

Article

2050 Subnational Residential Natural Gas Demand Forecasting Using Pooled Panel Data

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Abstract

Spatially and sectorally disaggregated gas demand projections are essential for infrastructure planning and decarbonisation, yet records of consumption and its drivers often span only a few years, which is insufficient for conventional time-series methods and risks overfitting in complex machine learning models. Pooling observations across regions can provide the sample size and variation in demand and its drivers these models need. We test this approach on residential natural gas demand in Turkey's 81 provinces, comparing Random Forest, CatBoost, Support Vector Regression and linear regression with fixed effects for projections to 2050 under five Shared Socioeconomic Pathways (SSPs). In cross-validation, the machine learning models roughly halved linear regression's relative error, but tree-based models stay largely within the range of historical consumption, flattening projections for the highest-consuming provinces. Model choice shapes the 2050 projections more than the socioeconomic pathway. Under SSP2, the four models span 74 TWh, whereas for any one model, the five scenarios, which differ only in their population and GDP trajectories, span 4–17 TWh. Past consumption is the strongest predictor in the machine learning models. Among the other drivers, population and household composition outweigh climatic variables such as degree days. Total residential gas demand in Turkey nearly doubles from 209 TWh in 2025 to 412 TWh in 2050, with models and scenarios ranging from 358 to 463 TWh. Under the no-new-policy baseline, direct emissions reach 67–80 MtCO_{2e} by 2050 without peaking, a challenge for Turkey's economy-wide net-zero target for 2053.

Keywords: residential natural gas demand; pooled panel data; machine learning; multi-model comparison; Shared Socioeconomic Pathways; data scarcity; Turkey



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1. Introduction

Subnational residential natural gas demand projections are essential for infrastructure planning, supply security, and decarbonisation policy, yet they remain difficult to produce where distribution networks are still expanding and historical data are limited. Turkey (Türkiye) is a case in point. Residential natural gas consumption has expanded rapidly since the sector's liberalisation in the early 2000s [1], rising from negligible levels to 18,941.8 million m³ (corresponding to 201.5 TWh) in 2024, representing 35.8% of total national gas consumption [2]. This growth reflects both infrastructure expansion, with distribution networks progressively reaching previously unconnected provinces, and urbanisation-driven increases in household connections. Unlike the electricity grid, which covers 100% of Turkish provinces [3], natural gas infrastructure remains in an

active expansion phase, with several regions only recently gaining access while others are still awaiting connection. This uneven spatial development, combined with the sector's heating-dominated demand profile and the tendency of network build-out to lock households into gas for many years, makes subnational natural gas demand forecasting methodologically challenging.

Despite methodological advances in energy demand forecasting, gaps remain in subnational, long-horizon projections for residential natural gas under data-constrained conditions. Existing studies predominantly address the national scale [4,5], short-term operational forecasting [6–8], or regional questions where historical data span multiple decades [9,10]. Provincial-level projections extending to mid-century remain limited, particularly in countries where natural gas infrastructure continues to expand and where demographic and economic heterogeneity across regions necessitates spatially disaggregated analysis. Natural gas demand forecasting typically employs simple statistical models or applies machine learning to short-term predictions with rich feature sets. However, the literature offers few systematic comparisons of algorithm suitability under severe temporal constraints, and few explicit assessments of framework transferability across energy carriers.

This study addresses these gaps by developing a multi-model approach for subnational residential natural gas demand forecasting under data scarcity, building on a framework previously applied to electricity demand [11]. Natural gas demand is dominated by heating, unlike the more balanced heating–cooling profile of electricity use [12,13]. The ongoing expansion of gas distribution networks also sets this context apart from mature electricity grids, where coverage is typically universal. In expanding gas networks, consumption growth reflects both increasing per-household demand and the addition of newly connected households, a compounding effect absent in electricity forecasting. Residential gas demand also involves infrastructure lock-in effects and technology substitution dynamics, including heating electrification and efficiency standards, that differ from those in electricity planning contexts [14]. Applying the framework to gas therefore requires re-evaluating algorithm suitability for a heating-dominated demand served by an expanding network. This research contributes by systematically comparing the algorithms for subnational, long-horizon gas demand under data scarcity and testing whether a framework developed for electricity also works for a second energy carrier.

The available historical base comprises only ten usable annual observations from twelve years of provincial data. Such data scarcity is common wherever demand records have only recently been disaggregated by region, end use, or fuel type, and is particularly acute in countries where energy sector liberalisation and infrastructure modernisation have occurred in recent years [15]. This constraint eliminates many advanced forecasting approaches [16]. We initially screened twelve algorithms spanning traditional statistical models, neural networks, kernel methods, and tree-based ensembles. Deep learning architectures and the gradient boosting implementations XGBoost and LightGBM were unable to produce physically plausible projections, exhibiting overfitting, unstable extrapolation behaviour, and in some cases negative consumption values for certain provinces, despite extensive regularisation attempts. Three machine learning methods, Random Forest (RF), CatBoost, and Support Vector Regression (SVR), produced reliable results alongside a linear regression benchmark, each with distinct extrapolation behaviour. CatBoost is a gradient boosting algorithm whose ordered boosting is designed to limit overfitting on small samples. To overcome the temporal constraint, we pooled cross-sectional variation across all 81 Turkish provinces into a single panel dataset, which supplies the sample size and the variation in demand and its drivers that the models need. This pooled panel structure allowed the algorithms to learn how socioeconomic and climatic drivers shape residential

gas consumption from variation across provinces, including provinces at different stages of network maturity, rather than from temporal variation within any single province.

By integrating Shared Socioeconomic Pathways (SSP) for population and gross domestic product (GDP) projections, the framework enables scenario-based demand forecasts under alternative demographic and economic trajectories to 2050, consistent with the socioeconomic narratives widely used in Intergovernmental Panel on Climate Change (IPCC) assessments and national climate policy frameworks [17]. Model performance varies with the scale of provincial consumption [18], so behaviour in high-demand provinces should be examined directly rather than through aggregate validation metrics alone [19,20]. Turkey ratified the Paris Agreement in 2021 and aims to achieve net-zero emissions by 2053, a target that current trajectories do not yet support [21]. The Climate Law No. 7552 of 2025 frames national climate policy around the net-zero emissions target, with sectoral reduction strategies and a national emissions trading system [22,23]. These projections therefore carry direct implications for its climate commitments and nationally determined contributions (NDC), which we examine through the emissions implied by projected demand.

Prices, building policy and heating technology also shape demand. Retail tariffs are approved by the Energy Market Regulatory Authority (EMRA) under the Natural Gas Market Law [24], and the state-owned BOTAŞ accounted for 95.65% of natural gas imports in 2025 [25]. The NDC lists heat pumps, district heating, retrofits and nearly zero-energy building standards for the building sector [26], and mature gas markets can undergo technology-driven fuel switching in space heating [27]. These factors are held constant here, and the projections are a no-new-policy baseline against which such measures can be assessed.

This study employs multiple forecasting algorithms for two purposes. The first is to capture uncertainty in projections where limited data make single-model results unreliable [28–30]; the second is to determine which types of algorithms forecast most effectively when training data are scarce [31,32]. Using Turkey as a case study, we provide detailed residential natural gas demand forecasts for all 81 provinces through 2050 under five SSP scenarios, and translate these into direct end-use CO₂ emissions to assess alignment with Turkey's NDC and its 2053 net-zero target. By evaluating algorithmic behaviour across provinces with order-of-magnitude differences in consumption, we show that the spread across models exceeds the variation introduced by socioeconomic scenarios in this data-scarce setting. The methodology, while building on a framework originally developed for electricity [11], addresses gas-specific challenges and may be transferable to other contexts with similar data and infrastructure constraints, subject to testing elsewhere.

The remainder of this paper proceeds as follows. Section 2 reviews existing literature on natural gas demand forecasting. Section 3 details the methodological framework, including variable selection, data sources, SSP scenario implementation, and the rationale for provincial panel modelling. Section 4 describes model construction, hyperparameter optimisation, validation procedures, and comparative algorithm assessment. Section 5 presents national and provincial demand projections to 2050 alongside emissions implications and spatial heterogeneity analysis. This section also discusses limitations and proposes directions for future research. Section 6 concludes with policy implications for infrastructure planning and decarbonisation strategy in Turkey and beyond.

