مركـز الملـك عبـدالله للدراسـات والبحوث البترولية
King Abdullah Petroleum Studies and Research Center

Methane Emissions Baseline Forecasts for Saudi Arabia Using the Structural Time Series Model and Autometrics

Anwar A. Gasim, Lester C. Hunt, and Jeyhun I. Mikayilov

May 2023

Doi: 10.30573/KS--2023-DP08

About KAPSARC

KAPSARC is an advisory think tank within global energy economics and sustainability providing advisory services to entities and authorities in the Saudi energy sector to advance Saudi Arabia's energy sector and inform global policies through evidence-based advice and applied research.

This publication is also available in Arabic.

Legal Notice

Key Points

As a party to the Paris Agreement, Saudi Arabia submitted a baseline target to reduce its emissions as part of its nationally determined contribution (NDC). Baseline targets rest on the development of a counterfactual baseline emissions scenario that shows how emissions would evolve if there were no further efforts to reduce emissions. Saudi Arabia's baseline scenario has not yet been made publicly available.

Two different econometric methods *within a univariate framework* are used to develop baseline methane (CH4) emission forecasts, implicitly extending current drivers, trends, and policies into the future without the need to make assumptions about factors such as economic growth in coming decades. Using two different econometric methods can also provide a robustness check, as each method has its own strengths and weaknesses.

In our modeling of total CH4 emissions in Saudi Arabia, both econometric methods produce rising CH4 emissions projections, but the paths and rates of increase differ between the two methods. This highlights the sensitivity of baseline emission projections to the choice of method.

We use averaging to combine the two methods to generate our baseline CH4 emissions projection for Saudi Arabia, which suggests that CH4 emissions would grow from 117.5 MtCO2eq in 2019 to 137.5 MtCO2eq by 2030, the target year for the Global Methane Pledge. By 2060, the year of the net-zero ambition, our baseline indicates that Saudi Arabia's CH4 emissions would grow to approximately 197.2 MtCO2eq.

Summary

Reducing methane (CH4) emissions is key to near-term efforts to limit global warming. CH4 is the second most abundant anthropogenic greenhouse gas (GHG) in the atmosphere after carbon dioxide (CO2). The production, transport, and consumption of fossil fuels, in addition to waste and agriculture, account for most anthropogenic CH4 emissions globally (IPCC 2018). Although CH4 has only a 12-year lifetime in the atmosphere, it is 84 times more potent per ton than CO2 in a 20-year period and 28 times more potent in a 100-year period (IPCC 2018). The drastically stronger short-term potency of CH4 explains why its short-term impact on global warming is considerably greater than that of CO2. Therefore, meeting the goals of the Paris Agreement necessitates not only decarbonization but also significant CH4 emissions reductions, especially in the near term.

Over 120 countries, including Saudi Arabia, have signed the Global Methane Pledge (2022). Saudi Arabia has been implementing policies to reduce CH4 emissions since the mid-1970s (Saudi Vision 2030 2016). Given the importance of CH4 as a fuel and the fact that flaring and venting release GHG emissions, Saudi Arabia installed a vast gas-collection system in 1982 (Al Suwailem 2020). This network of gas-gathering facilities and pipelines, constructed to collect, process, and utilize gas, has resulted in a substantial reduction in gas flaring and venting. As a continuation of these efforts, in December 2018, Saudi Arabia joined the “Zero Routine Flaring by 2030 Initiative” (Kingdom of Saudi Arabia 2022), which was initiated by the World Bank. Moreover, the Kingdom aims to convert waste materials into organic fuels and targets diverting 94% of the country’s solid waste away from landfills as one of the goals of the Saudi Green Initiative (Kingdom of Saudi Arabia 2022), which will further contribute to reducing CH4 emissions.

To better understand how these measures affect the trajectory of CH4 emissions in Saudi Arabia, it is important to understand where emissions would be in the absence of these measures. In other words, it is important to build a counterfactual scenario that projects CH4 emissions when none of these measures are implemented. This counterfactual baseline scenario is essential to the GHG emissions target set in Saudi Arabia’s nationally determined contribution (NDC), which is a baseline target set relative to a counterfactual GHG emissions baseline scenario.

This paper contributes to the development of baseline emissions scenarios, which are a key ingredient in Saudi Arabia’s NDC, by using econometric methods to produce a baseline for CH4 emissions in Saudi Arabia up to 2060. Different methods, such as econometric, computable general equilibrium, or bottom-up engineering models, can be used to produce baseline scenarios. Each method has its own strengths and weaknesses. Econometric methods attempt to “capture” behavior from historical data of the target variable. The econometric model is then used to forecast how the target variable will evolve based on those historical data.

This paper uses a univariate econometric modeling framework to generate a baseline scenario for CH4 emissions in Saudi Arabia up to 2060. We employ econometric techniques that consider nonstochastic trends and exogenous interventions in the behavior of the modeled variable. The structural time series modeling (STSM) method (Harvey 1989) and the autometrics multipath machine-learning algorithm (Doornik and Hendry [2018], among others) are both used for modeling and projecting.

The utilized methodologies have different modeling philosophies that, when compared and combined, can be used as an “insurance policy” to produce

robust forecasting results (Castle et al. 2021). Using a consistent underlying framework, both modeling approaches utilized the same historical data, ranging from 1984 to 2019, with the same general dynamic functional specification. The final preferred models were then used to forecast CH4 emissions up to 2060, with the combined average projections from the two models used as the baseline scenario.

Our baseline scenario shows that Saudi Arabia's business-as-usual, or baseline, CH4 emissions would grow from 117.5 MtCO2eq in 2019 to 137.5 MtCO2eq by 2030, the target year for the Global Methane Pledge. For 2060, the year of the net-zero ambition, our baseline indicates that Saudi Arabia's CH4 emissions would grow to approximately 197.2 MtCO2eq. Although our method is generally more accurate and useful for the nearer-term projection, it still provides useful information in its longer-term projection. Our projected baseline scenario equips policymakers with a valuable understanding of the efforts needed to achieve the Kingdom's climate goals in both the near and long terms, especially those goals associated with CH4 emissions, as it illustrates the extent to which those efforts could push Saudi Arabia's CH4 emissions onto a more sustainable pathway.

Introduction

Reducing CH_4 emissions is key to near-term efforts to limit global warming. CH_4 is the second most abundant anthropogenic GHG in the atmosphere after CO_2. Anthropogenic activities account for the majority of CH_4 emissions, with natural sources accounting for the remainder (Staniaszek et al. 2022). The production, transport, and consumption of fossil fuels, waste, and agriculture account for most anthropogenic emissions of CH_4 globally (IPCC 2018). Although CH_4 has only a 12-year lifetime in the atmosphere, it is 84 times more potent per ton than CO_2 during a 20-year period (IPCC 2018). The potency of CH_4 when compared to CO_2 explains its considerably greater short-term impact on global warming. Therefore, meeting the goals of the Paris Agreement necessitates not only decarbonization but also significant CH_4 emissions reductions, especially in the near term.

Saudi Arabia has set ambitious goals to reduce GHG emissions, both through its NDC and its participation in the Global Methane Pledge. Saudi Arabia submitted its updated NDC to the United Nations Framework Convention on Climate Change (UNFCCC) in late 2021 (Kingdom of Saudi Arabia 2021). In the updated NDC, the Kingdom stated its aim to eliminate, prevent, and reduce GHG emissions by 278 million tonnes of CO_2 equivalent ($MtCO_2eq$). This goal more than doubled the previous target proposed in the original NDC submitted in late 2015 (Kingdom of Saudi Arabia 2015). Moreover, Saudi Arabia's updated NDC highlights the important role of the Global Methane Pledge and Saudi Arabia's participation in it.

Over 120 countries, including Saudi Arabia, have signed the Global Methane Pledge (UN 2021). The participants agree to reduce global CH_4 emissions from 2020 levels by at least 30% by 2030 (Global Methane Pledge 2021). According to the Global Methane Pledge (2022), CH_4 accounts for roughly half of the rise in the mean global average temperature since preindustrial times. The countries that have signed the pledge together account for nearly half of all anthropogenic CH_4 emissions (Global Methane Pledge 2022). According to the UN (2021), reducing human-made CH_4 emissions is one of the most cost-effective ways to slow global warming and its negative consequences. Unlike CO_2, CH_4 is easily monetized given its role as an important fuel and feedstock.

