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Long-term dynamics and future trajectories of natural gas production: a global, regional, and Iranian assessment

Afshin Gholamalipour, Mohammadali Allahrabbi Shirazi, Hossein Yousefi*

School of Energy Engineering and Sustainable Resources, College of Interdisciplinary Science and Technology, University of Tehran, Tehran, Iran

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*Corresponding author

Email address:

Hosseinyousefi@ut.ac.ir

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ABSTRACT

Natural gas plays an important role in sustainable energy supply and future planning. This study examines trends in global natural gas production, Asia, the Middle East, and Iran, and outlines its outlook using several analytical methods. Annual data for the period 1970-2025 were examined using trend analysis and time series forecasting methods. The significance of trends was determined using the Mann-Kendall test, and the rate of change was determined using Sen's slope estimator. Then, an ARIMA model was developed to forecast production up to 2035, and its accuracy was evaluated using RMSE, MAE, and MAPE criteria. The results showed that production increased in all four ranges and was statistically significant ($p < 0.001$). The Z-statistic values were between 9.69 and 10.83. Sen's slope estimates showed annual increases in production in the world, Asia, the Middle East, and Iran of 594.60, 295.04, 145.48, and 50.39 TWh/year, respectively. The ARIMA forecast also indicated that this increase would continue until 2035. Global production would increase from 41,964.71 TWh in 2025 to about 48,159.54 TWh. Production in Asia, the Middle East, and Iran in 2035 was also predicted to be about 18,096.72, 9,348.25, and 3,305.26 TWh, respectively. MAPE values below 10% indicate the model's accuracy in representing historical production behavior. By examining trend significance, estimating growth rates, and forecasting, we can better understand long-term changes in natural gas production.

1. Introduction

Over the past few decades, natural gas has become a major global energy source, playing a key role in power generation, industrial activities, and sustainable energy supply [1]. Burning natural gas emits less carbon than coal and oil. For this reason, many countries consider it an intermediate fuel for the transition to low-carbon energy systems [2]. Despite the rapid development of renewable energy technologies, natural gas remains strategically important. Gas-fired power plants can adjust generation to meet grid needs and help stabilize the grid when renewable power fluctuates [3]. For this reason, it is essential to examine long-term trends in natural gas production to assess future energy supply capacity, energy market stability, and energy security policies [4]. Over the past five decades, global natural gas production has increased dramatically, but different

regions have contributed unevenly to this growth. Research shows that the geographical distribution of natural gas production and regions' contributions to global supply have changed significantly over time [5]. In Asia, rapid economic growth and rising energy demand have increased the region's share of the global gas market [6,7]. The Middle East has also become a major global gas production hub, supported by vast natural gas reserves and growing production capacity [8]. Iran, which has one of the world's largest natural gas reserves, has also significantly increased its production capacity in recent decades. Fluctuations in this country's production can affect the structure of the gas market at the regional and global levels [9,10]. Examining past gas production trends at the global, regional, and national levels helps clarify structural changes in the natural gas market. Accurate production forecasting is also essential for energy planning, resource

management, and infrastructure development in the gas industry. Various studies have used economic models, statistical methods, and artificial intelligence to forecast energy production and consumption [11].

Natural gas production data typically have two main components: long-term trends shaped by increasing production capacity, and short-term fluctuations affected by economic conditions, technological changes, and policies. For this reason, simple forecasting models may not adequately capture all features of these data [12]. Statistical methods for trend identification, such as the Mann–Kendall test and Sen's slope estimator, allow assessment of the significance of historical trends and determination of the true rate of change. Despite extensive research in energy forecasting, many previous studies have focused on short-term forecasts or on specific countries and gas fields. Few studies have examined long-term historical trends and gas production prospects simultaneously at global, regional, and national scales. Accordingly, the main objective of the present study is to develop a combined framework based on Trend decomposition and Time-series forecasting to examine the past developments and future trajectory of natural gas production from 1970 to 2035. First, the study examines the trend in natural gas production in the world, Asia, the Middle East, and Iran using the Mann-Kendall test to assess the statistical significance of production changes. Then, the study calculates long-term changes using Sen's slope estimator. Finally, the ARIMA model is developed to forecast production up to 2035. The study's main innovation is combining non-parametric trend analysis with time-series modeling for a comprehensive assessment of past and future natural gas production. This approach also provides a new understanding of Iran's future position in the global natural gas market.

2. Literature review

The role of natural gas in energy security and long-term planning has driven increased research on its analysis and forecasting in recent years. Suganthi and Samuel [13] compared statistical models, artificial neural networks, and hybrid methods. Their results showed that statistical models such as ARIMA perform acceptably for time series with stable behavior; however, when data exhibit nonlinear behavior, hybrid models can reduce forecast error. Ediger et al. [14] also studied fossil fuel production and consumption in Turkey using time series forecasting methods. Using historical data, they built models that predicted long-term energy trends with reasonable accuracy. Azadeh et al. [15] presented an energy forecasting framework that combined statistical methods with ANN. The results showed that combining linear and nonlinear models reduced forecast errors compared with using a single model. This study was one of the first to emphasize the advantages of using multiple methods simultaneously for energy time series analysis.

