., 2017). The objects of current study are evaluating the performances of various models (i.e. Local linear structural, Naïve, Holt, Random walk, ARIMA) for forecasting tourism data and predicting the number of tourists during 2020 and 2022.

# 2. METHODOLOGY

## 2.1. Methods

The data of tourist number to Kurdistan Region (KR) from 2007 to 2018, entered in R program. Before forecasting the number of tourists, accuracy assessment of the 15 prediction models (i.e. Naïve, Holt, Random walk, ARIMA) was performed. For evaluating forecast accuracy of methods, the data from 2007 to 2014 were utilized as a training data set, and the data from 2015 to 2018 used as an experiment data set of accuracy measures. Then, based on error measurements matrix (i.e. RMSE, MAE, MAPE, MASE), the most accurate method was selected to forecast the number total of tourists during 2019 to 2022 to KR, then, forecasts were performed for each governorate in KR, especially during 2020 and 2022.

### *2.1.1. Forecasting models*

In order to select more suitable forecasting methods, in this study, 15 prediction models were compared.

1. Forecasts from Cubic Smoothing Spline: it is calculated according to Hyndman et al. (2005):

$$\theta_2^4 - c_1\theta_2^3 + c_2\theta_2^2 - c_1\theta_2 + 1 = 0,$$

$$\theta_1 = \frac{\theta_2}{1+\theta_2}\left(\psi / \lambda_* - 4\right), \text{ and } \sigma_3^2 = \sigma^2 \lambda_* / \theta_2 \ ,$$

where $c_1 = 4 + \left(1+\psi^2\right) / \lambda_*$, and

$$c_2 = 6 - 2\left(1 + 4\psi + \psi^2\right) / \lambda_* + \psi^2 / \lambda_*^2$$

2. Forecasts from the linear regression model:

- tslm is principally a wrap for lm(), besides, it permit variables “trend” and “season” (Hyndman et al., 2018).

3. Forecasts from Naïve method: it is a simplified wrapper of rwf() (Hyndman et al., 2018).

4. Forecasts from Random walk with drift: it is calculated according to the equation:

$$Y_t = c + Y_{t-1} + Z_t,$$

where $Z_t$ is a normal iid error.

5. Forecasts from Simple exponential smoothing (ses): it is an appropriate wrapper of ets().

6. Forecasts from Exponential smoothing adjusted for trend or Holt’s method: it is an appropriate wrapper of ets() and is a kind of exponential smoothing technique usually utilized to manage a linear trend (Chen, Bloomfield, & Cubbage, 2008).

7. Forecasts from HoltWinters: it is an appropriate wrapper of ets() (Hyndman et al., 2018)

8. Forecasts from Theta model: it is depicted in Assimakopoulos and Nikolopoulos (2000) and it is the same as Simple exponential smoothing with drift.

9. Forecasts from the Bagged Model: in this method est() is utilized and it is depicted by Bergmeir et al. (2016).

10. Forecasts from BATS model: as depicted by De Livera et al. (2011) it uses exponential smoothing.

11. Forecasts from ETS(M,N,N): it is based on the classification of methods as depicted in Hyndman et al. (2008).

12. Forecasts from ARIMA (7,3,1) model: ARIMA (7,3,1) model was selected to forecast tourist forecast of KR, because it has the low AICc (62.33). It is based on “arima” function in the stats package in R with the option of a drift expression (Hyndman et al., 2018).

13. Forecasts from ARFIMA (0,0.35,0) model: this model estimated *p* and *q* based on Hyndman and Khandakar (2007) algorithm and *d* based on Haslett and Raftery (1989) algorithm.

14. Forecasts from Neural Network Time Series NNAR(1,1) model: for predicting univariate time series it utilizes the neural network with one hidden layer and lagged inputs (Hyndman et al., 2018).


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15. Forecasts from Local linear structural model: this model is forecast based on the structure of the time series and results (Hyndman et al., 2018).

#### 2.1.2. *Accuracy assessment measurements*

In order to compare the accuracy of forecasting methods, in this study, the following accuracy assessment matrix was utilized.

1. Mean Error (ME) is calculated according to:

$$ME = \frac{\sum_{i=1}^{n} y_{i} - x_{i}}{n}.$$

2. Root Mean Squared Error (RMSE) is calculated by the formula:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} (p_i - a_i)^2}{n}},$$

where $a$ – actual target, $p$ – predicted target.