For decades, Saudi Arabia has been implementing various measures to reduce its GHG emissions, including CH_4. Given the importance of CH_4 as a fuel and the fact that flaring and venting release large quantities of GHG emissions, Saudi Arabia installed a vast gas-collection system in 1982 (Al Suwailem 2020). This network of gas-gathering facilities and pipelines, constructed to collect, process, and utilize gas, resulted in a dramatic reduction in gas flaring and venting. These efforts continued for decades. For example, Saudi Arabia significantly reduced gas flaring from 2.3% of raw gas production in 2009 to 0.5% of raw gas production in 2017 through the expansion of its master gas-collection system (Kingdom of Saudi Arabia 2022, 62). Beyond the oil and gas industry, Saudi Arabia also implemented various programs aimed at lowering CH_4 emissions in solid waste management, such as the development of landfill gas-gathering and flaring systems and the conversion of waste materials to organic fuels.

In its NDC, Saudi Arabia chose to adopt a baseline target, with its GHG emission reduction goal being set relative to a baseline scenario. The IPCC (2022) defined this baseline scenario as a projection of emissions "based on the assumption that no mitigation policies or measures will be implemented beyond those that are already in force and/or are legislated or planned to be adopted." The IPCC (2022) added that baseline scenarios "are not intended to be predictions of the future, but rather counterfactual constructions that can serve to highlight the level of emissions that would occur without further policy effort."

The Saudi NDC does not yet disclose quantitative information about its baseline. Providing a transparent, quantitative baseline can support domestic climate policymaking and send crucial signals to various actors on the direction of travel, enabling the development of well-informed policies and interventions. Moreover, parties to the Paris Agreement are expected to provide information necessary for clarity, transparency, and understanding when communicating their NDCs (UNFCCC 2015).

There have been extensive discussions of the difficulties and challenges associated with developing quantitative baseline projections (Vaidyula and Hood 2018). Baselines are sensitive not only to a range of assumptions about the drivers of GHG emissions but also to the choice of method for generating the baseline. Baseline scenarios can be simulated using different methods, from integrated assessment models to bottom-up engineering models to statistical methods. Within the latter, both univariate and multivariate techniques can be used. Univariate analysis is used to describe statistical techniques that focus on a single variable, such as CH4 emissions. Other explanatory variables, such as gross domestic product (GDP), that influence CH4 emissions are not included but instead are embodied in the historical behavior of the CH4 emissions variable. Multivariate analysis is used to describe statistical techniques in which multiple variables are included—both a dependent variable, such as CH4 emissions, and explanatory variables, such as GDP and population. The choice between univariate and multivariate techniques is based on the forecasting goal and data availability. Since no explanatory variables are used with univariate techniques, there is no need to forecast an explanatory variable such as GDP to generate a CH4 emissions projection. As noted by Belbute and Pereira (2020), univariate forecasts implicitly extend past trends, policies, and drivers into the future, thereby creating a natural baseline scenario. In contrast, with multivariate techniques, a GDP forecast is essential to generate a multivariate projection of CH4 emissions, assuming that GDP is one of the explanatory variables in the model. Nonetheless, a multivariate model can be valuable in helping policymakers understand how emissions might deviate from the baseline if different policies were adopted, since multivariate models include levers such as economic growth that can be adjusted. Ultimately, there is great value in using and comparing different methods to understand how emissions might evolve, and this paper contributes by using a univariate statistical approach.

We adopt a univariate statistical approach to develop baseline projections for CH4 emissions for Saudi Arabia up to 2060. We apply econometric methods that account for nonstochastic trends and exogenous interventions in the CH4 emissions variable's behavior. Specifically, we use the STSM technique (Harvey 1989) and autometrics multipath machine-learning algorithm (Doornik and Hendry [2018], among others) to model and project CH4 emissions in Saudi Arabia. Although similar in some ways, the two approaches are based on different econometric modeling philosophies, and using both therefore provides a robustness check on the estimated models and projections while also allowing us to combine projections as an "insurance policy."

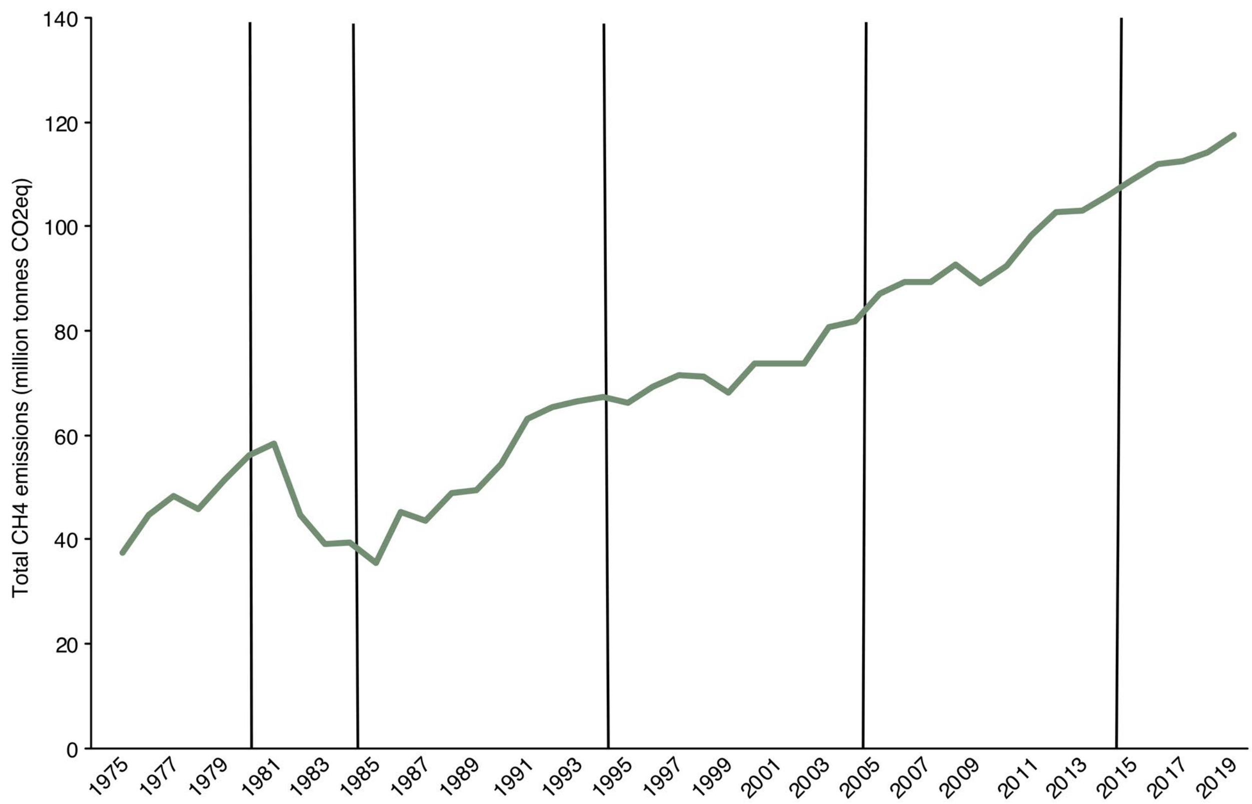
Using the combined projection, our baseline projections suggest that CH4 emissions would grow from 117.5 $MtCO_2eq$ in 2019 to 137.5 $MtCO_2eq$ by 2030, the target year for the Global Methane Pledge. By 2060, our baseline projection suggests that CH_4 emissions would grow to 197.2 $MtCO_2eq$, although the confidence intervals by 2060 become very wide, reflecting the great uncertainties associated with such longer-term forecasts. Nevertheless, our projected baseline scenario is a valuable tool for policymakers, providing an indication of the efforts needed to achieve the Kingdom’s climate goals in the near and long terms and illustrating the extent to which those efforts could push Saudi Arabia’s baseline CH_4 emissions onto a more sustainable pathway.