2. Previous Works

Natural gas demand forecasting has become more important for energy planning and policy formulation as countries seek to balance energy security with environmental objectives. Table A1 in Appendix A summarises the literature by method, input features, geographic coverage, sector, temporal resolution, and the length of both the historical

record and the forecast horizon. Read together, the studies show a field organised around short-horizon operational forecasting, with long-horizon work concentrated at national scale and little explicit attention to the length of record on which a forecast rests.

Traditional statistical methods have long formed the foundation of natural gas demand forecasting. Classical time series approaches such as Autoregressive Integrated Moving Average (ARIMA) and Seasonal ARIMA (SARIMA) remain widely used due to their theoretical strength and interpretability [33]. These models capture temporal dependencies and seasonal patterns in energy consumption data. Exponential smoothing techniques, including Holt-Winters and exponential smoothing state space models, offer alternative statistical frameworks that perform consistently across various applications [34]. More specialised statistical methods, such as Trigonometric, Box-Cox, ARMA, Trend, Seasonal (TBATS), which handles multiple seasonal patterns and complex seasonality, have also been implemented [35]. Regression-based approaches, such as ordinary least squares and its variants, remain fundamental tools for understanding demand determinants and establishing baseline forecasts [36]. What these approaches share is a dependence on long, regularly sampled series from which temporal structure can be estimated, which restricts their use where the record is short. Alongside these statistical foundations, computational advances have enabled more complex modelling approaches [37].

Machine learning techniques have been widely adopted in recent years, offering a range of predictive approaches for complex non-linear relationships. Artificial neural networks, such as multilayer perceptrons, have been applied to capture complex patterns in natural gas consumption data [38]. Support vector machines (SVM) are another commonly used approach. These methods perform well with limited data and can handle high-dimensional feature spaces [38]. Ensemble methods have gained prominence in the literature [39], with RF and gradient boosting algorithms demonstrating strong forecasting performance across multiple studies [40]. More recent implementations have incorporated advanced techniques such as XGBoost and LightGBM, which offer computational efficiency alongside predictive accuracy [41,42]. Long short-term memory (LSTM) networks have also been explored for their capacity to model long-term dependencies in sequential data [10]. The shift towards machine learning reflects broader trends in energy forecasting, where model complexity has increased alongside data availability and computational resources [43]. Model capacity and data volume have therefore risen together, which leaves open how the more flexible of these methods behave when only the first of the two is available.

Beyond purely statistical or machine-learning approaches, hybrid and specialised methodologies are another active research area. Just-in-time learning with Gaussian process regression combines local modelling with probabilistic forecasting capabilities [34]. Fuzzy systems engineering approaches incorporate expert knowledge and handle uncertainty in demand patterns [44]. Monte Carlo simulation paired with stochastic processes provides probabilistic demand projections that account for inherent uncertainties [8]. Multivariate Generalised Autoregressive Conditional Heteroskedasticity (M-GARCH) models capture volatility dynamics and interdependencies between demand and influencing factors [38]. Bottom-up approaches, especially those integrating geographic information systems, enable detailed spatial resolution by aggregating household-level consumption patterns [45]. These specialised techniques often address specific forecasting challenges, such as uncertainty quantification, spatial heterogeneity, or policy scenario analysis, that standard time-series or machine-learning models may not adequately capture [46]. Comparative analyses frequently benchmark advanced methods against naive baselines such as random walk or simple moving averages to demonstrate incremental improvements [35], with a subset of research explicitly examining model performance across different forecasting

horizons, where accuracy typically degrades with longer prediction windows [47]. A naive baseline establishes that a method improves on doing nothing, which is a weaker test than discriminating among several plausible candidates estimated on identical data.

Input feature selection varies across studies, reflecting different forecasting objectives, data availability, and temporal resolutions. Historical consumption data is consistently a primary input, with lagged values capturing autoregressive patterns and consumption trends [48]. Temperature-related variables, especially HDD and CDD, appear in nearly all studies. Raw temperature data and weather forecasts are also incorporated to capture short-term demand fluctuations [49]. Economic indicators are commonly included in medium- to long-term forecasting models [50], with GDP and GDP per capita as primary proxies for economic activity and prosperity. Population variables account for demographic-driven changes in demand [4]. Price variables, including natural gas, electricity, and competing-fuel prices, enable the estimation of price elasticities and substitution effects [50]. The number of consumers or households connected to natural gas networks captures the impacts of infrastructure expansion [6]. Building characteristics and housing stock variables inform bottom-up and cross-sectional analyses [51]. Temporal features such as day-of-week indicators, holiday effects, and seasonal indices help models capture calendar-based consumption patterns [8]. Trade variables, including imports and exports, appear in national-level long-term projections [5]. More specialised studies incorporate meteorological variables beyond temperature, such as wind speed, pressure, precipitation, humidity, and solar irradiance [45], as well as behavioural and socio-demographic factors including household income, employment status, education levels, and psychological determinants of energy consumption [52]. Recent studies have also begun incorporating pandemic-related indicators to account for structural breaks in consumption patterns [41]. Feature choice therefore tracks temporal resolution more closely than it tracks the forecasting question, with weather and calendar variables at daily resolution and socioeconomic aggregates at annual resolution.

Beyond variable selection, temporal resolution and forecasting horizons vary considerably across the literature based on different purposes and end-users of demand forecasts. Much of the literature addresses daily forecasting, especially for operational planning and short-term supply management [49]. These high-frequency forecasts typically employ weather-responsive models that can capture day-to-day variations in consumption [53]. Monthly resolution balances operational detail against data manageability, appearing frequently in studies that balance granularity with longer historical data requirements [54]. Annual forecasting dominates long-term planning studies, where the focus shifts from weather-driven fluctuations to structural economic and demographic trends [55]. Prediction horizons similarly span a wide spectrum. One-day-ahead and weekly forecasts address immediate operational needs [7], while monthly and seasonal forecasts extending up to one year support tactical planning and procurement strategies [35]. Multi-year projections ranging from five to thirty years ahead inform strategic infrastructure investments and policy development [9]. The most ambitious studies extend projections several decades into the future to support long-term energy transition scenarios and climate policy analysis [56]. Data availability often constrains temporal resolution and forecasting horizon, with daily models typically using shorter historical periods [7], while annual models frequently draw on datasets spanning two to four decades [9].

Geographic scope and sectoral focus also differentiate forecasting approaches. Regional forecasts, typically targeting specific cities, provinces, or distribution zones, dominate the short to medium-term forecasting literature [57]. These studies often benefit from more homogeneous consumption patterns and closer alignment with utility service territories. National-level forecasts address country-wide planning needs and policy formulation [55].

International and global analyses, though less common, enable cross-country comparisons and examine worldwide energy transition pathways [56]. The residential sector receives most attention, given its substantial share of natural gas consumption and sensitivity to weather conditions [36]. Commercial sector demand is frequently analysed alongside residential consumption due to similar temperature sensitivities [48]. Industrial demand, with its distinct drivers tied to production processes rather than weather, appears less frequently as a stand-alone focus [44]. Total or aggregate demand forecasts that cover all sectors serve comprehensive energy planning purposes [58].

Spatial resolution and forecast horizon are not independent in this literature, and the two are close to mutually exclusive. Every study in Table A1 that projects to 2040 or beyond is national or global in scope [9,10,45,56]. Among the regional studies that produce forecasts, almost all extend no more than three years ahead; the exception covers all sectors in a single city and stops at 2035 [57]. Long-horizon subnational projections for a single fuel and sector, the resolution at which distribution network investment is actually decided, are therefore close to absent.

A further dimension that differentiates forecasting studies, yet receives little explicit attention, is the length of the historical record available for model estimation. Daily and monthly studies typically draw on several years of high-frequency observations, yielding thousands of training samples even over relatively short windows [7,49]. Annual studies at national scale frequently rely on two to four decades of historical data [9,55], providing sufficient temporal depth for autoregressive specifications and conventional time-series methods. By contrast, subnational annual studies in emerging economies often face severe data limitations, with consistent provincial records sometimes spanning only a decade or less, particularly where sectoral disaggregation became available only after market liberalisation. Under such conditions, methods that rely on long historical sequences become inapplicable, and even flexible machine learning algorithms risk overfitting when the number of temporal observations is small relative to the number of predictors. Record length is rarely treated as a design constraint in its own right, despite its growing relevance for countries with recently disaggregated energy data and ongoing infrastructure expansion.