In the natural gas field, Wang et al. developed a hybrid NMGM-ARIMA model by combining the Metabolic Nonlinear Grey Model and ARIMA to forecast monthly shale gas production in the United States. They used monthly production data from 2014 to 2016 and compared the proposed model's performance with the MGM, ARIMA, and NGM models. The proposed model's MAPE was 2.396%, the

lowest among the models examined. These results indicate that combining linear and nonlinear models can improve gas production prediction accuracy [8]. In this study, Wang and Jiang [11] developed two hybrid models, NMGM-ARIMA and ARIMA-ANN, to predict shale gas production in the US states of Pennsylvania and Texas. These two states account for about 60% of the total US shale gas production. The MAPE values for the NMGM-ARIMA model in Pennsylvania and Texas were 3.16% and 1.64%, respectively, while the ARIMA model's were 3.53% and 2.03%, respectively. The ARIMA-ANN model also performed better in these two states, with MAPE values of 2.06% and 1.38%, respectively.

In a more recent study, Manigandan et al. [16] used SARIMA and SARIMAX models to forecast natural gas consumption and production in the United States. The results showed that Seasonal ARIMA-based models can represent the temporal patterns of gas consumption well. Introducing exogenous variables into the SARIMAX model also improved forecasting performance. This study emphasized the importance of time series models in examining the future behavior of the natural gas market. Yucesan et al. [17] also compared regression, time series models, and machine learning methods to forecast natural gas consumption in Turkey. The authors evaluated model performance using MAPE, MSE, and R^2 criteria. The combined SARIMAX-ANN model performed best, with a MAPE of 0.357; in contrast, the ARIMA-ANN model had a MAPE of 0.5. These results show that combining statistical models with Artificial Intelligence can improve forecasting accuracy.

Qiao et al. [18] proposed a hybrid wavelet-transform-based model for natural gas production and consumption forecasting. In this method, the initial time series is divided into several parts, and each part is modeled separately. Their findings emphasized that decomposing the data before modeling can reduce time-series complexity and improve forecast accuracy. Alakent et al. [19] presented a Just-In-Time Learning Gaussian Process Regression (JITL-GPR) model to forecast monthly natural gas demand in two cities in Turkey. The study used gas consumption data from 2014–2024 and compared the proposed model's performance with SARIMA and ETS. The results showed that the JITL-GPR model had lower forecast errors and better identified seasonal patterns and trends in natural gas consumption. Koç et al. [20] investigated forecasting Gazprom's natural gas supply to Europe using ARIMA, ELM, and MLP. The findings showed that the MLP model outperformed the ARIMA model because it better captured nonlinear relationships in the data. Firoozeh et al. [21] developed a hybrid BiLSTM-XGBoost model to forecast natural gas consumption in the household sector. In this study, they used gas consumption and meteorological data from Zanjan province for 2017 to 2022. The results showed that the proposed hybrid model had lower RMSE and MAPE values and higher prediction accuracy than the LSTM and GRU models. Sung et al. [22] developed the SARIMAX-LSTM model for short-term energy forecasting by combining statistical methods and deep learning. This combination helped the model identify both linear patterns and nonlinear relationships in the data.

Du et al. [23] also presented a multivariate hybrid model for natural gas price forecasting using Feature Selection. The results showed that using effective market variables and

appropriate feature selection methods reduced error indices such as MAE and RMSE compared to baseline models. Salisu et al. [24] developed the GARCH-MIDAS model to forecast fluctuations in natural gas futures prices in the United States. This study examined how the Climate Concern Index (CCI) at the national and state levels affects natural gas market volatility. The results showed that increasing climate concerns have a positive and significant effect on natural gas price fluctuations. Models using state-level CCI data also showed better forecasting performance than the basic GARCH-MIDAS-GECON model and the national index-based model.

In recent years, several studies in Iran and elsewhere have aimed to forecast and estimate trends related to natural gas. These studies have used various statistical and computational methods and forecasting models to improve estimates of production, consumption, and the future behavior of the natural gas market [25-30]. Despite significant advances in natural gas forecasting, a review of previous studies shows that most of the research has focused on short-term forecasts of gas consumption, energy prices, or specific geographic regions, and less attention has been paid to comprehensive analysis of long-term trends in natural gas production at global, regional, and national scales. In addition, many studies have attempted to forecast the future without statistically significant examination of historical trends and actual rates of change, while understanding past production behavior is a fundamental prerequisite for achieving reliable forecasts. Accordingly, the present study presents a hybrid framework based on Trend Analysis and Time-Series Forecasting. In the first step, the existence and direction of natural gas production trends are examined using the Mann-Kendall Test. The study then measures the long-term rate of change using Sen's Slope Estimator and uses the ARIMA model to predict the likely trajectory of natural gas production in the world, Asia, the Middle East, and Iran through 2035.

3. Methodology

3.1 Data source and description

This study used annual production data from 1970 to 2025 to examine long-term changes in natural gas production and forecast its future. These data were obtained from the Our World in Data database [31]. Examining data spanning more than five decades helps clarify long-term trends, structural changes, and the gradual increase in natural gas production capacity. Short-term studies typically focus on monthly or seasonal fluctuations, but longer-term annual data provide a clearer picture of fundamental production shifts shaped by energy infrastructure expansion, increased extraction capacity, policy shifts, and global gas market developments. This study covers natural gas production in the world, Asia, the Middle East, and Iran. Examining these four levels helps to compare global trends and regional developments and to clarify Iran's position in the world's natural gas supply. All natural gas production values are expressed in terawatt hours (TWh). Using a common unit allows for direct comparison of production rates across regions of different economic and geographical sizes. Following collection, the raw data were organized into chronological annual series, with each observation representing the annual natural gas production

volume for a specific region. The general structure of the data used in this research is defined by the relationship 1:

$$X_{r,t} = \text{Production}_{r,t} \quad (1)$$

$X_{r,t}$ represents the natural gas production volume;

r denotes the region under study (World, Asia, Middle East, Iran);

t represents the year under review within the 1970–2025 period.