Background

CH4 emissions in Saudi Arabia almost tripled between 1975 and 2019 (Climate Watch 2022). Figure 1 illustrates the evolution of CH4 emissions, revealing the generally upward-sloping trend and the various speeds at which CH4 emissions grew during different periods. Figure 1 also highlights the fall in the early 1980s, when Saudi Aramco installed the Master Gas System (MGS)—a gas network system designed to collect, process, and transport gas for utilization (Al Suwailem 2020), which resulted in a dramatic reduction in gas flaring and venting.

Between 1975 and 1981, CH4 emissions grew on average by 4.9% a year, rising from 37.5 to 58.3 mtCO2eq. During the following five years (1981–1985), CH4 emissions declined by 8.3% a year following the launch of the MGS, reaching a trough of 35.5 mtCO2eq in 1985. CH4 emissions grew relatively rapidly in the following decade (1986–1995), at 6.8% annually, in line with rapid increases in population and oil and gas production in Saudi Arabia (Saudi Central Bank 2022). During the subsequent decade (1996–2005), the rate of growth slowed to 2.8%. It slowed again to 2.3% in 2006–2015, reflecting Saudi Arabia's increasing focus on reducing CH4 emissions, especially those from the oil and gas sector. Between 2016 and 2019, the rate of growth slowed further to 1.9% as CH4 emissions reached 117.5 mtCO2eq in 2019.

Figure 1. Total CH4 emissions.



Source: PIK (2022).

The waste (solid waste disposal and industrial wastewater), oil and gas (oil refining, natural gas distribution, and natural gas leakage), and agriculture (mainly enteric fermentation) sectors accounted for most CH_4 emissions in Saudi Arabia, although the shares of these sectors changed considerably over time (Kingdom of Saudi Arabia 2014-2022).

It is worth mentioning that there appear to be uncertainties about both the amount of total CH_4 emissions and the contributions of different sectors to this total. In contrast to estimates for CO_2 emissions, CH_4 emissions estimates by the Kingdom of Saudi Arabia (2022) in its national communication, PIK (Gütschow et al. 2021), and the IEA (2022) differ considerably in both the total and the contributions of different sectors. Given the absence of a consistent time series from both the Saudi government and the IEA (2022), we use and model PIK data in this paper to project CH_4 emissions.

Methodologies and Data

Overview of Methodologies Employed

There are many ways to produce baseline emissions forecasts, such as integrated assessment modeling, computable general equilibrium, bottom-up engineering, and statistical approaches. The first three approaches are generally data-intensive and require many assumptions but can arguably provide users with more control over the underlying drivers and how they may influence emissions in the future. Statistical approaches are far less data-intensive, especially when using a univariate framework, which requires nothing more than historical time series data on emissions. One advantage of simple univariate statistical models is their forecasting performance. Stock and Watson (2010) and Castle et al. (2015), for example, discussed how simple univariate models typically perform better in forecasting.

In this paper, we utilize the STSM and autometrics, two statistical approaches, to generate baseline projections for CH4 emissions within a univariate framework. To the best of our knowledge, very few studies appear to have used either method. Gasim et al. (2022) appears to be the exception, since they produced CO2 baseline forecasts for Saudi Arabia using these two techniques up to 2060. This paper, therefore, complements their work by also using the STSM and autometrics to provide CH4 baseline emissions forecasts to 2060. Similar to Gasim et al. (2022), we use these methods because of their ability to explain the data with a combination of trends and interventions that can capture the effects of shocks and policy changes on total CH4 emissions. Despite the two methods' similarities, they differ in the way they incorporate the interventions (see the Methodology section in the Appendix for further details). Following the approach used by Gasim et al. (2022) in generating their CO2 baseline scenario, we set our CH4 emissions baseline to be the average of the baseline forecasts produced by the STSM and autometrics.

To ensure model comparability between the STSM and autometrics, we start the estimation procedure with a consistent general univariate model. In both approaches, we model the natural logarithm of total CH4 emissions, denoted by lower-case ch_{4t}, where t denotes the year. We include four lags of the dependent variable to capture autoregressive behavior in the equations with data for the period 1984–2019. Four lags were chosen given the need for a reasonable number of lags in a univariate model and the number of observations, which is consistent with Enders (2015). The four-year lag implies an estimation period of 1988–2019. That is, the selected maximum lag is four, and the optimal lag number is then selected based on several diagnostic tests as well as model selection criteria under the general-to-specific (Gets) modeling approach (Hendry and Doornik 2014).

The general specification that is used as a starting point with both methods is shown below:

$$ch_{4_t} = intercept + \alpha_1 ch_{4_{t-1}} + \alpha_2 ch_{4_{t-2}} + \alpha_3 ch_{4_{t-3}} + \alpha_4 ch_{4_{t-4}} + random\ error\ term \qquad (1)$$

From this general starting point, a specific "preferred" or "final" equation is obtained by adding statistically significant interventions (also known as dummy variables) and dropping the nonsignificant right-side variables while monitoring an array of diagnostic tests. This is commonly known as the Gets approach. More details on the methodologies, data, and chosen estimation period can be found in the Appendix. According to Castle et al. (2021), a combination of forecasts is a good “insurance policy,” and they demonstrate that this works well across many settings. Hence, in this paper, the baseline projection is the average of the projections from the two different methods.

Data

The time series CH4 emissions for Saudi Arabia were taken from Climate Watch (2022) and were sourced from the PRIMAP-hist national historical emissions time series dataset v2.3.1 (Gütschow et al. 2021). This dataset is based on countries’ official inventories submitted to the UNFCCC, with various methods used to fill in the gaps. Nevertheless, we found discrepancies between the official Saudi submissions to the UNFCCC and the PRIMAP-hist numbers. Although the dataset stretches all the way back to 1750, we set 1988–2019 as the estimation period to reduce potential data-related issues, as the oldest official Saudi GHG inventory stretches back only to 1990.

Econometric Results and Baseline Forecasts

Econometric Results

Preferred autometrics and STSM equations (which can also be referred to as specifications or models) were obtained using each econometric method. Starting from the general specification, the preferred specifications obtained with each method passed all the diagnostic tests.

Autometrics Preferred Model/ Specification

The final preferred specification estimated over the period 1988–2019 using the autometrics approach is given by

$$\widehat{ch_{4_t}} = 1.3636^{***} + 0.6965^{***}ch_{4_{t-1}} + 0.2069^{*}ch_{4_{t-2}} - 0.1871^{**}ch_{4_{t-3}} - 0.0566^{***}\ DIIS_{1999} - 0.0493^{***}\ DIIS_{2002} + 0.1135^{***}IIS_{1991} + 0.0072^{***}TIS_{2007} \qquad (2)$$

where $\widehat{\ }$ denotes a fitted (estimated) value and *, **, and *** represent coefficients that are statistically significant at the 10%, 5%, and 1% levels, respectively. (Full details of the estimated equation are provided in the Appendix.) In terms of the estimated coefficients, the autometrics equation includes three significant lagged dependent variable terms, which are the one-year, two-year, and three-year lags of the natural logarithm of CH4 emissions, with the coefficients on the one-year and two-year lags being positive and the coefficient on the three-year lag being negative, giving a positive combined effect of just over 0.7 (thus, the large positive effect that comes through in the first two years is subsequently dampened in the third year given the negative coefficient on the three-year lagged variable). In addition, four interventions are retained in the model following the autometrics selection procedure: two differenced impulse-indicator interventions for 1999 and 2002, one impulse-indicator intervention for 1991, and one trend-indicator intervention for 2017. It is not immediately obvious what causes some interventions, but there are obvious events that might be associated with others, such as the 1991 intervention, which probably reflects the Gulf War; the 2009 intervention, which probably reflects the aftermath of the global financial crisis; and the 2017 intervention, which might well reflect the early impact of Saudi Vision 2030 reforms (Saudi Vision 2030 2016).