3. Mean Absolute Error (MAE) is calculated by the formula:

$$MAE = \frac{\sum_{i=1}^{n} |E_i|}{n}.$$

4. Mean Percentage Error (MPE) is calculated by the formula:

$$MPE = \frac{\sum_{i=1}^{n} \frac{E_i}{Y_i}}{n}.$$

5. Mean Absolute Percentage Error (MAPE) is calculated according to:

$$MAPE = \frac{\sum_{i=1}^{n} \left|\frac{E_i}{Y_i}\right|}{n}.$$

6. Mean Absolute Scaled Error (MASE) is calculated by the formula:

$$MASE = \frac{\sum_{i=1}^{n} |E_i|}{\frac{n}{n-1} \sum_{i=2}^{n} |Y_i - Y_{i-1}|}.$$

# 3. FINDINGS

## 3.1. Accuracy assessment

Table 1 reveals that Local linear structural model and ARIMA (7,3,0) have superior in many error measurement matrices. A smaller MASE and RMSE value mean improved forecasting. The linear structural model generally has the small-

**Table 1.** Accuracy assessment of tourist forecasting models

| Models | ME | RMSE | MAE | MPE | MAPE | MASE |
|---|---|---|---|---|---|---|
| Cubic smoothing spline | 18,501.004 | 906,260.613 | 665,007.654 | 4.409 | 52.128 | 1.080 |
| Linear regression | 0.000 | 617,722.625 | 497,743.057 | –21.498 | 42.458 | 0.808 |
| Naïve | 221,408.182 | 699,300.881 | 615,912.909 | 7.512 | 41.791 | 1.000 |
| Random walk with drift | 0.000 | 663,325.100 | 493,356.500 | –10.010 | 34.886 | 0.801 |
| Simple exponential smoothing | 77,466.268 | 672,001.205 | 514,523.297 | –1.722 | 37.249 | 0.835 |
| Holt | –82,567.550 | 623,356.948 | 512,030.634 | –29.586 | 47.096 | 0.831 |
| Holt Winters | 216,371.300 | 711,840.634 | 553,373.900 | –0.120 | 34.728 | 0.898 |
| Theta | 119,780.619 | 728,915.631 | 647,787.249 | –15.156 | 60.350 | 1.052 |
| Bagged | 119,856.771 | 605,589.263 | 514,219.332 | –18.436 | 48.547 | 0.835 |
| BATS | 102,752.778 | 693,581.569 | 575,671.382 | –9.990 | 52.880 | 0.935 |
| ETS | 202,982.540 | 669,544.605 | 564,618.819 | 6.887 | 38.311 | 0.917 |
| ARIMA (7,3,0) | 953.878 | 2,954.158 | 1,239.108 | 0.079 | 0.098 | 0.002 |
| AFRIMA | 89,511.198 | 761,298.930 | 680,162.595 | –34.517 | 68.300 | 1.104 |
| Neural network | 87.194 | 468,063.695 | 390,600.249 | –12.968 | 31.252 | 0.634 |
| Structural time series | 0.141 | 0.957 | 0.740 | 0.000 | 0.000 | 0.000 |

est and zero or close to zero in all used error measurements. Its RMSE is 0.957 and its MASE is 0. ARIMA (7,3,0) has RMSE of 5,999.7 and MAE of 3,355.3, respectively. MASE of ARIMA (7,3,0) is 0.005. In contrast, some methods have very high error value such as Theta, Holt, and AFRIMA. For instance, the largest RMSE is 906,260.6 for Cubic smoothing method and the largest MASE is 1.104 of AFRIMA model. It means that it performed most inferior among other methods.

## 3.2. Tourist forecasting of Kurdistan Region

Some models predicted the number of tourists to KR in 2022 to be very high, 8,681,398 in ARIMA (7,3,0) and 6,082,702 in Cubic Smoothing Spline. In contrast, some models predicted the number decline in 2022, 1,769,684 according to ARFIMA (0,0.35,0) and 2,300,397 in NNAR (1,1) model. However, the majority of models predicted the number of tourists to KR will increase in 4 coming years and the number predicted to be between 3,000,000 and 3,700,000 in 2022 according to Naïve, Random walk with drift, Simple exponential smoothing, Holt, HoltWinters and Theta (Figure 1).