Accordingly, the final dataset consists of four independent time series, in accordance with Equation 2:

$$D = \{X_{World,t}, X_{Asia,t}, X_{MiddleEast,t}, X_{Iran,t}\} \quad (2)$$

Each series comprises 56 annual observations and was subsequently subjected to trend analysis and time-series forecasting. Table 1 presents the description of the dataset. Table 2 presents a selection from the main dataset used in this study, covering the first three years and the last three years of the study period.

Table 1. Description of the dataset

Parameter	Description
Energy indicator	Natural Gas Production
Data source	Energy Institute – Statistical Review of World Energy (2026), processed by Our World in Data
Time period	1970-2025
Temporal resolution	Annual
Unit	Terawatt-hours [TWh]
Studied regions	World, Asia, Middle East, and Iran
Data type	Historical time-series dataset
Data coverage	Global, regional, and national natural gas production
Data definition	Includes natural gas produced for Gas-to-Liquids (GtL) transformation; excludes flared and recycled gas
Forecasting horizon	2026-2035

3.2 Mann-Kendall trend test

The non-parametric Mann-Kendall (MK) trend test was employed to assess the presence and direction of long-term changes in natural gas production time series. This test is widely used in analyzing trends within environmental, climatic, and energy time series because, unlike parametric methods, it does not require the assumption of data normality and is less sensitive to outliers. Therefore, the Mann-Kendall test is a suitable method for examining long-term trends in natural gas production, which may be influenced by structural changes, increased production capacity, and energy market developments [32].

Table 2. Selected examples of the natural gas production dataset

Year	World [TWh]	Asia [TWh]	Middle East [TWh]	Iran [TWh]
1970	9760.88	237.092	103.38	34.955
1971	10441.183	316.131	161.553	84.544
1972	10955.471	371.769	200.021	114.004
2023	40660.945	14508.438	7246.13	2597.375
2024	41432.004	14796.603	7393.252	2622.034
2025	41964.707	15163.226	7582.915	2648.254

In this study, the Mann–Kendall test was used to examine the statistical significance of the trend in natural gas production between 1970 and 2025. This test indicates whether the observed changes are due to random fluctuations or reflect a significant increasing or decreasing trend. In this study, we apply the MK test independently to four time series, World, Asia, the Middle East, and Iran, to examine the historical behavior of natural gas production at global, regional, and national scales. For a time series comprising n observations, the Mann–Kendall test statistic is calculated based on the pairwise comparison of successive observations [33, 34]:

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^n \text{sign}(x_j - x_i) \quad (3)$$

where x_i and x_j are the natural gas production values at times i and j , and the sign function is defined as Equation 4 [33, 34]:

$$\text{sign}(x_j - x_i) = \begin{cases} 1, & x_j - x_i > 0 \\ 0, & x_j - x_i = 0 \\ -1, & x_j - x_i < 0 \end{cases} \quad (4)$$

A positive value of the statistic S indicates an increasing trend, while a negative value indicates a decreasing trend in the time series. For large samples, the statistic S approximates a normal distribution, and the standardized Z -statistic is calculated using Equation 5 [33, 34]:

$$Z = \begin{cases} \frac{S-1}{\sqrt{\text{Var}(S)}}, & S > 0 \\ 0, & S = 0 \\ \frac{S+1}{\sqrt{\text{Var}(S)}}, & S < 0 \end{cases} \quad (5)$$

where $\text{Var}(S)$ is the variance of the test statistic, and for data without ties, it is calculated using Equation 6 [34]:

$$\text{Var}(S) = \frac{n(n-1)(2n+5)}{18} \quad (6)$$

In this study, a significance level of $\alpha = 0.05$ is adopted. Accordingly, if the p -value is less than 0.05, the null hypothesis (H_0), stating the absence of a significant trend, is rejected, and the existence of a statistical trend is confirmed. The hypotheses of the Mann–Kendall test are defined as follows:

H_0 : No monotonic trend exists

H_1 : A monotonic trend exists.

The Mann–Kendall test is a key preliminary step in forecasting and is used to assess whether a significant trend exists in the natural gas production time series.

In addition to helping interpret historical production changes, the test results provide a basis for selecting and developing an ARIMA model to forecast natural gas production up to 2035. Also, using the MK results and Sen's slope estimator together allows examination of two distinct characteristics of the trend: whether a statistically significant trend exists and the actual rate of annual production change.

3.3 Sen's slope estimator

After examining the existence and significance of long-term trends in natural gas production with the Mann–Kendall test, Sen's Slope Estimator was used to estimate the magnitude and intensity of changes. The Mann–Kendall test determines whether a significant trend exists, while Sen's Slope estimates the trend slope and shows the variable annual rate of change. Therefore, this method helps interpret historical trends in natural gas production more accurately at global, regional, and national scales. Sen's Slope Estimator is a robust, non-parametric method for estimating the slope of a time-series trend. Its main advantage over conventional linear regression methods is that it is less sensitive to outliers and abnormal fluctuations. Due to this feature, Sen's Slope is widely used in research related to climate change, water resources, energy production, and long-term trend analysis. In the present study, Sen's Slope is calculated for each of the four time series of the world, Asia, the Middle East, and Iran to determine the annual rate of change in natural gas production during the period 1970–2025. The slope between any two temporal observations is calculated using Equation 7:

$$Q(i) = \frac{x_j - x_i}{j - i} \quad (7)$$

where:

$Q(i)$ is the slope value between two temporal observations; x_j and x_i are the natural gas production values in years j and i ;

j and i are time indices corresponding to different years.