STSM Preferred Model/ Specification

The final preferred specification estimated over the period 1988–2019 using the STSM approach is given by

$$\widehat{ch_{4_t}} = \hat{\gamma}_t + 0.5333^{***}\ ch_{4_{t-1}} - 0.2007^{*}\ ch_{4_{t-2}} + 0.3386^{***}\ \Delta ch_{4_{t-3}} \qquad (3a)$$

where the estimated trend ($\hat{\gamma}_t$) is given by the following equation:

$$\hat{\gamma}_t = 2.6706^{***} + 0.0160^{***}t - 0.1983^{***}\ Irr_{1989} - 0.0767^{***}\ Irr_{1999} - 0.0578^{***}\ Irr_{2009} \qquad (3b)$$

Again, *, **, and *** represent coefficients that are significant at the 10%, 5%, and 1% levels, respectively (fuller details of the estimated equation are given in the Appendix). Δ is a difference operator, while Irr_t is a dummy variable that takes a value of “1” at time t and “0” otherwise. In terms of the estimated coefficients, the STSM equation includes one-year and two-year lags of the natural logarithm of CH4 emissions as well as the three-year lag of the difference in the natural logarithm of CH4 emissions. The sum of the estimated coefficients on the lagged natural logarithm of CH4 emissions in the equation is just over 0.3, which is somewhat lower than that for the autometrics model. However, the trend is found to be strongly upward-sloping with an underlying growth of 1.6% per annum with outlier interventions for 1989, 1999, and 2009. Again, similar to the autometrics interventions, it is possible to find an explanation for some of these interventions, such as the 1991 intervention (reflecting the Gulf War) and the 2009 intervention (reflecting the aftermath of the global financial crisis).

Methane Emissions Baseline Forecasts

The preferred autometrics and STSM estimated specifications detailed in the previous section were used to generate total CH4 baseline forecasts until 2060 for Saudi Arabia. Unlike the CO2 projections in Gasim et al. (2022), there is a wide disparity between the CH4 projections from the two different methods, as discussed below and presented in Table 1 and Figure 2.

Autometrics Methane Emissions Baseline Forecast

As shown in Figure 2a, despite the inclusion of interventions in the specific equation through the autometrics procedure, the CH4 projection resulting from the estimated model is driven by the sum of the coefficients on the lagged dependent variable (approximately 0.7). Thus, the projection of CH4 emissions for Saudi Arabia stabilizes at approximately 122.2 million tonnes of CO2eq by the mid-2020s. The historical growth rate of CH4 has generally decreased over the years, and the autometrics projection appears to extend this declining growth rate trend into the future, leading to a flattening pattern of CH4 emissions. Although the preferred model includes a trend with a positive sign, it ends in 2017, further contributing to the flattening trend. Figure 2a also illustrates the 95% confidence intervals for the autometrics projections. The confidence intervals using autometrics grow larger toward 2060 but generally remain somewhat tight around the forecasted values. Relative to the STSM forecasts, the confidence intervals with autometrics are wider.

STSM Methane Emissions Baseline Forecast

For the STSM specific equation, the estimated overall autoregressive effect (approximately 0.3) is almost half the size of that found for the autometrics model. Therefore, this autoregressive part of the equation drives the baseline forecast upward less than the autometrics equation does. However, this weaker upward-sloping effect of the STSM is more than “compensated for” by the strongly upward-sloping deterministic trend (with an annual growth rate of approximately 1.6%). Consequently, the CH4 emissions projection from the estimated STSM model is higher than that from the autometrics approach, rising relatively strongly throughout the baseline forecast period, as illustrated in Figure 2b. The STSM model projection appears to extend the generally upward-sloping trend of CH4 emissions in Saudi Arabia, unlike the autometrics model, which appears to emphasize the recently declining growth rates. Figure 2b also illustrates the 95% confidence intervals for the STSM projections. Relative to the autometrics forecasts, the confidence intervals with the STSM are narrower.

Average Methane Emissions Baseline Forecast

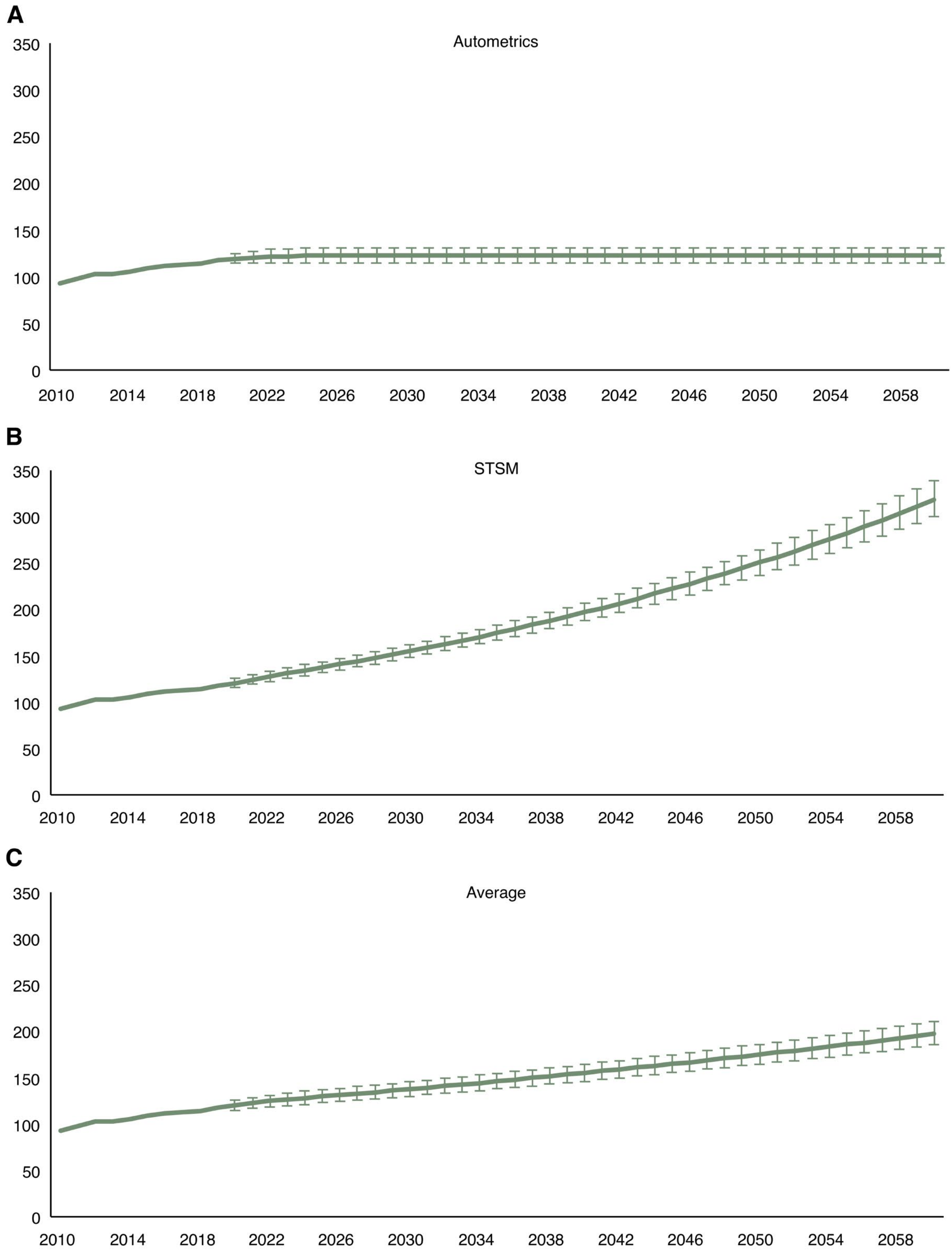
Given the repeated finding that "simple combination forecasts outperform sophisticated adaptive combination methods in empirical applications" (Stock and Watson 2004, 428), we use the simple average of our projections from the two models as an "insurance policy" (Castle et al. 2021) with the aim of generating a more accurate baseline projection. Combining forecasts can lead to narrower confidence intervals, but we adopt a more conservative approach by applying a simple average to obtain the standard errors for our combined forecast. Table 1 and Figure 2c show that, unlike the baseline CO2 projections in Gasim et al. (2022), there is some disparity between the baseline CH4 projections from each method. The autometrics baseline forecast suggests that by 2030, Saudi Arabia would be emitting approximately 122 MtCO2eq of CH4 emissions and would remain at this level until 2060. However, the STSM baseline forecast suggests that Saudi Arabia would be emitting approximately 150 MtCO2eq of CH4 in 2030 and approximately 320 MtCO2eq in 2060. Given the disparity, we believe the prudent approach to producing a CH4 baseline forecast for Saudi Arabia is to take the average of these forecasts (average of the natural logarithm forecasts), as shown in Table 1 and Figure 2c. Our averaged baseline, illustrated in Figure 2c, suggests that without changes to current policies, CH4 emissions would rise to approximately 137.5 MtCO2eq in 2030 and approximately 197.2 MtCO2eq in 2060.