Among examined models to tourist forecasting, especially those well performed for demonstration the trend of the forecast, Local linear structural and ARIMA (7,3,0) model best performed based on error measurement metrics like RMSE, MAE and MASE. Therefore, they selected to forecast the number of tourists during 2020 and 2022 in KR.

Generally, predicted numbers of tourist to KR in ARIMA (7,3,0) is very bigger than Local linear structure. In Table 2, linear structural predicted the number to be 3,137,618, with probability of it to be 4,436,332 in 80% high and 1,838,903 in 80% low interval. In 2022, the number was predicted to increase to 3,462,348 with the probability of it to be 5,404,043 in 80% low interval and 1,520,654 in 80% low interval. Table 3 demonstrates that ARIMA (7,3,0) predicted the number of tourists to KR to increase to 3,748,416 in 2020 and will increase dramatically in 2022 to 8,681,398.

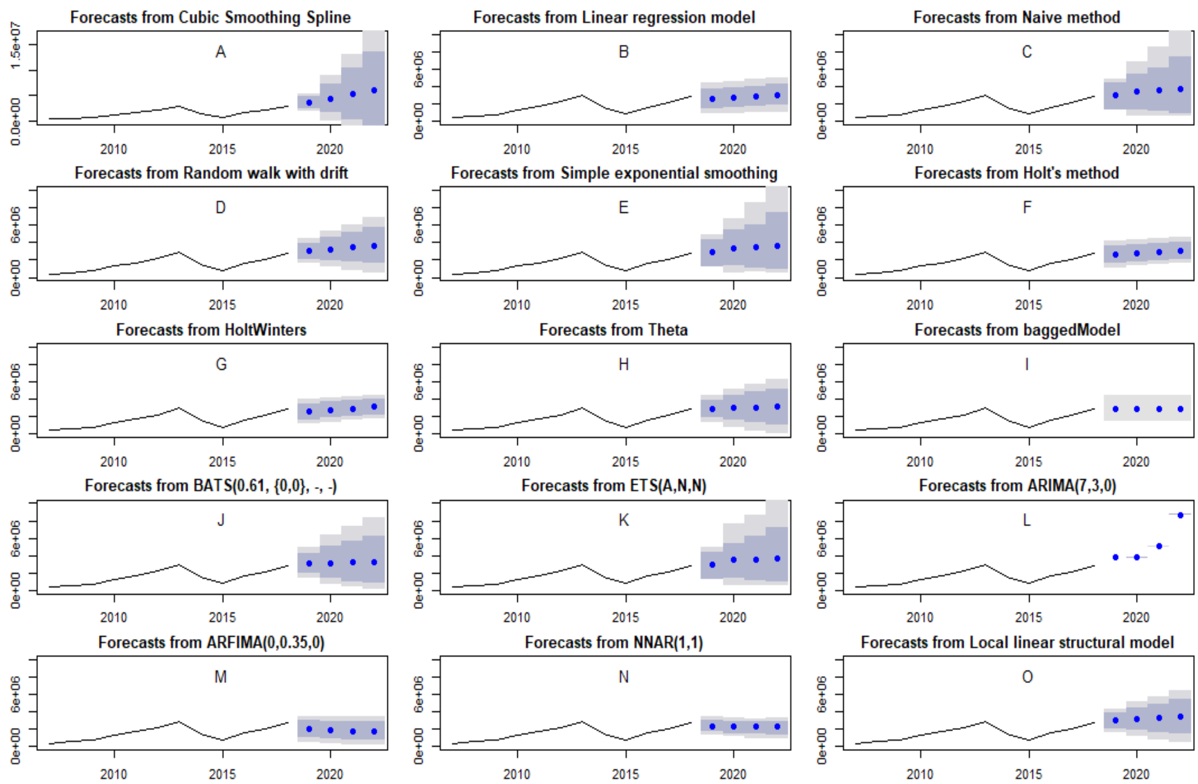


**Figure 1.** Total tourist to KR (2007–2018) along with 4-year forecasts and 80% and 95% prediction intervals


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**Table 2.** Forecasted number of tourists to KR from Local linear structural

| Year | Point forecast | Lo. 80 | Hi. 80 | Lo. 95 | Hi. 95 |
|---|---|---|---|---|---|
| 2019 | 2,975,252 | 2,084,342 | 3,866,163 | 1,612,722 | 4,337,783 |
| 2020 | 3,137,618 | 1,838,903 | 4,436,332 | 1,151,406 | 5,123,830 |
| 2021 | 3,299,983 | 1,663,276 | 4,936,690 | 796,856 | 5,803,110 |
| 2022 | 3,462,348 | 1,520,654 | 5,404,043 | 492,783 | 6,431,913 |