After calculating the slope between all possible pairs of data points, the final value of Sen's slope is considered to be equal to the median of the obtained slopes: $Q_{Sen} = \text{Median}(Q_i)$.

A positive Q_{Sen} value of this estimator indicates an increasing trend in natural gas production and an annual increase in production; a negative value indicates a decreasing trend. Its absolute value indicates the intensity of the changes; such that larger values indicate a faster change in production over time.

In this study, using the Mann–Kendall test and Sen's slope estimator together allows evaluation of historical trends in natural gas production in two steps. First, the Mann–Kendall

test examines the statistical significance of the observed trend. Then, Sen's slope estimates the actual rate of change. Together, these methods provide a more accurate comparison of production growth rates in the world, Asia, the Middle East, and Iran, and a solid basis for interpreting ARIMA-based forecasting results.

3.4 ARIMA forecasting model

After analyzing historical trends and determining the long-term rate of change, the Autoregressive Integrated Moving Average (ARIMA) model was used to predict the future trend of natural gas production. ARIMA is one of the most widely used statistical methods for time series forecasting, using past data to identify time dependencies and estimate future values. Its interpretable structure and applicability to energy time series have led researchers to use this model in various forecasting studies. The ARIMA model consists of three main components: Autoregressive (AR), Integrated (I), and Moving Average (MA). The AR component models the relationship between the current value and past observations. The I component prepares the time series for stationarity through differencing. The MA component also accounts for past errors when modeling the current value. The model is defined by three parameters, (p, d, q), representing the AR order, the degree of differencing, and the MA order, respectively. The general structure of the ARIMA model is represented as ARIMA(p, d, q) [35]. After applying differencing, the ARIMA model is mathematically expressed according to Equation 8:

$$\phi(B)(1-B)^d X_t = \theta(B)\epsilon_t \quad (8)$$

In Equation (8), X_t represents the amount of natural gas production at time t. The symbol B represents the Backward shift operator; $\phi(B)$ and $\theta(B)$ are the AR and MA functions, respectively, and ϵ_t represents the random error of the model.

In this study, a separate ARIMA model is developed for each of the world, Asia, the Middle East, and Iran time series. First, the stationarity of the data is examined, and then the model parameters are selected based on statistical criteria. The final model is used to predict natural gas production until 2035. To evaluate the model's performance, the predicted values are compared with the actual data, and the RMSE, MAE, and MAPE criteria are calculated. This evaluation measures the model's accuracy and examines its ability to predict the future path of natural gas production.

3.5 Forecast accuracy evaluation

The accuracy of the ARIMA model was evaluated by comparing predicted and actual values using three statistical criteria: Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE). These metrics are commonly used to evaluate time series forecasting model error. Table 3 details the metrics used in this study. y_t represents the actual value, $\bar{y}_t$ represents the predicted value, and N represents the number of observations. The lower these metrics, the more accurately the model reflects past natural gas production behavior. A smaller error can also indicate more reliable future predictions. Figure 1 shows the main stages of the research: data collection, trend analysis, rate-of-change estimation, and time-series forecasting. These stages examine long-term changes in natural gas production and map its future trajectory.

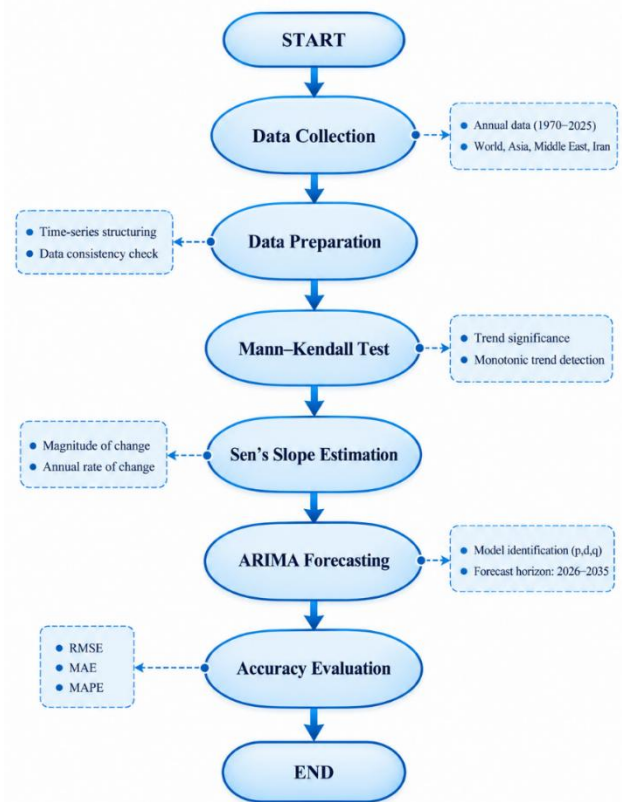


Figure 1. Research methodological framework

Table 3. Introduction to the criteria for evaluating model performance [35]