Table 1. Saudi Arabia's total CH4 emissions (in MtCO2eq).

Year	Autometrics	STSM	Average
1984	39.3	39.3	39.3
1990	54.5	54.5	54.5
2000	73.8	73.8	73.8
2010	92.5	92.5	92.5
2019	117.5	117.5	117.5
2025	122.2	137.7	129.7
2030	122.2	154.7	137.5
2035	122.2	174.6	146.1
2040	122.2	196.9	155.1
2045	122.2	222.1	164.7
2050	122.2	250.4	174.9
2055	122.2	282.4	185.7
2060	122.2	318.5	197.2

Source: Authors' calculations. Data up to 2019 are from Climate Watch (2022).

Figure 2. Saudi Arabia's historical total CH4 emissions (2010–2019) in MtCO2eq and projections (2020–2060) in MtCO2eq. The 95% confidence intervals are illustrated.



Source: Authors' calculations. Data up to 2019 are from Climate Watch (2022).

Conclusion and Policy Implications

To address climate change, Saudi Arabia, like many other countries, set a baseline GHG emissions target in its NDC. Baseline targets rest on the construction of baseline scenarios for GHG emissions, so a deeper understanding of how baseline emissions would evolve in Saudi Arabia is vital for understanding the target. In Saudi Arabia, the two most important GHGs are CO_2 and CH_4. However, the Saudi NDC does not yet disclose quantitative information about its baselines for any of these GHGs. Providing a transparent, quantitative baseline can support domestic climate policymaking and send crucial signals to various actors on the direction of travel, enabling the development of well-informed policies and interventions. Nevertheless, developing baselines is challenging (Vaidyula and Hood 2018), especially in countries such as Saudi Arabia that are undergoing rapid transformation. Building on the work of Gasim et al. (2022), who appear to have been the first to estimate CO_2 emissions baselines for Saudi Arabia using econometric methods, in this paper, we model and forecast baseline CH_4 emissions using a similar econometric framework.

Since reducing CH_4 emissions is key to near-term efforts to limit global warming, Saudi Arabia, along with over 100 other countries, joined the Global Methane Pledge, which aims to reduce global CH_4 emissions by 30% by 2030 compared to 2020. Although CH_4 has only a 12-year lifetime in the atmosphere, it is 84 times more potent per ton than CO_2 over a 20-year period (IPCC 2018). Its potency compared to that of CO_2 explains its considerably greater short-term impact on global warming. This fact underscores the importance of modeling and projecting CH_4 emissions.

This paper contributes to the development of quantitative baseline CH_4 emissions scenarios for Saudi Arabia, which are a key ingredient in its NDC. We model and project the baseline for CH_4 emissions in Saudi Arabia up to 2060 using a univariate econometric modeling framework. Specifically, we use both the STSM (Harvey 1989) and the autometrics multipath machine-learning algorithm (Doornik and Hendry [2018], among others) to model and project CH_4 emissions.

Our baseline scenario shows that Saudi Arabia's business-as-usual, or baseline, CH_4 emissions would grow from 117.5 $MtCO_2eq$ in 2019 to 137.5 $MtCO_2eq$ by 2030, the target year for the Global Methane Pledge. For 2060, the year of the net-zero ambition, our baseline indicates that Saudi Arabia's CH_4 emissions would grow to approximately 197.2 $MtCO_2eq$. It should be noted that one weakness of such statistical univariate methods is that the evolution of emissions in the distant future, even in a baseline, is likely to be less similar to how emissions were evolving in the 1990s, 2000s and 2010s, on which our univariate models are based. Therefore, our method is generally more useful for nearer-term forecasting. Nevertheless, our projected baseline scenario is a valuable tool for policymakers, providing an indication of the efforts needed to achieve the Kingdom's climate goals in the near and long terms. In particular, it illustrates the extent to which those efforts could push Saudi Arabia's baseline CH_4 emissions onto a more sustainable pathway.

References

Al Suwailem, Majed. 2020. “Saudi Arabia’s Gas Flaring Mitigation Experience.” KAPSARC Commentary.

Arab News. 2021. “Saudi Arabia to reach net zero carbon by 2060: Crown Prince Mohammed bin Salman.” https://www.arabnews.com/node/1953441/business-economy

Belbute, José M., and Alfredo M. Pereira. 2020. “Reference Forecasts for CO2 Emissions from Fossil-fuel Combustion and Cement Production in Portugal.” *Energy Policy* 144:111642. https://doi.org/10.1016/j.enpol.2020.111642

Castle, Jennifer L., Michael P. Clements, and David F. Hendry. 2015. “Robust approaches to forecasting.” *International Journal of Forecasting*. 31(1):99-112. DOI: https://doi.org/10.1016/j.ijforecast.2014.11.002

Castle, Jennifer L., David F. Hendry, and Andrew B. Martinez. 2017. “Evaluating Forecasts, Narratives and Policy Using a Test of Invariance.” *Econometrics* 5(3):39. http://dx.doi.org/10.3390/econometrics5030039

Castle, Jennifer L., Jurgen A. Doornik, and David F. Hendry. 2021. “Selecting a Model for Forecasting.” *Econometrics* 9(3):26. https://doi.org/10.3390/econometrics9030026

Doornik, Jurgen A., and David F. Hendry. 2018. *Empirical Econometric Modelling Using PcGive: Volume I, 8th Edition.* London: Timberlake Consultants Press.

Enders, Walter. 2015. *Applied Econometrics Time Series*. Hoboken, NJ: Wiley.

Global Methane Pledge, 2022. “Global Methane Pledge.” https://www.globalmethanepledge.org/

Gütschow, Johannes, Annika Günther, Mika Pflüger. 2021. “The PRIMAP-hist national historical emissions time series v2.3.1 (1850-2019).” *Zenodo.* Doi:10.5281/zenodo.5494497.

Harvey, Andrew C., 1989. *Forecasting, Structural Time Series Models and the Kalman Filter*. Cambridge University Press, Cambridge, UK.

Harvey, Andrew C. and Koopman, Siem J., 1992. “Diagnostic checking of unobserved-components time series models.” *Journal of Business & Economic Statistics* 10:377–389. DOI: 10.1080/07350015.1992.10509913

Hendry, David F. 2020. “First in, First out: Econometric Modelling of UK Annual CO2 Emissions, 1860–2017.” Accessed March 3, 2022. https://www.nuffield.ox.ac.uk/economics/papers/2020/2020W02_CO2UKEmissionsModel20.pdf

Hendry, David F., and Jurgen A. Doornik. 2014. *Empirical Model Discovery and Theory Evaluation: Automatic Selection Methods in Econometrics*. Cambridge, M.A.: The MIT Press. https://www.jstor.org/stable/j.ctt9qf9km

International Energy Agency (IEA). 2022. “World Emissions of CO2, CH4, N2O, HFCs, PFCs and SF6.”

Intergovernmental Panel on Climate Change (IPCC). 2022. “Definition of Terms Used Within the DDC Pages.” https://www.ipcc-data.org/guidelines/pages/glossary/glossary_b.html#:~:text=In%20the%20context%20of%20transformation,or%20planned%20to%20be%20adopted

KAPSARC. 2022. “Energy Policy Solutions.” Accessed June 20, 2022. https://eps.kapsarc.org/Scenarios/home

Kingdom of Saudi Arabia, 2015. “The Intended Nationally Determined Contribution of the Kingdom of Saudi Arabia under the UNFCCC.” Submitted to The United Nations Framework Convention on Climate Change (UNFCCC). https://www4.unfccc.int/sites/NDCStaging/Pages/All.aspx

———. 2021. “Updated First Nationally Determined Contribution.” Submitted to The United Nations Framework Convention on Climate Change (UNFCCC) https://www4.unfccc.int/sites/NDCStaging/Pages/All.aspx

———. 2022. “Fourth National Communication (NC4).” Submitted to The United Nations Framework Convention on Climate Change (UNFCCC). March 2022. Accessed June 5, 2022. https://unfccc.int/sites/default/files/resource/7123846_Saudi%20Arabia-NC4-1-Fourth%20National%20Communication%20NC4%20Kingdom%20of%20Saudi%20Arabia%20March%202022.pdf

Koopman, Siem Jan, Andrew C. Harvey, Jurgen A. Doornik, and Neil Shephard. 2007. *Stamp: Structural Time Series Analyser, Modeller and Predictor: STAMP 8*. London: Timberlake Consultants Press.