**Table 3.** Forecasted number of tourists to KR from ARIMA (7,3,0)

| Year | Point forecast | Lo. 80 | Hi. 80 | Lo. 95 | Hi. 95 |
|---|---|---|---|---|---|
| 2019 | 3,762,714 | 3,753,440 | 3,771,987 | 3,748,531 | 3,776,896 |
| 2020 | 3,748,416 | 3,729,320 | 3,767,513 | 3,719,210 | 3,777,622 |
| 2021 | 5,062,295 | 5,025,288 | 5,099,301 | 5,005,698 | 5,118,891 |
| 2022 | 8,681,398 | 8,622,665 | 8,740,132 | 8,591,573 | 8,771,223 |

## 3.3. Tourist forecasting of Erbil Governorate in 2020 and 2022

The number of tourists to Erbil Governorate according to Local linear structural model forecast be 1,693,656 with probability to decrease to 806,581 in 80% low interval and increase to 2,580,730 in 80% high interval (Figure 2O and Table 4). In 2022, the number predicted to be 1,874,841 with possibility to be between 548,586 and 3,201,097 in 80% interval. ARIMA (7,3,0) model suggested the number of tourists to Erbil Governorate is very higher than the suggested number in the linear structural model. It predicted to be 1,067,482 in 2020 and in 2022 it increases dramatically to 3,129,778 (Figure 2L and Table 5).