While the literature reviewed above shows considerable methodological diversity, three gaps stand out for the purposes of this study. First, spatially and sectorally disaggregated demand projections are essential for infrastructure planning and decarbonisation policy, yet long-horizon provincial-level projections remain uncommon, in part because the historical records required by conventional time-series methods are unavailable at this resolution in many emerging economies. Second, where data are scarce, the natural response of pooling cross-sectional variation across spatial units to compensate for limited temporal depth has been applied only sporadically in energy demand forecasting, and the implications of this design choice for algorithm performance have not been systematically examined. Third, comparisons of how different machine learning algorithms behave when training data covers only a small fraction of the projection horizon are rare, despite evidence that model choice can introduce uncertainty comparable to or larger than that arising from socioeconomic scenarios. These gaps are particularly consequential for countries undergoing rapid infrastructure expansion, where most energy planning models originated in developed-country contexts with longer data histories and more stable network coverage [15]. The present study addresses these gaps by pooling panel data across all 81 Turkish provinces to overcome the temporal constraint imposed by a ten-year historical record, systematically comparing three machine learning algorithms drawn from an initial screening of twelve, and quantifying the contribution of model uncertainty alongside scenario uncertainty in provincial residential gas demand projections to 2050.

3. Methodology

Residential natural gas demand in Turkey poses distinct forecasting challenges. The sector has a heating-dominated consumption profile, with annual variation driven by climatic differences. Yet historical data at provincial resolution are available for only a decade, and distribution networks continue to expand into previously unconnected provinces. This combination, a short temporal record paired with a 25-year projection horizon, rules out conventional time-series methods that rely on long historical sequences and exposes flexible machine learning algorithms to substantial overfitting risk. We address this constraint by pooling cross-sectional variation across all 81 provinces into a single panel dataset, yielding 810 province-year observations from only ten years of data. The pooled panel structure allows algorithms to learn the relationship between socioeconomic and climatic drivers and residential gas consumption from spatial differences across provinces, rather than relying on temporal variation within any single province. The remaining methodological choices (variable selection, algorithm shortlisting, and validation strategy) follow from this design.

3.1. Variable Selection

Energy demand forecasting studies typically incorporate a range of explanatory variables depending on temporal resolution, geographic scope, and data availability. Historical consumption patterns are fundamental inputs in autoregressive specifications [48], while temperature-related indicators, especially HDD and CDD, appear almost universally given the thermal dependence of energy demand [4]. Economic indicators such as GDP and GDP per capita capture prosperity-driven consumption changes [50], and population variables account for demographic trends [4]. Household counts and consumer connections reflect infrastructure penetration [6], whereas price variables enable estimation of demand elasticities where reliable long-term projections exist [50]. For this study, we selected provincial population, GDP, household counts categorised by type (single-person, family, and multi-person), and climatic indicators (HDD and CDD) as predictor variables, together with a COVID-19 indicator. SVR, RF and CatBoost also use each province's consumption in its three preceding available years and their mean; LRFE uses province fixed effects instead, as described in Section 4.2.

HDD merit particular emphasis for natural gas forecasting because residential gas consumption in Turkey is overwhelmingly heating-driven, with heating accounting for the dominant share of household gas consumption [59]. Unlike electricity, where annual consumption reflects both heating and cooling requirements across the year, natural gas consumption varies predominantly with annual heating needs. Total demand is therefore highly sensitive to year-to-year climatic variation.

Table 1 illustrates this heating dominance using TURKSTAT's household energy consumption survey data. Space heating accounts for 78.2% of all residential energy use, with water heating and cooking making up the remainder at 13.3% and 8.5%, respectively. Natural gas is the single largest contributor, supplying 58.3% of total household energy, of which 44.5 percentage points are attributed to space heating alone. Solid biomass, hard-coal, and lignite collectively add another 30.3% of space heating demand. LPG is used almost exclusively for cooking, and solar thermal is limited to water heating.

Turkey's climatic diversity ranges from coastal Mediterranean zones with lower annual heating requirements to continental interior and mountainous eastern regions with substantially higher heating demands. This geographic variation, combined with year-to-year climatic fluctuations, makes HDD essential for capturing both spatial and temporal differences in consumption [60].

Table 1. Distribution of total household primary energy consumption by source and end-use purpose. TurkStat collected the original data through a stratified random sampling survey of Turkish households (reference year 2022); therefore, values represent estimated proportions rather than exact measurements.

Energy Source	Space Heating	Water Heating	Cooking	Total
Natural gas	44.47%	8.45%	5.34%	58.27%
Solid biomass	13.32%	0.37%	0.21%	13.90%
Hardcoal	9.44%	0.11%	0.02%	9.58%
Lignite	7.56%	0.05%	0.02%	7.62%
Solar heat	0.00%	4.05%	0.00%	4.05%
Geothermal heat	3.28%	0.07%	0.00%	3.34%
LPG	0.00%	0.14%	2.94%	3.09%
Fuel-oil	0.03%	0.00%	0.00%	0.03%
Other sources	0.11%	0.01%	0.00%	0.11%
Total	78.21%	13.25%	8.53%	100.00%

Natural gas prices have been identified in prior studies as a relevant factor for residential demand, particularly in price-sensitive developed markets. In the Turkish context, however, residential tariffs are shaped by subsidies, regulatory interventions, and geopolitical influences on import contracts, and are therefore not included among the explanatory variables. Residential gas prices in Turkey are highly centralised, with a single nationwide wholesale tariff. Consumer-level provincial price series were not available for the panel used in this study. With only ten annual observations, a national price index is also difficult to separate from the common annual trend, and we are not aware of SSP-consistent price projections for Turkish provinces. Prices are therefore held constant, as in a no-new-policy baseline. Similarly, infrastructure-related variables such as the number of residential subscribers, connection rates, and network length were excluded as predictor features. This exclusion was necessary because the data are not consistently disaggregated by sector and province for all years of the study period, which prevented their systematic inclusion in the panel analysis. Moreover, in the pooled panel structure, population and household counts co-vary with the number of grid-connected households during the network expansion phase, so these variables partly absorb infrastructure-related effects. The proxy is weakest where networks were built or expanded during the study period, as discussed in Section 5.4.

The selection process focused on variables that capture the socioeconomic heterogeneity and climatic variability observed across Turkey's provinces whilst maintaining data availability and projection feasibility. Variable selection was further guided by preliminary model evaluation metrics and analyses of feature importance to verify the predictive value of each chosen variable. Figure 1 shows how the selected variables enter the modelling pipeline, including data sources, variable selection, algorithm tuning, and scenario-driven prediction outputs.