Patole, Shambhu C. 2021. “Time Series Forecasting of Methane Emissions from Livestock using Machine Learning.” M.Sc. research project. Accessed May 31, 2022. http://norma.ncirl.ie/5210/1/shambhuchandrakantpatole.pdf

Rehman Shafiq U., Ijaz Husain, Muhammad Z. Hashmi, Elsayed E. Elashkar, Jameel A. Khader, and Mohammed Ageli. 2021. “Forecasting and modeling of atmospheric methane concentration.” *Arabian Journal of Geosciences* 14:1667. DOI: 10.1007/s12517-021-07998-0

Rivža Peteris, Bērziņa Laima, Mozga Ivars, and Lauva Didzis. 2015. “Long-Term Forecasting of Agricultural Indicators and GHG Emissions in Latvia.” 25th Congress Nordic View to Sustainable Rural Development.

Samoilov I.A., and A.I. Nakhutin. 2009. “Estimation and Medium-term Forecasting of Anthropogenic Carbon Dioxide and Methane Emission in Russia with Statistical Methods.” *Meteorologiya I Gidrologiya* 6:25–32. DOI: 10.3103/S1068373909060028

Saudi Vision 2030. 2016. “Saudi Vision 2030.” https://www.vision2030.gov.sa/media/rc0b5oy1/saudi_vision203.pdf

Shabaneh, Rami, Bertrand Williams-Rioux, and Fahad Bin Haji. 2022. “Moving Saudi Arabia’s Role in the Global Methane Pledge Forward.” KAPSARC Instant Insight. Accessed June 6, 2022. https://www.kapsarc.org/research/publications/moving-saudi-arabias-role-in-the-global-methane-pledge-forward/

Staniaszek, Zosia, Paul T. Griffiths, Gerd A. Folberth, Fiona M. O’Connor, Luke Abraham, and Alexander T. Archibald. 2022. “The role of future anthropogenic methane emissions in air quality and climate.” *Climate and Atmospheric Science* 5:21. DOI: 10.1038/s41612-022-00247-5

Stock, James H., and Mark W. Watson. 2004. “Combination forecasts of output growth in a seven-country data set.” *Journal of Forecasting* 23:405–430. DOI: 10.1002/for.928

———. 2010. “Modelling Inflation after the Crisis.” NBER Working Paper Series 16488. DOI: 10.3386/w16488

Tarazkar Mohammad Hassan, Dehbidi Navid Kargar, Ansari Rohul Ameen, Pourghasemi Hamid Reza. 2020. “Factors affecting methane emissions in OPEC member countries: does agricultural production matter?” *Environment, Development and Sustainability* 23:6734–6748.

Tutak Magdalena and Brodny Jaroslaw. 2019. “Forecasting methane emissions from hard coal mines including the methane drainage process.” *Energies* 12(20):3840. DOI: 10.3390/en12203840

United Nations Environment Programme and Climate and Clean Air Coalition. 2021. “Global Methane Assessment: Benefits and Costs of Mitigating Methane Emissions.” Accessed June 5, 2022. https://www.unep.org/resources/report/global-methane-assessment-benefits-and-costs-mitigating-methane-emissions

United Nations Framework Convention on Climate Change (UNFCCC). 2015. “Paris Agreement.” 2015. https://unfccc.int/sites/default/files/english_paris_agreement.pdf

———. 2021. “Nationally Determined Contributions under the Paris Agreement. Synthesis Report by the Secretariat.” Report presented at the Glasgow Climate Change Conference, Glasgow, Scotland, October/November 2021. https://policycommons.net/artifacts/1815006/cma2021_08_adv/2551290/

———. 2022. “GHG Profiles - Non-Annex I.” https://di.unfccc.int/ghg_profile_non_annex1

Vaidyula, Manasvini, and Christina Hood. 2018. “Accounting for Baseline Targets in NDCs: Issues and Options for Guidance.” Climate Change Expert Group Paper No. 2018(2). https://doi.org/10.1787/2227779X

Yusuf, Rafiu O., Zainura Z. Noor, and Mohd A. Hassan. 2015. “Historical and projected methane emission determination in Malaysia (1980-2020).” *Sustainable Environmental Research* 25(1): 37-45.

Yusuf, Rafiu O., , Zainura Z. Noor, Ahmed H. Abba, Mohd A. Hassan, Mohammed R. Majid, and Nasiru I. Medugu. 2014. “Predicting methane emissions from livestock in Malaysia using the ARIMA model.” *Management of Environmental Quality: An International Journal*. 25(5):585-599. DOI: 10.1108/MEQ-01-2013-0001

Appendix

A.1. Literature Review

Several studies have attempted to identify a CH_4 environmental Kuznets curve (EKC) hypothesis for a group of countries, including Saudi Arabia. However, given the focus of this research, we restrict the review to papers that dealt with modeling and forecasting potential trajectories for CH_4 emissions.

Employing multivariate linear regression models and annual Russian data over the period 1990–2006, Samoilov and Nakhutin (2009) modeled anthropogenic carbon dioxide and CH_4 emissions and produced forecasts for 2010. Using a univariate modeling approach, Yusuf et al. (2014) applied the autoregressive integrated moving average (ARIMA) approach, modeled total Malaysian CH_4 emissions for the 1980–2008 sample period and produced forecasts for the 2009–2020 horizon. In a similar study, using the same approach, Yusuf et al. (2015) modeled Malaysian sector-specific CH_4 emissions for the 1980–2011 sample period and produced forecasts up to 2020. Rivža et al. (2015) utilized a macroeconomic model to forecast agricultural GHG emissions, including CH_4 emissions, for 2030 in Latvia. Tutak and Brodny (2019) modeled CH_4 emissions from Polish hard coal mines for data from 1993 to 2018, employing an artificial neural network framework, and generated forecasts for 2025. Rehman et al. (2021), in the case of Pakistan, India, and China, modeled the CH_4 concentration in the air using different univariate estimation techniques and data from 1970 to 2012 and generated forecasts for 2020. Patole (2021) provided a review of papers devoted to forecasting CH_4 emissions, mainly sector-specific, and generated forecasts for CH_4 emissions from livestock by 2024, utilizing machine learning techniques. Patole (2021) used worldwide data covering 1961–2019 for modeling exercises.

As an example of testing the EKC hypothesis for CH_4 emissions, Tarazkar et al. (2020), in the case of OPEC member countries, modeled CH_4 emissions by applying panel estimation techniques to data ranging from 1995 to 2012 and tested the validity of the EKC hypothesis. In their modeling exercises, Tarazkar et al. (2020) included an index of agricultural crop production and an index of livestock production, in addition to the widely used income and energy consumption proxies, as drivers of CH_4 emissions.

Shabaneh et al. (2022) provided insight into the current state of CH_4 emissions in Saudi Arabia as well as the sources of these emissions. Furthermore, Shabaneh et al. (2022) highlighted Saudi Arabia's promises and plans for contributing to the Global Methane Pledge, as one of the parties, to reduce CH_4 emissions by 2030. A version of the Energy Policy Simulator (EPS, KSA) by KAPSARC (2021) was calibrated to make business-as-usual as well as various policy scenarios for CH_4 emissions by 2050. The EPS projected value for CH_4 emissions, in the business-as-usual scenario, for 2050 is 148.18 million tonnes.

As the reviewed literature demonstrates, to the best of our knowledge, no individual paper has been devoted to modeling and forecasting Saudi Arabian CH_4 emissions. In addition, considering the capabilities of different modeling/forecasting techniques, we are not aware of any paper forecasting CH_4 emissions utilizing methods such as STSM and autometrics via the Gets modeling approach, which enables exogeneous interventions to be captured through stochastic trends and the selection of drivers utilizing machine-learning algorithms.