Error Metric	Advantages	Disadvantages	Formula
RMSE	Sensitive to large errors, identifies major deviations	Strongly affected by outliers	$RMSE = \sqrt{\frac{1}{N} \sum_{t=1}^N (y_t - \bar{y}_t)^2}$
MAE	Simple, interpretable, easy model comparison	Does not reflect error magnitude differences	$MAE = \frac{1}{N} \sum_{t=1}^N y_t - \bar{y}_t $
MAPE	Scale-independent, suitable for comparison	Unstable near zero values	$MAPE = \frac{100}{N} \sum_{t=1}^N \left \frac{y_t - \bar{y}_t}{y_t} \right $

4. Results and discussion

4.1 Long-term trends

Figure 2 shows the changes in natural gas production from 1970 to 2025 from two perspectives. Figure 2a shows production volume, while Figure 2b compares production growth relative to the 1970 base year. Together, these graphs provide a clearer picture of production volume and its growth rate in the study areas. The production volume shows that natural gas has increased in all geographical areas studied. This trend indicates an expansion of gas supply capacity over the past five decades. Global production increased from approximately 9,760.88 TWh in 1970 to 41,964.71 TWh in 2025, more than quadrupling during this period. While Figure 2a shows differences in production volume between regions, Figure 2b compares their relative growth using a common base year. Accordingly, production growth in some regions has far outpaced global growth. In Asia, natural gas production has increased from 237.09 TWh in 1970 to 15,163.23 TWh in 2025, an increase of almost 64 times. In the Middle East, production also rose from 103.38 to 7,582.92 TWh, an increase of about 73 times. This increase underscores the Middle East's position as one of the world's main natural gas supply centers. In Iran, natural gas production has also changed significantly during this period. Production increased from 34.95 TWh in 1970 to 2,648.25 TWh in 2025, about 75.8 times the base-year amount. Therefore, Iran has the highest relative production growth among the regions studied. However, higher relative growth does not necessarily mean higher production volume. Despite a significant increase in production in Iran compared to the base year, its production is still less than the total production of Asia, the Middle East, and the world.

4.2 Mann-Kendall trend significance

The MK test statistically examined the trend in natural gas production in the world, Asia, the Middle East, and Iran. This test was applied to all four time series over the study period, and the results are reported in Table 4.

In all four time series, the S statistic is positive, indicating an increasing trend in natural gas production. The high Z-statistic values (between 9.69 and 10.83) also provide strong statistical evidence supporting this trend during the study period. The p-value in all examined ranges is less than the 0.05 significance level. Therefore, we reject the null hypothesis (H_0) of no uniform trend, and the increasing trend in production is statistically significant in all four ranges. The highest Z value belongs to the world and Asia, at 10.83 for both. In Iran, the value of 9.69 also indicates a very significant increasing trend. Accordingly, the growth in Iranian gas production aligns with the broader trend of rising global supply and cannot be attributed solely to short-term fluctuations. These results clarify the existence and direction of the long-term trend in natural gas production at the global, regional, and national levels and address one of the study's main objectives.

4.3 Sen's slope-based growth assessment

The MK test identifies a uniform trend, while Sen's slope method estimates the annual rate of change and is less sensitive to short-term fluctuations and outliers. Therefore, this method enables quantitative comparisons of natural gas production trends across different geographical scales. Table 5 presents Sen's slope estimates for the four time series studied. Sen's slope (β) is positive in all regions; this is consistent with the MK test results and the significant upward trends. Sen's slope on a global scale was estimated at 594.60 TWh/year. This value indicates that global natural gas production increased by about 595 TWh/year during the study period. Among the regions studied, Asia had the highest annual production increase rate, at 295.04 TWh/year. This estimator reached 145.48 TWh/year for the Middle East, completing the significant increase in production in this region.