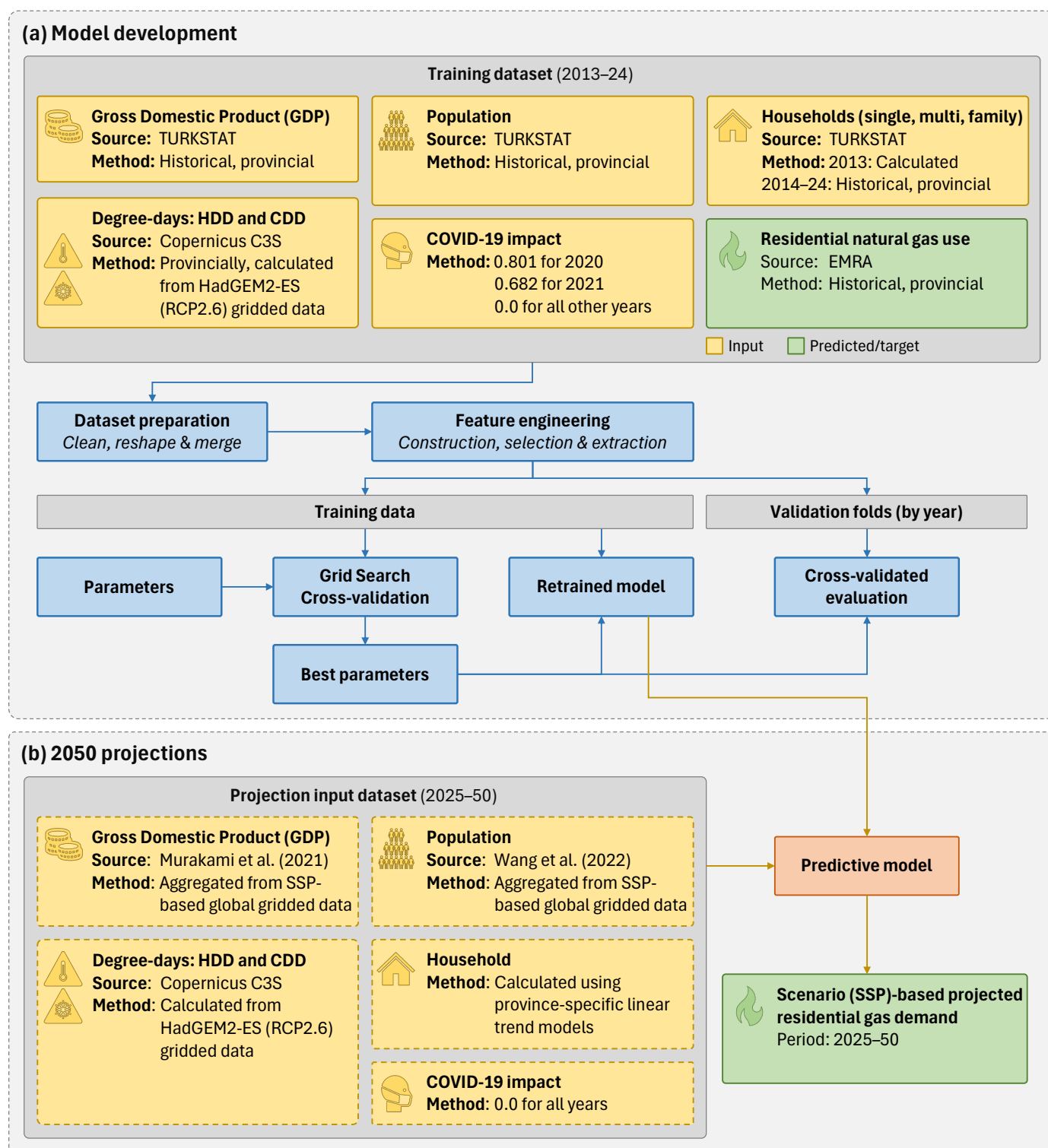


Figure 1. Overview of the research framework. The framework has two main parts: (a) model development, which involves collecting training data from 2013 to 2024, feature engineering, training and validating the model, and evaluating it by year-ordered cross-validation [2,61–67]; and (b) projecting natural gas demand through 2050 using SSP-aligned inputs from 2025 to 2050 to generate forecasts at the provincial level. For SVR, RF and CatBoost, feature engineering adds lagged consumption and its three-year mean, and projections are generated recursively from each model’s earlier predictions [61,68,69]. HDD and CDD for both periods come from the HadGEM2-ES (RCP2.6) series.

3.2. Data Collection and Preparation

Data collection required several adjustments specific to residential natural gas. The main constraint was limited data availability. While TURKSTAT provides detailed historical data for electricity consumption, it does not disaggregate residential natural gas figures in the same way. We therefore drew on alternative sources, which yielded a shorter and incomplete time series. Several provinces gained access to residential natural gas distribution networks only during the study period, recording zero or near-zero consumption in earlier years. These observations were retained without removal or imputation; the methodological rationale is set out in Section 4. These limitations, together with the heating-dominated demand profile and the uneven regional roll-out of infrastructure, shaped the analysis. We compared four models (RF, CatBoost, SVR, and Linear Regression with Fixed Effects, LRFE) to test whether the results held despite the smaller dataset. Panel data allowed us to draw on information across provinces, which matters because some provinces gained access to residential gas only recently. Each variable and its preparation are described below.

Natural gas consumption : Provincial residential natural gas consumption data were extracted from the annual sector reports of the Energy Market Regulatory Authority (EMRA) for the period 2013–2024 [2]. The original consumption values, reported in standard cubic metres (Sm^3), were converted to energy units (GWh) using the standard conversion factor of $10.64 \text{ kWh}/\text{Sm}^3$, a gross calorific value of $9155 \text{ kcal}/\text{Sm}^3$ [70]. This conversion ensures consistency with international energy reporting standards and allows for direct comparison with other studies. Although these reports often include a sectoral breakdown of natural gas consumption for each year, the 2014 and 2015 reports lacked disaggregated figures for the residential sector. As a result, residential consumption values for those two years were unavailable. To avoid introducing artificial patterns into the training data, interpolation was not applied. The years 2014 and 2015 were therefore excluded from the analysis to maintain data consistency across all variables.

Heating and cooling degree-days: Climate data were obtained from the Copernicus Climate Change Service [61] as gridded temperature values derived from the HadGEM2-ES global climate model [71] under Representative Concentration Pathway 2.6 [72]. Provincial-level annual HDD and CDD spanning 2013–2050 were calculated using the U.K. Met Office methodology [73], with base temperatures of 15.5°C for HDD and 22°C for CDD. Using one series for 2013–2024 and 2025–2050 puts training and projection inputs on the same basis, without splicing historical and projected climate data.

Population: Population figures for 2013–2024 were sourced from TURKSTAT [62]. SSP-aligned population projections were generated through spatial aggregation of global gridded datasets [68]. Province-specific compound annual growth rates for each SSP scenario were applied to TURKSTAT's latest official provincial population data (2024), which anchors the continuous annual projections through 2050 to official statistics.

Households: Provincial household data categorised into single-person, multi-person, and family households were derived from TURKSTAT for 2014–2024, with 2013 calculated based on provincial household sizes [63]. Future household projections used province-specific linear regression, achieving R^2 values exceeding 0.9 in 99% of provinces for single-person households, with comparable fits across other household categories. Extended-family households were excluded because their counts did not follow a linear trend. Household projections are common to all SSPs. The implied household size, population divided by households in the three categories, falls by 25–37% between 2024 and 2050, and no province falls below 1.86 persons; only relative changes in this ratio are meaningful because extended families are excluded.

Gross domestic product: Provincial GDP data for 2013 to 2023 were sourced from TURKSTAT [64–67] and converted to US dollars using World Bank annual average exchange rates [74]. Future provincial GDP projections were derived by spatially aggregating global gridded datasets [69]. Province-specific compound annual growth rates for each SSP scenario were applied to official 2023 GDP figures, generating continuous annual trajectories through 2050. The historical series is nominal, converted from current Turkish lira at market exchange rates, and includes price and exchange-rate effects; the projections apply real SSP growth rates to the 2023 level and are in constant 2023 US dollars.

COVID-19 impact: The COVID-19 pandemic affected residential energy usage patterns worldwide, primarily due to lockdown measures and extended periods at home [75]. We included the pandemic as a predictor variable, quantified by a numerical indicator (0 to 1) representing the proportion of the year during which schools operated remotely or were closed. Turkey’s school closures lasted from 14 March 2020 to 6 September 2021 [76,77], which allows the model to capture pandemic-related shifts in residential energy consumption patterns.

3.3. Shared Socioeconomic Pathways

We employ the five SSP scenarios developed by [17], which have been widely used in climate and energy research, including Intergovernmental Panel on Climate Change (IPCC) assessments [78]. SSP1 represents sustainable development with low mitigation and adaptation challenges; SSP2 depicts intermediate trajectories with moderate challenges; SSP3 illustrates fragmented regionalism with high challenges; SSP4 portrays inequality with difficult adaptation for vulnerable populations; and SSP5 envisions fossil-fuelled rapid growth with severe mitigation challenges [79,80]. SSPs are particularly relevant for natural gas forecasting because infrastructure decisions (such as network extensions, heating investments, grid expansion) depend on assumed socioeconomic trajectories. Natural gas consumption exhibits stronger spatial heterogeneity than electricity due to infrastructure availability constraints, so scenario-based projections are needed to capture regional development trajectories. SSP-based projections are explicitly applied to GDP and population inputs. Other variables remain scenario-independent, which keeps the results comparable with international energy research and aligned with broader climate policy frameworks [81]. Households, HDD, CDD and the COVID-19 indicator are the same in all five scenarios. HDD and CDD still change over time along the single HadGEM2-ES (RCP2.6) climate pathway, and household counts follow province-specific trends.