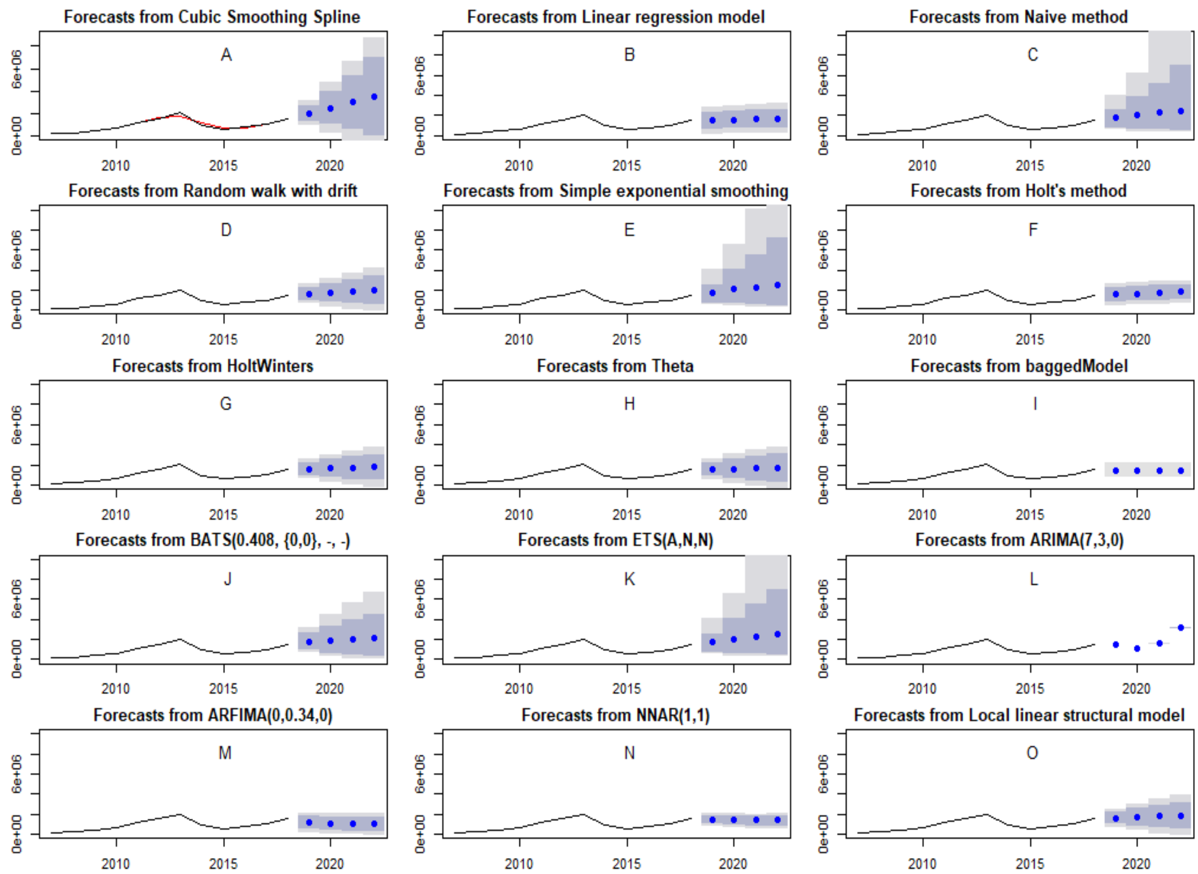


**Figure 2.** Total tourist to Erbil Governorate (2007–2018) along with 4-year forecasts and 80% and 95% prediction intervals

**Table 4.** Forecasted number of tourists to Erbil Governorate from Local linear structural model

| Year | Point forecast | Lo. 80 | Hi. 80 | Lo. 95 | Hi. 95 |
|---|---|---|---|---|---|
| 2019 | 1,603,063 | 994,535 | 2,211,591 | 672,399 | 2,533,726 |
| 2020 | 1,693,656 | 806,581 | 2,580,730 | 336,992 | 3,050,319 |
| 2021 | 1,784,249 | 666,311 | 2,902,186 | 74,511 | 3,493,986 |
| 2022 | 1,874,841 | 548,586 | 3,201,097 | 0 | 3,903,175 |

**Table 5.** Forecasted number of tourists to Erbil Governorate from ARIMA (7,3,0)

| Year | Point forecast | Lo. 80 | Hi. 80 | Lo. 95 | Hi. 95 |
|---|---|---|---|---|---|
| 2019 | 1,533,333 | 1,527,153 | 1,539,512 | 1,523,882 | 1,542,783 |
| 2020 | 1,067,482 | 1,055,317 | 1,079,648 | 1,048,877 | 1,086,088 |
| 2021 | 1,591,796 | 1,567,741 | 1,615,851 | 1,555,007 | 1,628,585 |
| 2022 | 3,129,778 | 3,091,508 | 3,168,048 | 3,071,250 | 3,188,307 |

## 3.4. Tourist forecasting of Sulaymaniyah Governorate in 2020 and 2022

Among examined models to tourist forecasting, Local linear structural and ARIMA (10,1,10) model best performed based on error measurement metrics. In 2020, the number of tourists to Sulaymaniyah Governorate according to Local linear structural model is forecasted to be 1,083,468 with probability to decrease to 771,103 in 80% low interval and increase to 1,395,832