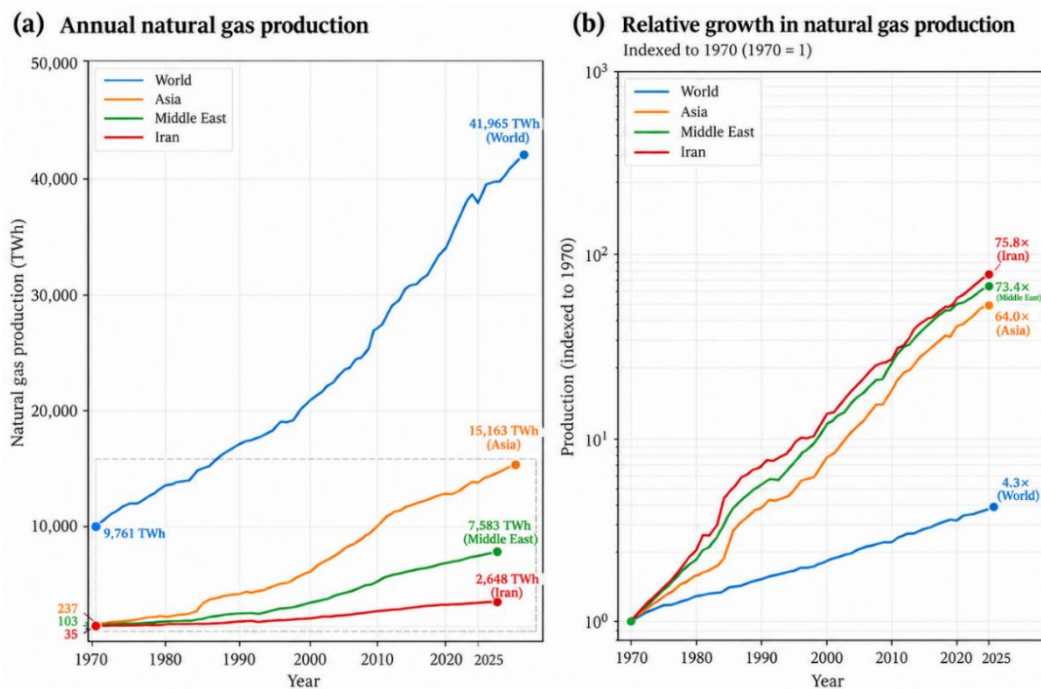


Figure 2. Natural gas production trends: (a) Absolute trends; (b) Relative growth

Table 4. Statistical evaluation of natural gas production trends

Region	S statistic	Z-value	p-value	Trend
World	1534	10.83	<0.001	Increasing
Asia	1534	10.83	<0.001	Increasing
Middle East	1532	10.82	<0.001	Increasing
Iran	1372	9.69	<0.001	Increasing

Table 5. Estimation of the rate of change of natural gas production using Sen's slope method

Region	Sen's slope (β) [TWh/year]	Trend direction
World	594.6	Increasing
Asia	295.04	Increasing
Middle East	145.48	Increasing
Iran	50.39	Increasing

Table 6. Statistical error metrics for forecast evaluation

Region	Selected ARIMA Model	RMSE	MAE	MAPE (%)
World	ARIMA(0,2,1)	970.36	730.73	1.85
Asia	ARIMA(0,2,1)	1183.73	1060.52	7.45
Middle East	ARIMA(0,2,1)	430.39	380.85	5.41
Iran	ARIMA(0,2,1)	86.17	79.37	3.45

This result indicates significant production growth in the Middle East, both in absolute terms and in the long-term rate of change. In Iran, $\beta = 50.39$ TWh/year also indicates a continuous increase in natural gas production over the 56-year study period. To examine the pattern of changes and distribution of the calculated slopes in more detail, Figure 3 shows all Pairwise slopes and their final median for each time series. Each point represents the slope between two observations at different times. The center line represents the Sen slope, which captures the dominant trend in the data. Beyond showing the final slope estimate, this plot helps assess the trend's stability and the dispersion of changes over the study period. As shown in Figure 3, differences in the median lines across regions highlight variations in the scale of annual growth; specifically, the "World" series shows the highest absolute rate of change, while Iran shows the lowest absolute slope.

4.4 Forecast validation and future trajectories

This section forecasts natural gas production through 2035 using the ARIMA model. The models selected for each region were determined based on the optimal time-series structure and the lowest AIC value. To avoid overly optimistic evaluations, the models were initially trained using data from the 1970-2015 period, while the final ten years (2016-2025) were reserved for out-of-sample validation. Subsequently, the model was fitted to the complete dataset to generate forecasts for the 2026-2035 period. Evaluation results indicate that the developed models achieve satisfactory accuracy for long-term natural gas production forecasting. The MAPE value for all regions was below 10%, demonstrating the model's acceptable performance in capturing the time series' historical behavior.

According to Table 6, the global model had the highest relative accuracy, with a MAPE of 1.85%, consistent with the high stability of the historical pattern of global production.

The higher absolute error values at scales such as the world and Asia can be attributed to the larger production volumes in these areas; consequently, the relative MAPE metric is a more appropriate measure for comparing performance across regions. Figure 4 shows the projected path of natural gas production for 2026–2035. Table 4 shows production data from 1970 to 2025 and ARIMA model forecasts for 2026 to 2035. The model estimates that global natural gas production will increase from 41,964.71 TWh in 2025 to about 48,159.54 TWh in 2035. This represents nearly 14.8 percent growth over ten years.

At the regional level, Asia is also expected to continue to play a significant role in increasing production. According to the model, production in this region will increase from about 15,163.23 TWh in 2025 to 18,096.72 TWh in 2035. For the Middle East, production is projected to rise from 7,582.92 TWh to about 9,348.25 TWh, indicating the region will continue to play an important role in global natural gas supply. In Iran, the model projects production to increase from 2,648.25 TWh in 2025 to about 3,305.26 TWh in 2035. This estimate aligns with the significant upward trend identified by the Mann-Kendall test and the positive value of Sen's slope, and the model predicts that Iran's historical growth path will continue.

4.5 Comparative discussion and limitations

A preliminary analysis suggests that natural gas production increased between 1970 and 2025. However, an upward trend in the raw data alone is insufficient to answer fundamental questions about the persistence, intensity, and future path of these changes. Increased production may reflect short-term fluctuations, changes in production scale, or cross-sectional capacity expansion. Therefore, beyond identifying production growth, this study aims to quantify and statistically evaluate long-term developments in natural gas production across different geographical scales.