4. Model Construction and Validation

4.1. Model Selection Process

The pooled panel structure introduced in Section 3 substantially expands the available training data, yet the projection horizon to 2050 still exceeds the historical window by a factor of two and a half. This residual asymmetry between training depth and extrapolation distance remains the defining methodological constraint of the study, and it shaped algorithm selection at every stage. We screened twelve methods spanning traditional statistical models, neural networks, kernel methods, and tree-based ensembles, and evaluated each on standard error metrics and on whether it produced physically plausible long-term trajectories suitable for infrastructure planning [82]. Algorithms that achieved acceptable in-sample accuracy but generated implausible out-of-sample projections, such as negative consumption values, exponential blow-up, or monotonic flattening, were treated as unsuitable for the data-scarce regime, regardless of their reported performance on conventional metrics.

Deep learning architectures performed poorly under these data-constrained conditions. Feed-Forward Neural Networks suffered from severe overfitting despite extensive regularisation attempts, producing highly volatile predictions characterised by unrealistic consumption spikes and troughs. LSTM networks and Recurrent Neural Networks (RNN), although designed explicitly for sequential data processing, required more training samples than were available to learn meaningful temporal dependencies [31]. These models generated either monotonically flat projections or exponential growth patterns that contradicted established sector knowledge and physical constraints [83]. Several other advanced methods, including Convolutional Neural Networks and two widely used gradient boosting implementations, were unsuitable, yielding erratic, non-convergent, or otherwise unsatisfactory results. XGBoost and LightGBM, despite demonstrated success in various energy forecasting applications [84], exhibited excessive sensitivity to the limited training data. These methods frequently produced discontinuous, abrupt predictions and generated negative consumption values for certain provinces, a physical impossibility that makes such models unsuitable for practical application. Traditional statistical methods encountered different but equally limiting challenges. ARIMAX (ARIMA with Exogenous Variables) produced excessively wide prediction intervals due to parameter uncertainty. Exponential Smoothing methods were unable to capture the complex, multivariate interactions between socioeconomic drivers and consumption patterns. Hierarchical Time Series approaches, while theoretically appealing for multi-level spatial data, could not adequately model provincial heterogeneity given the limited historical observations available for parameter estimation.

Following this elimination process, only three machine learning methods produced reliable statistical results and forecast trajectories consistent with established energy demand evolution patterns. These methods maintained positive growth rates aligned with historical patterns, avoided unrealistic stagnation or decline, and exhibited bounded growth consistent with expected sectoral saturation rather than unbounded polynomial expansion. RF, CatBoost, and SVR share several characteristics that enhance their suitability for small-sample learning contexts.

Random Forest [85] employs an ensemble approach that aggregates predictions from multiple decision trees. In the selected configuration, each tree uses the full training set without bootstrap sampling, and each split draws on a random subset of predictors, which decorrelates the trees and limits overfitting. The method's ability to capture non-linear relationships without requiring explicit specification of functional forms makes it well-suited for modelling complex energy demand patterns where the underlying relationships may not be theoretically established.

CatBoost [86], an advanced gradient boosting algorithm, incorporates several innovations specifically designed for small datasets. Its ordered boosting technique reduces overfitting risks while maintaining computational efficiency. The algorithm's built-in mechanisms for dealing with parameter uncertainty under limited data conditions made it suitable for our application, where provincial heterogeneity must be captured despite sparse temporal observations.

Support Vector Regression [87] offers a different approach through its kernel-based methodology. By focusing on support vectors, the most informative data points that define the decision boundary, rather than using the entire dataset, SVR shows less sensitivity to sample-size limitations. SVR's margin-based formulation provides theoretical bounds on generalisation error, which offers some assurance when extrapolating beyond the training period [88]. Tuning selected the linear kernel, as discussed in Section 4.3, and the final SVR is therefore a regularised linear model with an ϵ -insensitive loss.

To establish a performance baseline and quantify the added value of non-linear machine learning approaches, we included a Linear Regression with Fixed Effects (LRFE) model. This traditional econometric approach has two purposes. First, it provides a benchmark for assessing whether the additional complexity of machine learning methods yields improvements. Second, it gives interpretable coefficient estimates that help understand the marginal effects of predictor variables on natural gas demand, insights relevant for policy analysis and scenario planning. The final selection is therefore a balanced portfolio of approaches. Ensemble methods (RF, CatBoost) apply different aggregation strategies, a kernel-based method (SVR) offers an alternative mathematical framework, and a linear benchmark (LRFE) provides interpretability and baseline performance. The diversity of approaches supports cross-validation of results and shows which aspects of the demand forecasting problem benefit most from non-linear modelling.

4.2. Pooled Panel Structure

Our approach rests on pooled panel data, which combines annual observations from all 81 Turkish provinces into a single panel of 810 province-year observations (81 provinces $\times$ 10 years). This design addresses the central constraint identified in Section 2, the unavailability of long historical records at provincial resolution. By treating the panel as a pooled cross-section over time, we obtain the sample size and variation that no single province's record can provide, allowing algorithms to learn the mapping from socioeconomic and climatic conditions to residential gas consumption from variation across provinces, including provinces at very different stages of network maturity, rather than relying on within-province temporal variation alone [89,90].

Because 2014 and 2015 are missing, the lags refer to the previous available years; the first lag for 2016 is the 2013 value. RF and CatBoost handle missing lags internally and train on 2016–2024 (729 province-years); SVR needs complete inputs and trains on 2018–2024 (567); and LRFE uses no lags and all 810. For 2025–2050, lags are generated recursively from observed 2022–2024 consumption and the model's own subsequent predictions, and errors can therefore accumulate over the horizon.

Province-level heterogeneity is preserved by including each province's own lagged consumption in SVR, RF and CatBoost, or province fixed effects in LRFE, rather than estimating separate models per province, an approach that would be infeasible given only seven to ten usable observations per province against eight to twelve predictors. Provinces that gained network access during the study period and recorded zero or near-zero consumption in early years were retained without imputation, as these observations carry information about the relationship between infrastructure availability and demand that is essential for projecting future consumption in provinces still expanding their networks. The pooled panel therefore captures both spatial heterogeneity in mature markets and the transition from unconnected to connected status, a feature unavailable to single-province or purely temporal models. Pooling makes estimation feasible at this record length; its gain over hierarchical or global-plus-local alternatives is not quantified here.

4.3. Hyperparameter Optimisation and Training

Hyperparameter optimisation employed exhaustive grid search combined with TimeSeriesSplit cross-validation from scikit-learn [91]. Unlike standard k-fold cross-validation, which randomly partitions data, TimeSeriesSplit creates sequential splits in the order in which observations appear in the dataset, and the splits respect temporal ordering when the data are ordered by year. This progressive expansion of the training set ensures that models are always trained exclusively on data from before the test period, preventing future information leakage, a requirement in time series forecasting [92]. Standard k-fold validation

would incorrectly allow models to train on 2024 data when predicting 2020 consumption, producing unrealistically optimistic performance estimates [93].

In tuning, the panel was ordered by province and then year. Each fold therefore held out all years of nine to thirteen provinces, and the hyperparameters of SVR, RF and CatBoost were selected for accuracy on provinces unseen in training. Evaluation used year-ordered folds, as described in Section 4.4. Repeating the grid searches on year-ordered folds selected the same SVR kernel and C , with an MAE within 0.3% of the configuration used here, and different settings for RF and CatBoost. On the evaluation folds, these settings lowered MAE by 1–6% for RF and 10–17% for CatBoost and left the model ranking unchanged, but the gains are optimistic because we selected the settings on the same years. LRFE has no hyperparameters.

Table 2 presents the hyperparameter search spaces explored for each algorithm. For RF, the number of estimators was varied over a wide range (10–990) to identify the optimal trade-off between model complexity and computational efficiency. The maximum tree depths (5, 8, 12) were selected to explore both shallow trees that provide high bias but low variance and deeper trees capable of capturing more complex interactions. The minimum sample parameters (split: 4–8, leaf: 2–6) control tree pruning, with higher values promoting simpler, more generalisable models that are resistant to overfitting [85].

Table 2. Hyperparameter ranges used for grid search in machine learning algorithms.