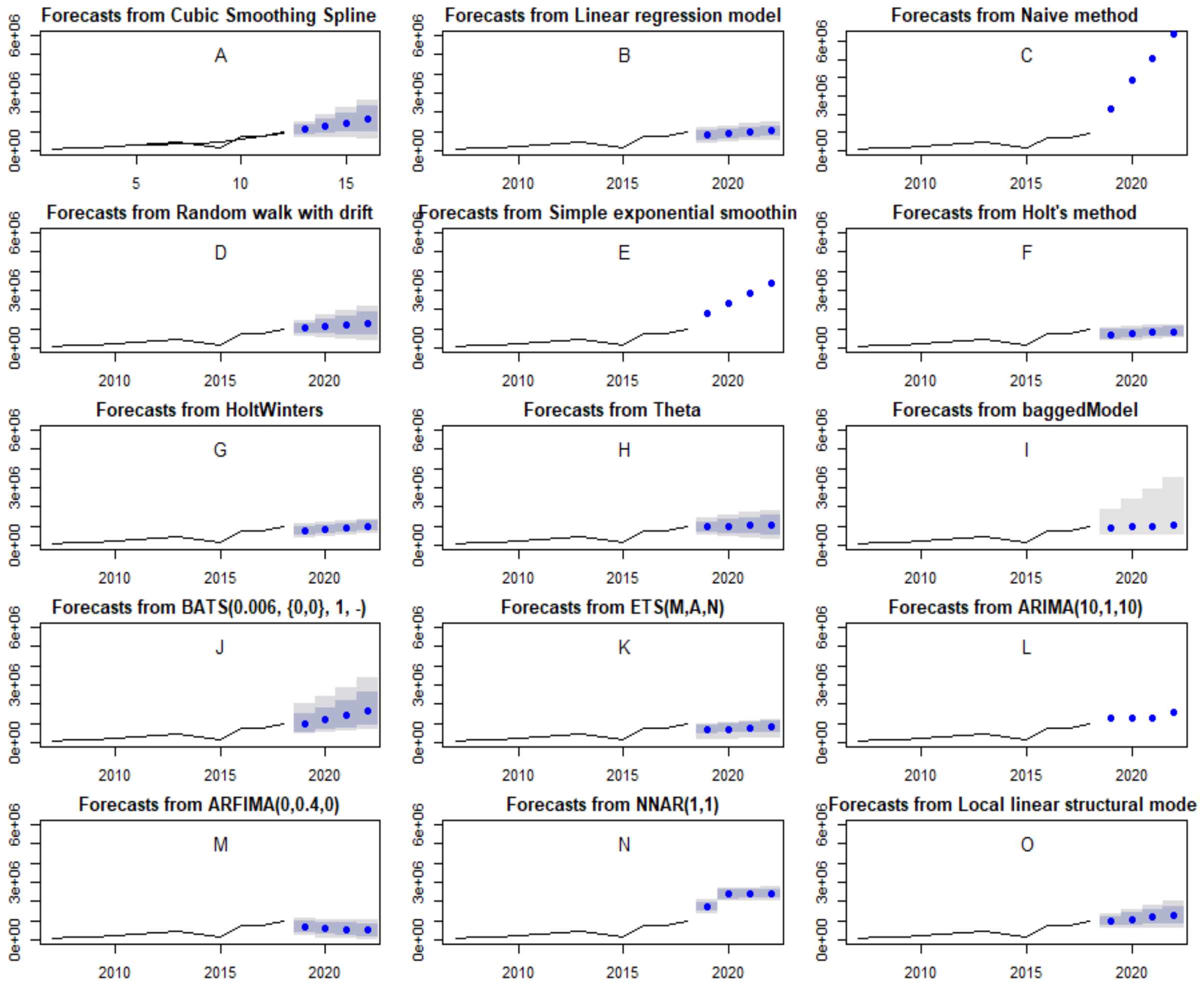


**Figure 3.** Total tourist to Sulaymaniyah Governorate (2007–2018) along with 4-year forecasts and 80% and 95% prediction intervals


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**Table 6.** Forecasted number of tourists to Sulaymaniyah Governorate from Local linear structural model

| Year | Point forecast | Lo. 80 | Hi. 80 | Lo. 95 | Hi. 95 |
|---|---|---|---|---|---|
| 2019 | 984,646 | 739,013 | 1,230,279 | 608,982 | 1,360,310 |
| 2020 | 1,083,468 | 771,103 | 1,395,832 | 605,747 | 1,561,188 |
| 2021 | 1,182,289 | 797,218 | 1,567,361 | 593,373 | 1,771,206 |
| 2022 | 1,281,111 | 817,929 | 1,744,293 | 572,735 | 1,989,486 |

in 80% high interval (Figure 3O and Table 5). In 2022, the number predicted to be 1,281,111. ARIMA (10,1,10) model suggested the number of tourists to Sulaymaniyah Governorate is very higher than the suggested number in the linear structural model. It predicted to be 1,310,090 and 1,591,304 in 2020 and in 2022, respectively (Figure 3L).

## 3.5. Tourist forecasting of Duhok Governorate in 2020 and 2022

Among examined models to tourist forecasting, Local linear structural and ARIMA (7,3,1) model best performed based on error measurement metrics. The number of tourists to Duhok Governorate in 2020 according to Local linear structural model forecast be 297,698 with probability to decrease to 64,857 in 80% low interval and increase to 530,538 in 80% high interval (Figure 4O and Table 7). In 2022 the number of tourists predicted to increase slightly to 319,137. According to ARIMA (7,3,1) model, it predicted to increase to 656,791 and 580,708 in 2020 and in 2022, respectively (Figure 4L).