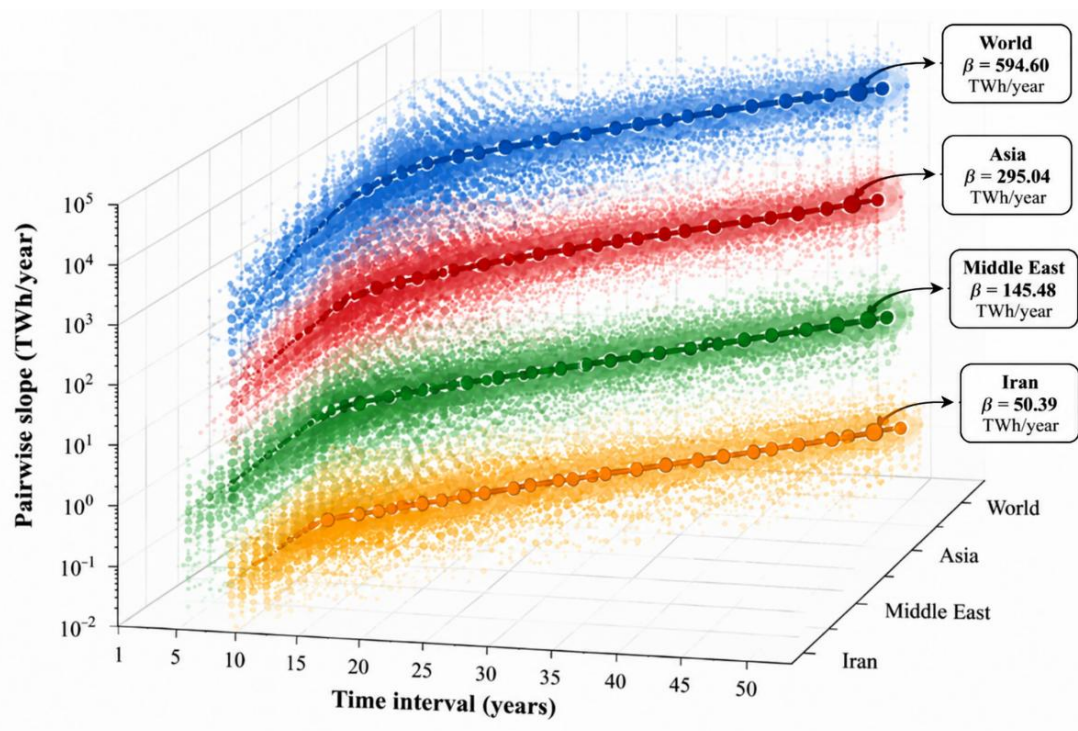


Figure 3. Pairwise slope distribution and Sen's slope estimation of natural gas production trends