Random Forest	
Number of estimators	10, 20, ..., 990
Maximum tree depth	5, 8, 12
Minimum samples to split	4, 6, 8
Minimum samples per leaf	2, 4, 6
Maximum features per split	sqrt, log2
Bootstrap sampling	disabled
CatBoost	
Number of iterations	100, 150, 200, 250, 300
Learning rate	0.01, 0.03, 0.05, 0.1
Tree depth	4, 6, 8
L2 regularization (leaf)	1, 3, 5, 10
Bagging temperature	0, 1, 2
Subsample ratio	0.8, 0.9, 1.0
Random subspace method (RSM)	0.6, 0.8, 1.0
Support Vector Regression	
Kernel type	RBF, polynomial, linear
Regularization parameter C	0.1, 1, 10, 100
ϵ -insensitive tube	0.01, 0.1, 0.5
Kernel coefficient γ	scale, 0.001, 0.01, 0.1
Polynomial degree	2, 3

CatBoost hyperparameters were selected to exploit the algorithm's advanced regularisation capabilities, following established practices [86]. The iteration range (100–300) was constrained to prevent overfitting while ensuring sufficient model capacity. Learning rates (0.01–0.1) were coupled with the number of iterations, since lower learning rates with more iterations tend to generalise better. The L2 regularisation parameter (1–10) provides additional protection against overfitting, which matters given our limited temporal observations. Bagging temperature (0–2) controls the randomness of the Bayesian bootstrap, while subsample ratio (0.8–1.0) and the random subspace method (0.6–1.0) introduce stochasticity that improves model stability.

For SVR, we evaluated radial basis function (RBF), polynomial, and linear kernels to capture different types of relationships in the data. The RBF kernel, with its infinite-dimensional feature mapping, can model highly non-linear patterns, while polynomial and linear kernels provide interpretable alternatives for simpler relationships [87]. The regularisation parameter C (0.1–100) controls the trade-off between model complexity and training error, with smaller values promoting smoother decision boundaries. The epsilon parameter (0.01–0.5) defines the tolerance margin where no penalty is applied to errors, which controls the number of support vectors. For the RBF kernel, gamma values included both ‘scale’ (automatic scaling based on features) and manual values (0.001–0.1), allowing the algorithm to control the influence radius of individual training examples.

The cross-validation strategy employed TimeSeriesSplit with three splits and a test size of 81 observations, equal to the number of provinces. Table 3A shows this configuration for the hyperparameter tuning phase. Ten annual observations leave too few years for a separate outer test set; tuning on provinces and evaluating on years limits the dependence between the two stages.

Table 3. Cross-validation framework for model development. Hyperparameters of SVR, RF and CatBoost were tuned on folds of provinces (A); all four models were evaluated on folds of years (B).

A. Hyperparameter tuning phase (3 splits, 81 observations per test fold)		
<i>Rows ordered alphabetically by province, then by year</i>		
Split 1:	Training: all preceding rows	Testing: third-last block of 81 rows
Split 2:	Training: all preceding rows	Testing: second-last block of 81 rows
Split 3:	Training: all preceding rows	Testing: last block of 81 rows
<i>Each test block holds all years of 9–13 provinces</i>		
<i>Best hyperparameters selected based on mean MAE across splits</i>		
B. Model evaluation phase (4 configurations; rows ordered by year)		
<i>Configuration 1: 2 splits, 1-year test</i>		
Split 1:	Training: 2013, 2016–2022	Testing: 2023
Split 2:	Training: 2013, 2016–2023	Testing: 2024
<i>Configuration 2: 3 splits, 1-year test</i>		
Split 1:	Training: 2013, 2016–2021	Testing: 2022
Split 2:	Training: 2013, 2016–2022	Testing: 2023
Split 3:	Training: 2013, 2016–2023	Testing: 2024
<i>Configuration 3: 2 splits, 2-year test</i>		
Split 1:	Training: 2013, 2016–2021	Testing: 2022–2023
Split 2:	Training: 2013, 2016–2022	Testing: 2023–2024
<i>Configuration 4: 3 splits, 2-year test</i>		
Split 1:	Training: 2013, 2016–2018	Testing: 2019–2020
Split 2:	Training: 2013, 2016–2020	Testing: 2021–2022
Split 3:	Training: 2013, 2016–2022	Testing: 2023–2024

Training years start in 2013 for LRFE, 2016 for RF and CatBoost, and 2018 for SVR.

The optimal hyperparameters for each model were determined by minimising the average mean absolute error (MAE) across the three splits, chosen for its interpretability and practical relevance in demand forecasting contexts. The optimisation process was computationally intensive, requiring evaluation of 12,114 model configurations across all algorithms (288 for SVR, 5346 for RF and 6480 for CatBoost), but it was necessary for reliable model selection given the challenging extrapolation task.

Following hyperparameter optimisation, the best-performing configuration for each algorithm was retrained on the complete training panel (2013–2024, excluding 2014 and 2015; Section 4.2 gives the years available to each model) to maximise the information available to the final models used to generate 2050 projections. This approach balances

validation against the practical requirement of using all available data for long-term forecasting, consistent with best practices in time series modelling for policy applications [93]. Table 4 lists the final configuration of each model.

Table 4. Final model specifications. The 8 base predictors are population, GDP, single-person, family and multi-person households, HDD, CDD and the COVID-19 indicator. Lags are each province's consumption in its three preceding available years. Software: Python 3.12.4, NumPy 1.26.4, scikit-learn 1.5.1, CatBoost 1.2.5 and statsmodels 0.14.2.

Model	Final Hyperparameters	Preprocessing	Predictors	Training Rows	Tuning Metric	Random Seed
LRFE	None (ordinary least squares with province fixed effects; standard errors clustered by province)	None	8 base predictors and province fixed effects	810 (2013, 2016–2024)	Not tuned	Not applicable
SVR	Kernel linear; $C = 100$; $\epsilon = 0.5$ (γ and degree inactive for the linear kernel)	Standardisation to zero mean and unit variance	8 base predictors, lags 1–3 and their mean	567 (2018–2024)	MAE	Not applicable
RF	80 trees; maximum depth 12; minimum samples to split 6; minimum samples per leaf 2; maximum features sqrt; bootstrap disabled	None	8 base predictors, lags 1–3 and their mean	729 (2016–2024)	MAE	42
CatBoost	300 iterations; learning rate 0.05; depth 4; L2 regularisation 1; bagging temperature 0; subsample 0.8; RSM 1.0	None	8 base predictors, lags 1–3 and their mean	729 (2016–2024)	MAE	42

4.4. Performance Evaluation Framework

Model evaluation employed multiple established metrics, since different metrics capture distinct aspects of prediction accuracy and model behaviour. The selection of evaluation metrics was guided by both theoretical considerations and practical constraints imposed by the characteristics of provincial natural gas consumption data. The primary evaluation metrics comprised MAE, root mean squared error (RMSE), coefficient of determination (R^2), and explained variance (EV).

Each metric was chosen for a particular purpose. MAE is the most straightforward, offering an average prediction error in physical units that is easy to interpret for planners and decision-makers. Because it penalises all errors equally, MAE is less affected by outliers than RMSE and tends to give a more cautious estimate of how the model usually performs, which matters in infrastructure planning, where the average error directly informs capacity decisions [94–96]. RMSE, by contrast, squares the prediction errors, amplifying the impact of larger mistakes. RMSE is therefore useful for spotting models that perform adequately most of the time but occasionally produce large errors, which in natural gas systems can mean supply shortfalls [97]. R^2 indicates how much of the variation in natural gas consumption the model can explain. Although it is a standard measure for comparing models, R^2 should be interpreted with caution in time-series analyses, as high values can sometimes hide systematic errors or weak performance during certain periods [31]. We report R^2 mainly for comparability with existing literature while recognising that it should not be the only measure of model quality. EV is another way to assess how much variation in the target variable the model captures, though it differs from R^2 in its treatment of the mean. Mean absolute percentage error (MAPE) is widely used in energy forecasting research, but it was not suitable for our analysis. In the early years of our study, some provinces had no natural gas consumption because infrastructure was not yet in place. These zeros in the denominator make MAPE either undefined or misleadingly high, which would distort the assessment of model performance. We therefore report the symmetric mean absolute percentage error (SMAPE), which divides each absolute error by the mean of the absolute actual and predicted values and omits cases where both are zero.