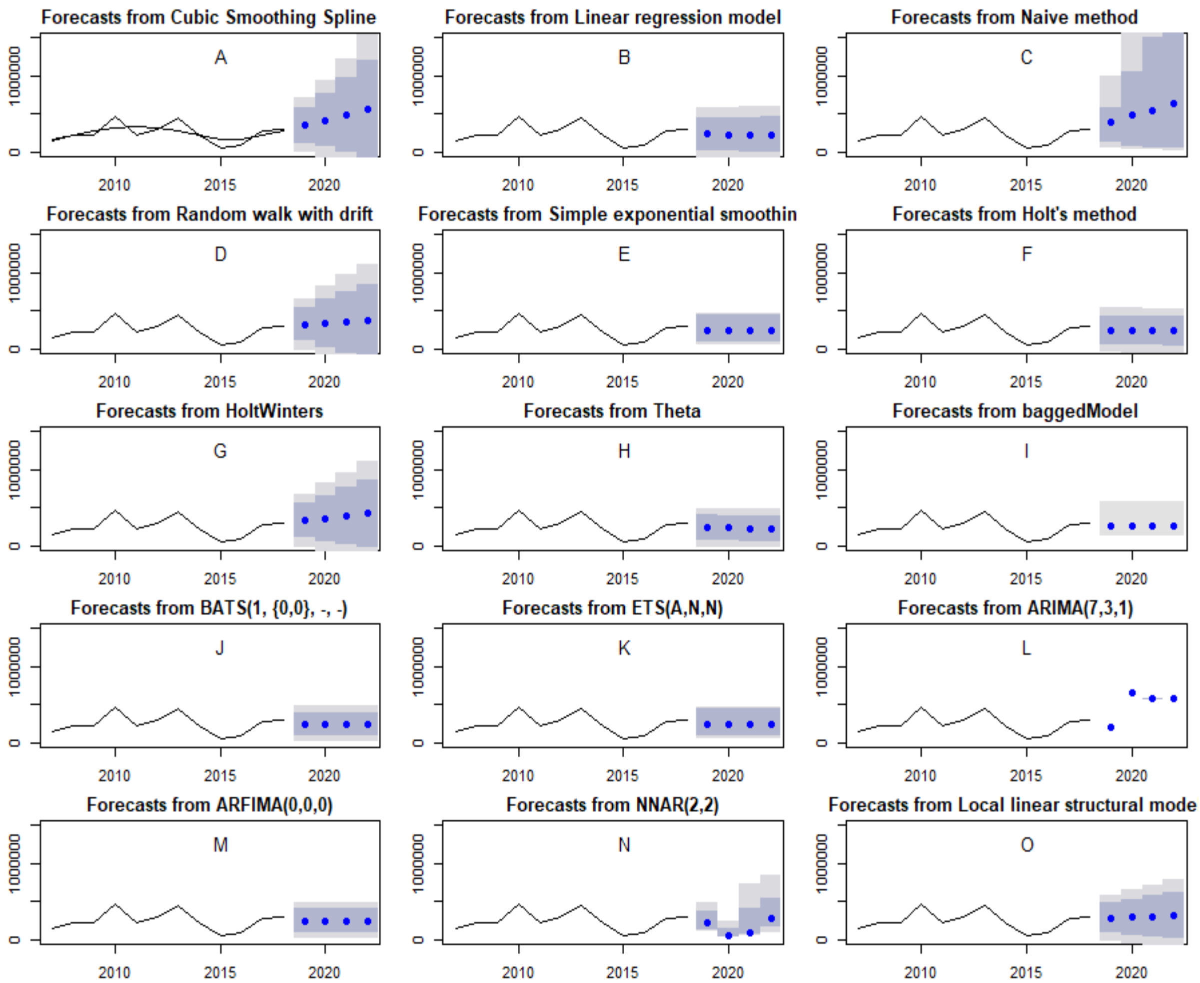


**Figure 4.** Total tourist to Duhok Governorate (2007–2018) along with 4-year forecasts and 80% and 95% prediction intervals