A.2. Detailed Methodologies

A.2.1. Autometrics

This method applies the autometrics multipath-search machine-learning algorithm (see Doornik and Hendry [2018], among others) to the Gets modeling approach (see Hendry and Doornik [2014], among others). The autometrics algorithm identifies potential interventions caused by policy changes and shocks whose omission might cause biased estimation results. It automatically assigns one-time pulse, blip, change in level, and break in trend dummies to each observation and chooses the significant ones by utilizing the block-search algorithm.

With autometrics, the following general specification is used to model the natural log of total CH4 emissions:

$$ch_{4_t} = \alpha_0 + \alpha_1 ch_{4_{t-1}} + \alpha_2 ch_{4_{t-2}} + \alpha_3 ch_{4_{t-3}} + \alpha_4 ch_{4_{t-4}} + \sum_1^T \vartheta_i\, IIS_t + \sum_1^T \tau_i\, SIS_t + \sum_1^T \varphi_i\, DIIS_t + \sum_1^T \omega_i\, TIS_t + \varepsilon_t \qquad \text{(A1)}$$

where

IIS_t = impulse-indicator saturation, which takes the value of "1" at time *t* and "0" otherwise;

SIS_t = step-indicator saturation, which takes the value of "1" until time *t* and "0" otherwise;

$DIIS_t$ = differenced impulse-indicator saturation, which takes the value of "1" at time *t*, "-1" at time *t+1,* and "0" otherwise;

TIS_t = trend-indicator saturation, which takes the value of "0" after time *t+1*, "-1" at time *t*, "-2" at time *t-1,* "-3" at time *t-2* and so on;

$\alpha_i, \vartheta_i, \tau_i, \varphi_i, \omega_i$ are regression coefficients to be estimated; and

ε_t = a random error term, $\varepsilon_t \sim NID\,(0, \sigma_\varepsilon^2)$.

The modeling procedure using the autometrics algorithm consists of two steps (Castle et al. [2017]; Hendry [2020], *inter alia*). The first step involves fixing the constant term and all four lagged values of the dependent variable while allowing the algorithm to search for and choose the intervention dummies using a very tight significance level (0.01%). If no interventions are found, then the procedure is repeated using slightly easier significance levels (0.1%, 1%, etc.) to search for potential interventions that are relevant to the relationship. The resultant specification from this procedure is known as the general unrestricted model (GUM). The second step involves fixing the dummies chosen in the first step while unfixing the four lagged values of the dependent variable and searching for the final specification, which is chosen based on the congruency criterion and multiple diagnostic tests. In the second step, given our baseline forecasting purposes, a relatively loose significance level is used (10%), as suggested by Castle et al. (2021). The multipath selection procedure is performed using the PcGive-15.10 econometric modeling program (Doornik and Hendry 2018). The final chosen specification is then used to produce a baseline forecast.

A.2.2. Structural Time Series Model (STSM)

The STSM allows users to model a variable, such as total CH4 emissions, while allowing for the possibility of a stochastic trend. As noted by Harvey (1989), this stochastic trend captures long-term movements in a time series variable that can be extrapolated into the future. To capture autoregressive behavior and ensure consistency between approaches, we start with the same autoregressive equation (with four lags) to model the natural logarithm of total CH4 emissions:

$$ch_{4_t} = \gamma_t + \alpha_1 ch_{4_{t-1}} + \alpha_2 ch_{4_{t-2}} + \alpha_3 ch_{4_{t-3}} + \alpha_4 ch_{4_{t-4}} + \varepsilon_t \quad \text{(A2a)}$$

where γ_t = the stochastic trend, also interpreted as a time-varying intercept, and

ε_t = a random error term, $\varepsilon_t \sim NID\ (0, \sigma_\varepsilon^2)$.

The stochastic trend is composed of a level μ_t and a slope β_t, which are defined as follows:

$$\mu_t = \mu_{t-1} + \beta_{t-1} + \eta_t \quad \text{(A2b)}$$

$$\beta_t = \beta_{t-1} + \xi_t \quad \text{(A2c)}$$

where $\eta_t \sim NID\ (0, \sigma_\eta^2)$ and $\xi_t \sim NID\ (0, \sigma_\xi^2)$ are mutually uncorrelated random disturbance terms. If the variances in either η_t or ξ_t are found to be zero, that component of the trend becomes deterministic. If both hyperparameters are found to be zero, the stochastic trend collapses into a deterministic trend.

As in autometrics, different types of dummy interventions (irregular, slope, and level) can be identified and added to the model (Harvey and Koopman 1992). These interventions capture important breaks and structural changes at certain dates during the estimation period. These interventions can be incorporated into the stochastic trend, which can be defined as follows:

$\gamma_t = \mu_t$ + irregular interventions + level interventions + slope interventions (A2d)

The estimation strategy involves initially estimating Eq (A2a), (A2b), and (A2c) by maximum likelihood coupled with the Kalman filter using the software package STAMP 8.40 (Koopman et al. 2007). Appropriate irregular, level, and/or slope interventions are identified and included in the model, and statistically nonsignificant lagged dependent variables are excluded while ensuring that the estimated final specification passes an array of standard diagnostic tests[1] and that the auxiliary residuals associated with the irregular, level, and slope components do not suffer from non-normality. This procedure produces a final preferred specification that can be used to produce a baseline forecast.

[1] These tests are detailed in the results section below.

A.3. Methane Estimation Results

A.3.1. Autometrics

Full details of the preferred autometrics specification that was obtained by following the methodology detailed above are provided in Table A1. This shows that the preferred model is well specified, passing all diagnostic tests. The specification includes three significant lagged dependent variable terms, which are the one-year, two-year, and three-year lags of the natural logarithm of CH4 emissions, with the coefficients on the one-year and two-year lags being positive and the coefficient on the three-year lag being negative, giving a positive combined effect of just over 0.7. In addition, four interventions are retained in the model following the autometrics selection procedure: two impulse-indicator interventions for 1999 and 2002, respectively; one impulse-indicator for 1991; and one trend-indicator intervention for 2017.

Table A1. Preferred autometrics specification

Time period	**1988–2019**
Estimated coefficients	
α_0	1.3636^{***}
α_1	0.6965^{***}
α_2	0.2069^{*}
α_3	-0.1871^{**}
α_4	–
Interventions/Indicator	
$DIIS_{1999}$	-0.0566^{***}
$DIIS_{2002}$	-0.0493^{***}
IIS_{1991}	0.1135^{***}
TIS_{2017}	0.0072^{***}
Goodness of fit	
R^2	0.994
$\bar{R}^2$	0.992
F	524.7
Residual diagnostics	
AR (1-2)	2.50
ARCH (1-1)	0.25
Normality	1.70
Hetero	0.41
Hetero-X	n/a
RESET	1.02

Source: Authors' calculations.
Notes:
*, **, and *** represent significance at the 10%, 5%, and 1% levels, respectively.
R^2 is the coefficient of determination.
$\bar{R}^2$ is the adjusted coefficient of determination.
F is the overall goodness-of-fit statistic distributed as $F_{(7, 24)}$.
AR (1-2) is the 2nd-order autocorrelation statistic distributed as $F_{(2, 22)}$.
ARCH (1-1) is the 1st-order autoregressive conditional heteroskedasticity statistic distributed as $F_{(1, 30)}$.
Normality is the Doornik and Hansen statistic and is approximately distributed as $\chi^2_{(2)}$.
Hetero is a heteroscedastic statistic distributed as $F_{(12, 18)}$, and Hetero-X is an alternative test for heteroscedasticity and misspecification, but there were not enough observations for the test.
RESET is the Ramsey RESET statistic distributed as $F_{(2, 22)}$.

A.3.2 STSM

Full details of the preferred STSM specification that was obtained by following the methodology detailed above are provided in Table A2. As in the autometrics model, the preferred model is well specified, passing all diagnostic tests. The specification includes one-year and two-year lags of the natural logarithm of CH4 emissions as well as the three-year lag of the difference in the natural logarithm of CH4 emissions. The difference term ($\Delta ch_{4_{t-3}}$) was introduced during modeling because the estimated coefficient of the three-year lag (α_3) was approximately equal in absolute terms but with the sign opposite to that of the estimated coefficient of the four-year lag (α_4). Therefore, the restriction that $\alpha_3 = -\alpha_4$ was imposed, which improved the fit of the model. Furthermore, three outlier interventions for 1989, 1999, and 2009 were required and included in the trend, as shown in Figure A1.