The evaluation framework employed multiple temporal validation configurations using TimeSeriesSplit to assess model stability across different forecast horizons, with the panel ordered by year so that each test fold contains one or two complete years of provincial data. Table 3B shows the four distinct evaluation configurations implemented, varying both the number of splits (2 and 3) and test set sizes (81 and 162 observations, corresponding to one and two years of provincial data, respectively). This multi-configuration approach was designed to evaluate model performance using test sets of varying lengths with one year (81 observations) and two years (162 observations), to examine how prediction accuracy behaves under different validation windows.

The rationale for these specific configurations reflects several methodological considerations. The one-year test size (81 observations) represents the minimum meaningful evaluation period in our panel structure, allowing assessment of model performance across all provinces for a complete annual cycle. The one-year window captures province-specific patterns while leaving sufficient training data. The two-year test size (162 observations) provides a more stringent test of model generalisation, relevant given our ultimate objective of 25-year extrapolation to 2050. By evaluating performance over two-year horizons, we gain insight into how prediction accuracy degrades with increasing temporal distance from the training period.

All implementations used scikit-learn [98] for consistent metric calculation, which keeps results comparable across models and reproducible. Each evaluation fold refits the model on earlier years only. Because test-year lags are observed values, the metrics measure one-year-ahead accuracy rather than the accumulated error of recursive projection.

The validation windows are shorter than the 25-year projection horizon, but extending them further would reduce the training set below the minimum needed for stable estimation across 81 provinces. We address this by reporting projections from four different algorithms, for the cross-model envelope to capture uncertainty that would be understated by any single model's validation metrics.

4.5. Model Evaluation: Actual Consumption Versus In-Sample Predictions

Figure 2a presents a comparison between historical actual natural gas consumption and in-sample model predictions for the period 2018–2024, obtained from the final models trained on all years. Model predictions over the historical period begin in 2018 rather than 2013, as SVR, RF and CatBoost use consumption values from the preceding three years as input features, a common approach in energy demand modelling to capture consumption momentum [48]. The first three years of data (2013, 2016, 2017) are therefore used to generate these inputs, and 2018 is the first year for which all four models have complete inputs. Out-of-sample accuracy is assessed separately in Section 4.7.

All four models tracked historical consumption closely in sample.

The temporal pattern includes a consumption decline in 2023. Most models (RF, CatBoost, and LRFE) project relatively flat or minimal growth while the actual demand shows a marked decrease from the 2022 peak. The SVR model diverges from this pattern, predicting continued upward growth despite the actual consumption decline, which suggests that it is less sensitive to recent trend reversals.

To further evaluate model performance across the spatial dimension, Figure 2b and Figure 2c present scatter plots comparing actual versus predicted consumption values for all provincial observations. Figure 2b displays the complete dataset, showing three distinct consumption clusters. Istanbul dominates the high-consumption range (approximately 40–55 TWh), Ankara occupies the mid-range cluster (approximately 15–25 TWh), and the remaining provinces form a dense cluster below 11 TWh. All four models maintain

close in-sample correspondence to the perfect prediction line ($y = x$) across these diverse consumption scales, with predictions tightly distributed around the diagonal.

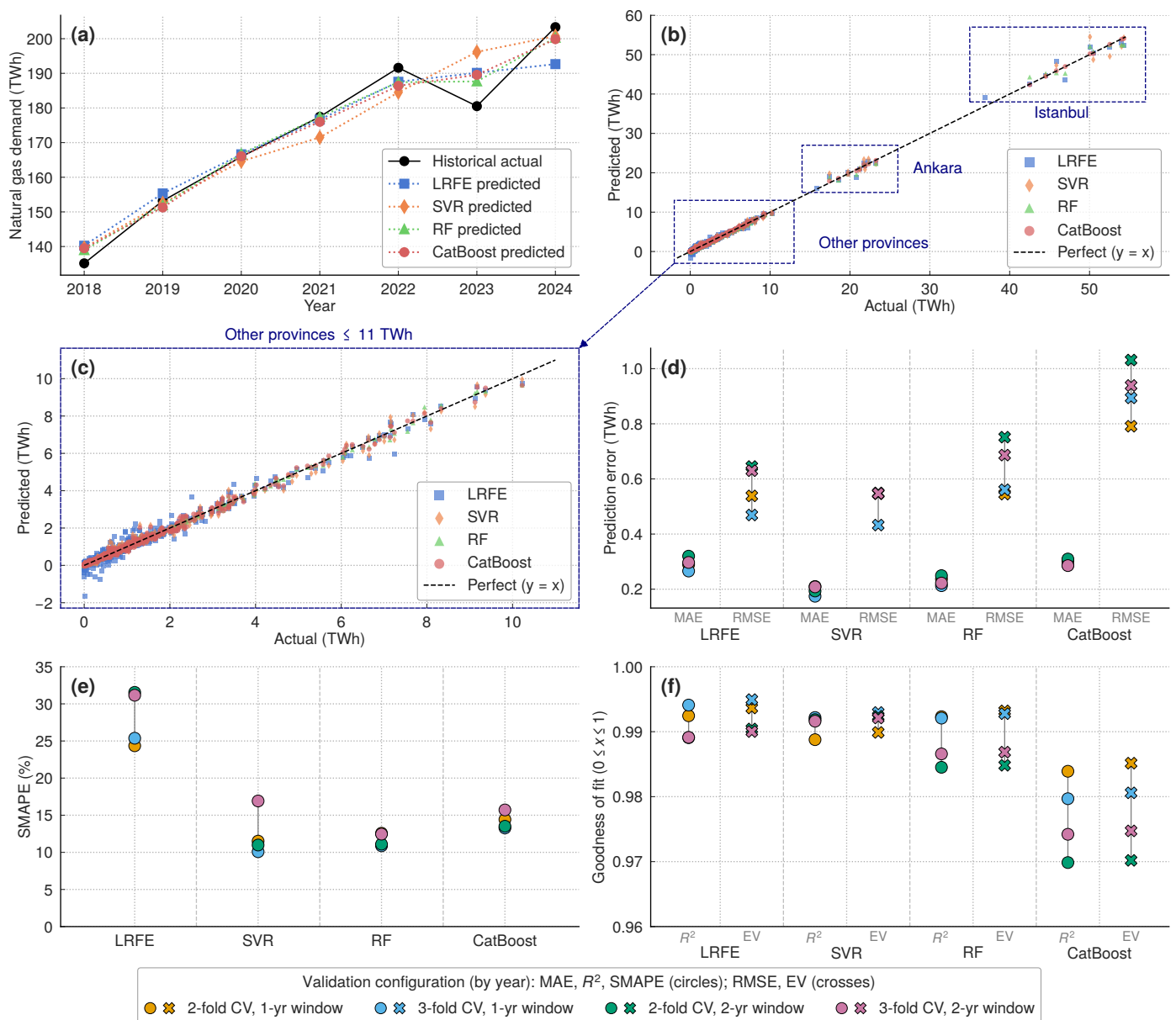


Figure 2. Model evaluation and validation results for provincial natural gas demand forecasting. (a) Historical actual consumption versus in-sample model predictions, 2018–2024. (b) Actual versus in-sample predicted consumption for all 81 provinces, showing three distinct consumption clusters: Istanbul (40–55 TWWh), Ankara (15–25 TWWh), and the remaining provinces (≤ 11 TWWh). (c) Detailed view of the lower consumption provinces (≤ 11 TWWh). (d) MAE and RMSE for four year-ordered validation configurations. (e) SMAPE. (f) R^2 and EV.

Figure 2c provides a detailed view of the lower consumption cluster, encompassing the majority of Turkish provinces with annual consumption below 11 TWWh. This zoomed perspective confirms that model performance remains consistent even at lower consumption scales, with all models maintaining close proximity to the perfect prediction line. The tight clustering of predictions across different model architectures suggests accurate capture of demand patterns regardless of provincial consumption magnitude.

The evaluation across temporal (Figure 2a) and spatial (Figure 2b,c) dimensions shows that the models reproduce the underlying relationships between natural gas demand and

the selected socioeconomic and climatic variables. Model performance across different architectures and consumption scales suggests that the selected features capture the main demand patterns for provincial-level forecasting in Turkey.