**Table 7.** Forecasted number of tourists to Duhok Governorate from Local linear structural model

| Year | Point forecast | Lo. 80 | Hi. 80 | Lo. 95 | Hi. 95 |
|---|---|---|---|---|---|
| 2019 | 286,978 | 92,663 | 481,293 | 0 | 584,158 |
| 2020 | 297,698 | 64,857 | 530,538 | 0 | 653,797 |
| 2021 | 308,418 | 39,211 | 577,624 | 0 | 720,134 |
| 2022 | 319,137 | 14,949 | 623,326 | 0 | 784,354 |

**Table 8.** Forecasted number of tourists to Duhok Governorate from ARIMA (7,3,1)

| Year | Point forecast | Lo. 80 | Hi. 80 | Lo. 95 | Hi. 95 |
|---|---|---|---|---|---|
| 2019 | 209,750 | 207,543 | 211,956 | 206,375 | 213,124 |
| 2020 | 656,791 | 654,110 | 659,471 | 652,691 | 660,890 |
| 2021 | 574,664 | 570,178 | 579,150 | 567,803 | 581,525 |
| 2022 | 580,708 | 575,504 | 585,911 | 572,750 | 588,666 |

## 4. DISCUSSION

Accuracy assessment is necessary to select the proper forecasting model with each case study number of tourist prediction. The accuracy of forecasting models varies based on data frequencies and forecasting horizon (Li et al., 2005; Song & Li, 2008; Witt & Song, 2001). Only some models performed well in literature is not sufficient to select them without measuring accuracy and perhaps it depends on some factors like the length and structure of the available data of tourists. In this study, among 15 examined models to tourist forecasting, Local linear structural and ARIMA (7,3,0) or ARIMA (7,3,1) model best performed based on error measurement metrics like RMSE, MAE and MASE. Our result agrees with Cho (2001) and Goh and Law (2002) in their conclusion that ARIMA outperforming other time series models. The result of our evaluation in contrast to Athanasopoulos et al. (2011) disclose that considering MAPE, Naïve and Theta are not capable of perform well compared to other methods.

The number of tourists to KR is predicted to increase by most experimented models, especially those demonstrated high accuracy. The number predicted to be between approximately three and a half and eight and half million persons. The number in the scale of governorates additionally predicted to increase in all KR governorates. However, we have to consider effects of different political and economic factors, which they shape the size of tourists to KR such as war, security, level of GDP in central and south of Iraq, Turkey and Iran. Because numerous crises and disasters have massive consequences on tourism, it is crucial to develop and utilizes forecasting methods that is capable of adapt to unanticipated events (Song & Li, 2008).

This study focused on the direction of the trend line of a number of tourists to KR more than seasonality on the timeline. Besides the number of tourists, prediction of income of tourism important for countries tourism is a considerable source of economy. Only considering the number of tourists to KR is ignores the time and expenditure that tourists spend in KR and it is not capable of determining actual tourism demand (Athanasopoulos et al., 2011).

## CONCLUSION

The research goal is to evaluate the performances of various methods for forecasting tourism data and predict the number of tourists during 2019 and 2022. The data of tourist number to KR from 2007 to 2018 were utilized in this study. The comparison of performance of 15 prediction models (i.e. Naïve, Holt, Random walk, ARIMA) occurred. Based on error measurements matrix (i.e. RMSE, MAE, MAPE, MASE), the most accurate method selected to forecast total the number of tourists from 2019 to 2022 to KR, then forecasts were performed for each governorate in KR.


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Our results demonstrate that among 15 examined models to tourist forecasting in KR, Local linear structural and ARIMA (7,3,0) model best performed based on error measurement metrics such as RMSE, MAE and MASE. The number of tourists to KR and each governorate in KR is predicted to increase by most experimented models, especially those which demonstrated higher accuracy.

Generally, predicted numbers of tourist to KR in ARIMA (7,3,0) is very bigger than Local linear structure. Linear structural predicted the number increase to 3,137,618 and 3,462,348 in 2020 and 2022, respectively, while ARIMA (7,3,0) predicted the number of tourists to KR increase rapidly to 3,748,416 and 8,681,398 in 2020 and 2022. However, we have to consider the effects of different political and economic factors which affect the number of tourists to KR such as war, security, level of GDP.

Increasing the number of tourists in the near future (four coming years) requires the KR government to prepare a plan to improve tourism facilities of both general and private sector such as hotels, motels, and roads. In addition, the increase of security and safety in the area is the main factor to attract a large number of tourists to Kurdistan.

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