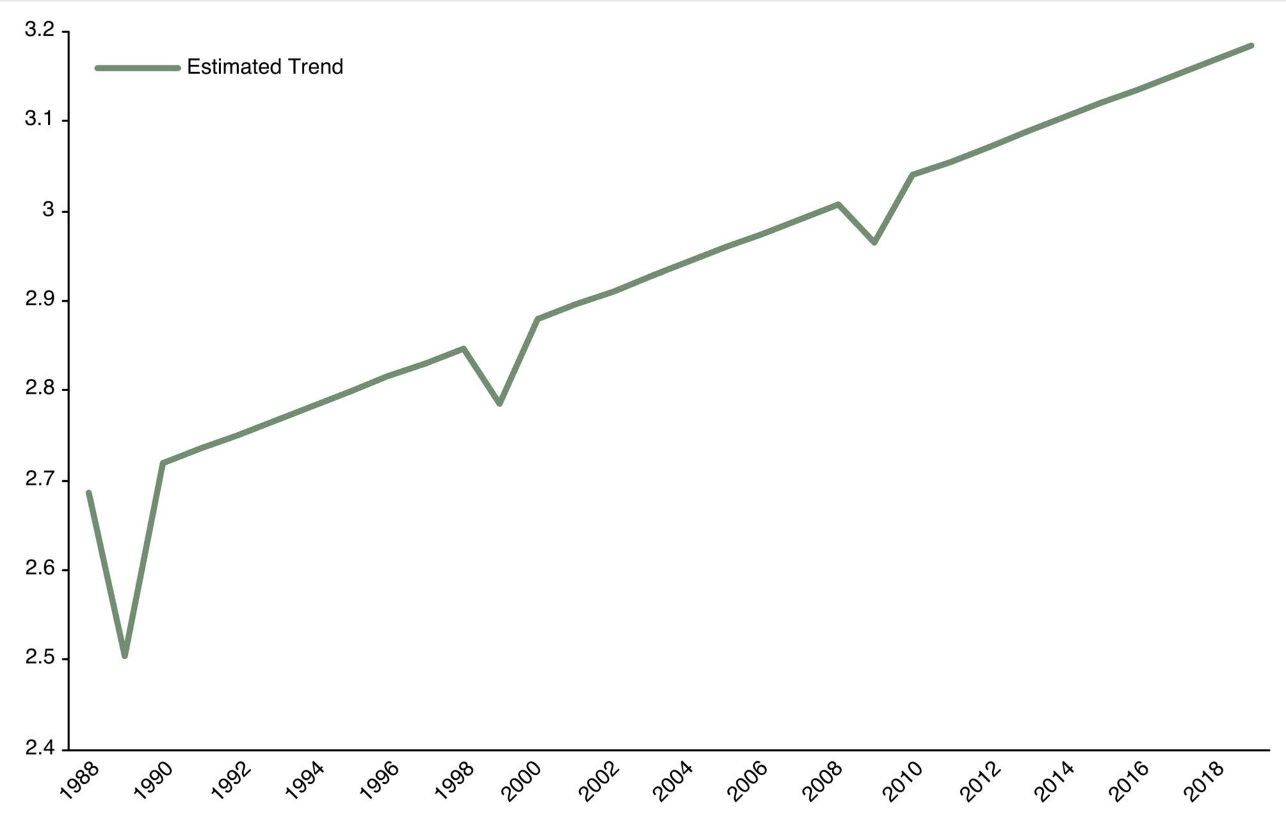
Table A2. Preferred STSM specification

Time period	1988–2019
Estimated coefficients	
α_1	0.5333***
α_2	–0.2007*
α_3	0.3386***
α_4	–0.3386***
Interventions	
Irregular 1989	–0.1983***
Irregular 1999	–0.0767***
Irregular 2009	–0.0578***
Residual diagnostics	
Normality	0.39
H (8)	0.51
r (1)	–0.13
r (2)	–0.08
r (3)	0.03
r (5)	–0.09
DW	2.16
Q (5,3)	1.27
Trend components	Fixed level
	Fixed slope
Goodness of fit	
p.e.v.	0.0003039
AIC	–7.5363
BIC	–7.1241
Auxiliary residuals	
Normality—Irregular	0.34
Normality—Level	1.49
Normality—Slope	1.04
Prediction failure	6.09

Source: Authors' calculations.
Notes:
*, **, and *** represent significance at the 10%, 5%, and 1% levels, respectively.
The estimated value of α_4 is equal, in absolute terms, to the estimated value of α_3 but with the opposite sign.
R^2 is the coefficient of determination.
R_d^2 is the coefficient of determination based on differences.
p.e.v. is the prediction error variance.
AIC is the Akaike information criterion.
BIC is the Bayesian information criterion.
Normality is the Bowman–Shenton statistic and is approximately distributed as $\chi^2_{(2)}$.
H (8) is a heteroscedasticity statistic distributed as $F_{(8, 8)}$.
r (1), r (2), r (3), and r (5) are the serial correlation coefficients at the equivalent residual lags, approximately normally distributed.
DW is the Durbin-Watson statistic.
Q (5,3) is the Box–Ljung statistic distributed as $\chi^2_{(3)}$.
Prediction failure is a predictive failure statistic distributed as $\chi^2_{(8)}$.

Appendix

Figure A1. Estimated trend (γ) from the STSM preferred specification.



Source: Authors' calculations.

Notes

Notes

Notes

About the Authors

Anwar Gasim

Anwar is an energy and environmental economist with a strong engineering background. His primary areas of interest are energy demand, greenhouse gas (GHG) emissions, energy efficiency, energy price reform, and carbon pricing. Anwar is leading the research project titled "Modeling Energy Demand, Emissions, and the Impacts of Energy Price Reform." This project includes studies on elasticities; energy and emissions forecasting; the economic, fiscal, and environmental impacts of energy price changes; and understanding what leads to successful energy policy outcomes. Anwar's research has been published in leading energy and environmental journals and has been picked up by multiple media publications, including Saudi Gazette, Asharq Al-Awsat, and Arab News. He holds an M.Sc. in electrical engineering from KAUST and a B.Eng. in the same field from the University of Liverpool.

Lester Hunt

Lester is a part-time professor of economics at the University of Portsmouth and a KAPSARC visiting researcher. Lester previously worked at the universities of Essex (1979-1980), Swansea (1980-1985 and 1987-1989), Surrey (1989-1991 and 1999-2017), and Portsmouth (1994-1998, and 2017 onwards). At Surrey he was Head of Economics (1999-2003) and Director of SEEC (2003-2015). At Portsmouth he was Head of Economics (1996 -1998) and Head of Economics and Finance (2017-2021). In addition to working in higher education, Lester was an economic advisor in the forecasting division of HM Treasury (1985-1987), an energy analyst/economist at Midlands Electricity (1991-1994) and a senior research fellow at KAPSARC (2015-2017). He was an editor of *The Energy Journal* from 2006 to 2022.

Jeyhun Mikayilov

Jeyhun is a fellow at KAPSARC. He received his B.A. and M.S. in mathematics from Azerbaijan State University (now Baku State University). Jeyhun holds a Ph.D. in applied mathematics and a D.S. in econometrics. Before joining KAPSARC, he was an associate professor in the Department of Statistics and Econometrics at Azerbaijan State University and the Department of Economics at Qafqaz University, where he taught econometrics, statistics, and mathematical economics. His other roles have included director of the Research Institute for Social Sciences and Humanities and head of the Center for Socio-Economic Research. Jeyhun's research focuses on applied time series econometrics, the economics of energy, the environment and sustainable development. He has authored over 40 scientific articles published in peer-reviewed journals and currently leads the "Modeling Energy Consumption and Its Impacts in Saudi Arabia" project at KAPSARC.

About the Project

This project, titled “Modeling Energy Demand, Greenhouse Gas Emissions, and the Impacts of Energy Price Reform,” seeks to provide an in-depth understanding of energy demand, GHG emissions, and energy price reform in Saudi Arabia. One of its key focus areas is understanding the potential evolution of domestic energy demand and greenhouse gas emissions in Saudi Arabia.

KAPSARC

مركز الملك عبدالله للدراسات والبحوث البترولية

King Abdullah Petroleum Studies and Research Center

www.kapsarc.org