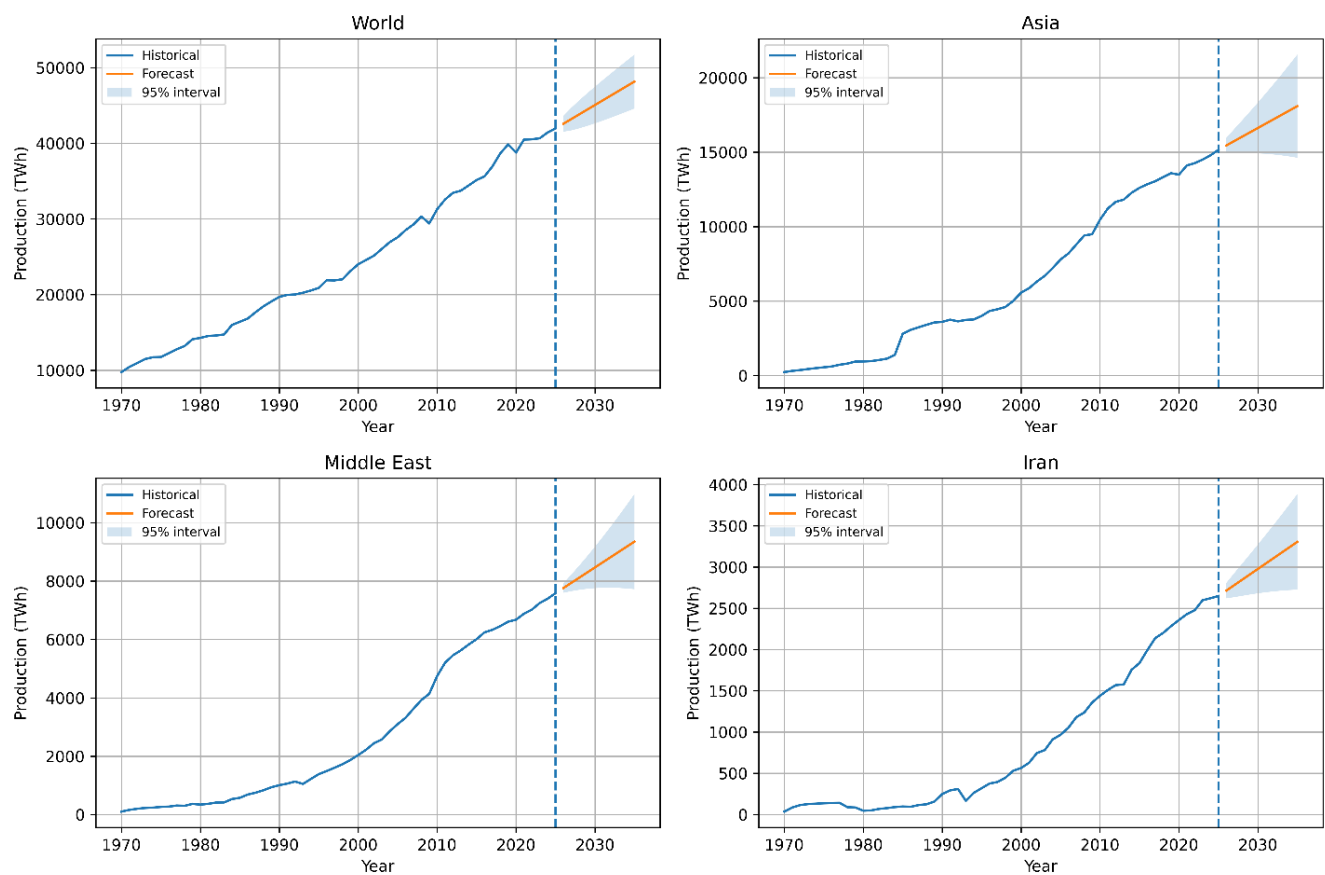


Figure 4. Natural gas production forecast until 2035 based on 4 geographical scales

The Mann-Kendall test results confirmed the statistical significance of the observed trends across all study areas. Therefore, the increase in production cannot be attributed solely to random changes. The Sen's slope estimator also allowed for comparison of regions that, despite a common upward trend, had different rates of change. For example, the difference between absolute growth in global production and relative growth in Iranian production shows that examining production volumes alone does not fully reveal the changing position of different regions. One of the study's main findings is that natural gas production growth over time has not followed a uniform pattern. Large-scale supply and capacity expansion have driven growth in global natural gas production. In contrast, Asia, the Middle East, and Iran have experienced significant structural changes relative to their initial production levels. Therefore, examining both production volumes and relative growth simultaneously provides a more accurate picture of the geographic changes in global natural gas supply. In this study, before building the forecasting model, we statistically examine the time series' past trend, a step that studies that directly use historical data for forecasting have paid less attention to.

This approach helps to interpret ARIMA forecasts alongside confirmed past trends and estimated rates of change. This integrates past and present natural gas production with its likely future trajectory within a single analytical framework. However, the present study has limitations. First, the ARIMA model relies on past time-series patterns and does not account for the direct impact of external factors, such as energy price fluctuations, climate policies, geopolitical conditions, infrastructure investment, and technological progress. Annual data suit long-term trend analysis but do not capture short-term and seasonal fluctuations in the gas market. Forecasts also assume past patterns will continue; therefore, sudden changes in the energy market structure can increase uncertainty. In addition to fossil fuels, renewable energy sources also provide a good basis for examining and predicting trend indicators. Building on this research, artificial intelligence and advanced numerical models can expand the scope of future studies in this field [36–39]. Multivariate and scenario-based models also allow researchers to consider economic, political, and technological factors when predicting the future path of natural gas production.

5. Conclusion

This study examined the long-term trend of natural gas production and its future prospects at the global, regional, and national levels by combining several analytical methods. First, the statistical significance of the trends was assessed using the Mann-Kendall test. Next, the Sen slope estimator was used to calculate the rate of change, and the ARIMA model was used to forecast production up to 2035. Together, these steps clarified the relationship between past production trends, the rate of change, and its possible future path. A review of data from 1970 to 2025 showed that natural gas production in the world, Asia, the Middle East, and Iran increased significantly. However, growth patterns in these regions differ, and their structural changes have followed different paths. The world and Asia have seen the largest increases in production volume, but a comparison of relative growth shows that the Middle East and Iran have changed significantly relative to their initial production levels. Therefore, examining production volume alongside relative growth helps better understand structural changes in global natural gas supply. The Mann-Kendall test results showed

that the increasing production trend in all areas studied was statistically significant and could not be attributed to random fluctuations alone. The Sen slope estimate also showed that the rate of production increase differed across these areas. The annual growth rates of production in the world, Asia, the Middle East, and Iran were estimated at 594.60, 295.04, 145.48, and 50.39 TWh per year, respectively. Therefore, to examine the evolution of natural gas production, consider both the trend and its rate of change. The ARIMA model predictions also show that, if past patterns continue, production will keep increasing until 2035. Based on these estimates, global production will increase from 41,964.71 TWh in 2025 to about 48,159.54 TWh in 2035. Production in Asia, the Middle East, and Iran is also projected to be about 18,096.72, 9,348.25, and 3,305.26 TWh in 2035, respectively. MAPE values below 10% across all ranges indicate the model's accuracy in representing historical production behavior and support its forecasting efficiency. The main achievement of this research is providing a simple, comprehensive framework for simultaneously analyzing past and future natural gas production. This framework combines three key components, trend, growth rate, and future production trajectory, into a single approach. It also allows comparison of production changes across geographical scales without complex computational structures and can be used in energy security studies, resource planning, and long-term supply assessment. However, forecasts must be interpreted with the inherent uncertainties of time-series forecasting in mind. Structural changes in the energy market, technological developments, macroeconomic policies, and geopolitical factors can change the actual trajectory of natural gas production. Therefore, future research should develop multi-factor and scenario-based models to provide a more comprehensive picture of the industry's long-term outlook.

Ethical issue

The authors are aware of and comply with best practices in publication ethics, specifically regarding authorship (avoidance of guest authorship), dual submission, manipulation of figures, competing interests, and compliance with research ethics policies. The authors adhere to publication requirements that the submitted work is original and has not been published elsewhere in any language.

Data availability statement

The manuscript contains all the data. However, more data will be available upon request from the corresponding author.

Conflict of interest

The authors declare no potential conflict of interest.

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