4.6. Model Evaluation: Feature Importance Analysis

Feature importance was measured with SHapley Additive exPlanations (SHAP) [99], which apply in the same way to all four models and are shown in Figure 3. For the linear-kernel SVR, attributions follow directly from the fitted linear function. In LRFE, province fixed effects absorb time-invariant differences between provinces, and its SHAP values therefore reflect within-province variation and are not comparable in magnitude with the other models.

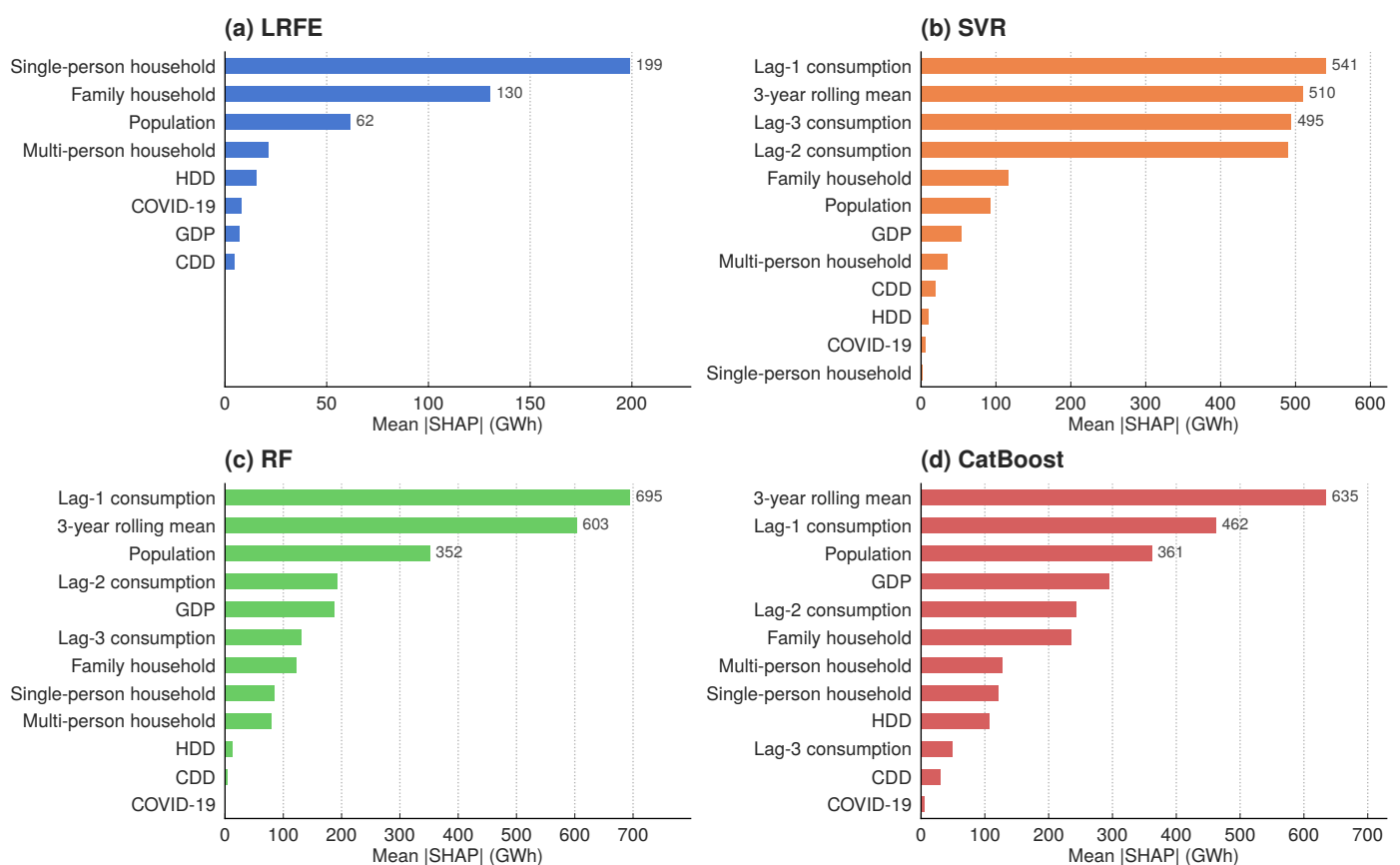


Figure 3. Mean absolute SHAP value (GWh) of each predictor in the final (a) LRFE, (b) SVR, (c) RF and (d) CatBoost models. LRFE has no lag features; its province fixed effects are not shown.

Lagged consumption dominates the three machine learning models. The first lag and the three-year mean rank highest in SVR, RF and CatBoost (462–695 GWh), as expected in a pooled panel in which provincial consumption ranges from near zero to more than 50 TWh.

Among exogenous drivers, demographic variables outweigh climate in all four models. Population leads in RF (352 GWh) and CatBoost (361 GWh), family households in SVR (116 GWh) and single-person households in LRFE (199 GWh). GDP ranks second in RF and CatBoost. HDD reaches at most 107 GWh (CatBoost), and the COVID-19 indicator at most 8 GWh.

These are predictive, not causal, importances, and correlated demographic variables share attribution, which makes the group-level comparison more reliable than individual ranks. The low weight of HDD is consistent with the annual pooled design, in which differences in population across provinces far exceed year-to-year differences in HDD within them; isolating weather effects requires monthly or within-province data.

4.7. Model Evaluation: Cross-Validation Performance Metrics

Figure 2d–f present evaluation metrics obtained through year-ordered time series cross-validation, using the four configurations described in Table 3B.

SVR had the lowest MAE in all four configurations (0.174–0.210 TWh) and the lowest RMSE in three. Averaged over configurations, MAE was 33% below LRFE for SVR, 21% below for RF and 1% above for CatBoost. RF and CatBoost had higher RMSE than LRFE in every configuration, which reflects occasional large errors. Two-year test windows raised MAE in six of eight comparisons.

Istanbul, the largest consumer, accounts for 41–73% of each model’s squared error in the three-split, one-year configuration. CatBoost under-predicts it by 8% and RF by 3%, consistent with the limited extrapolation of tree-based models discussed in Section 5; SVR over-predicts it by 4%. Without Istanbul, all three machine learning models have lower MAE than LRFE (0.142, 0.178 and 0.213 against 0.238 TWh for SVR, RF, CatBoost and LRFE).

Relative errors separate the models more clearly. Mean SMAPE was 11.8% for RF, 12.4% for SVR and 14.2% for CatBoost, against 28.1% for LRFE, as shown in Figure 2e. R^2 was high for all models (0.970–0.994) and highest for LRFE and SVR, as shown in Figure 2f, but across provinces spanning more than two orders of magnitude it mainly reflects separation between provinces, and error metrics are used to rank the models [31].

No model is best on every criterion. SVR has the lowest absolute error, RF the lowest relative error, and LRFE a high R^2 with the highest relative error. All four are retained, and Section 5 compares their projections.

5. Results and Discussion

5.1. National Gas Demand Projections

The national trajectories shown in Figure 4 are built up from province-level forecasts rather than modelled directly at the national scale. This bottom-up aggregation preserves provincial heterogeneity and ensures that national-level uncertainty reflects the propagation of errors in provincial models. Such errors are more consequential in high-consumption provinces such as Istanbul or Ankara, given their weight in national totals. In the near term, all four models produce tightly clustered results in all SSP scenarios, ranging between 208.0 and 210.4 TWh in 2025. The projections then diverge steadily, and by 2050 the combined model-scenario envelope ranges between 358 and 463 TWh.

Table 5 presents national residential natural gas demand projections at five-year intervals from 2025 to 2050 across all model-scenario combinations. Taking SSP2 as a central reference, a “middle-of-the-road” scenario, the multi-model mean nearly doubles from 209 TWh in 2025 to 412 TWh in 2050, with an average annual growth rate of 2.76% under SSP2. Model-specific trajectories under SSP2 nonetheless vary considerably. SVR produces the highest projection, rising from 209.9 to 439.8 TWh with 110% growth. RF and LRFE follow with similar expansion. RF grows from 208.1 to 425.6 TWh, a 105% increase, and LRFE rises from 208.4 to 418 TWh, a 101% increase. In contrast, CatBoost yields the most conservative forecast, an increase from 209.2 to 366 TWh and a 75% rise over the period.

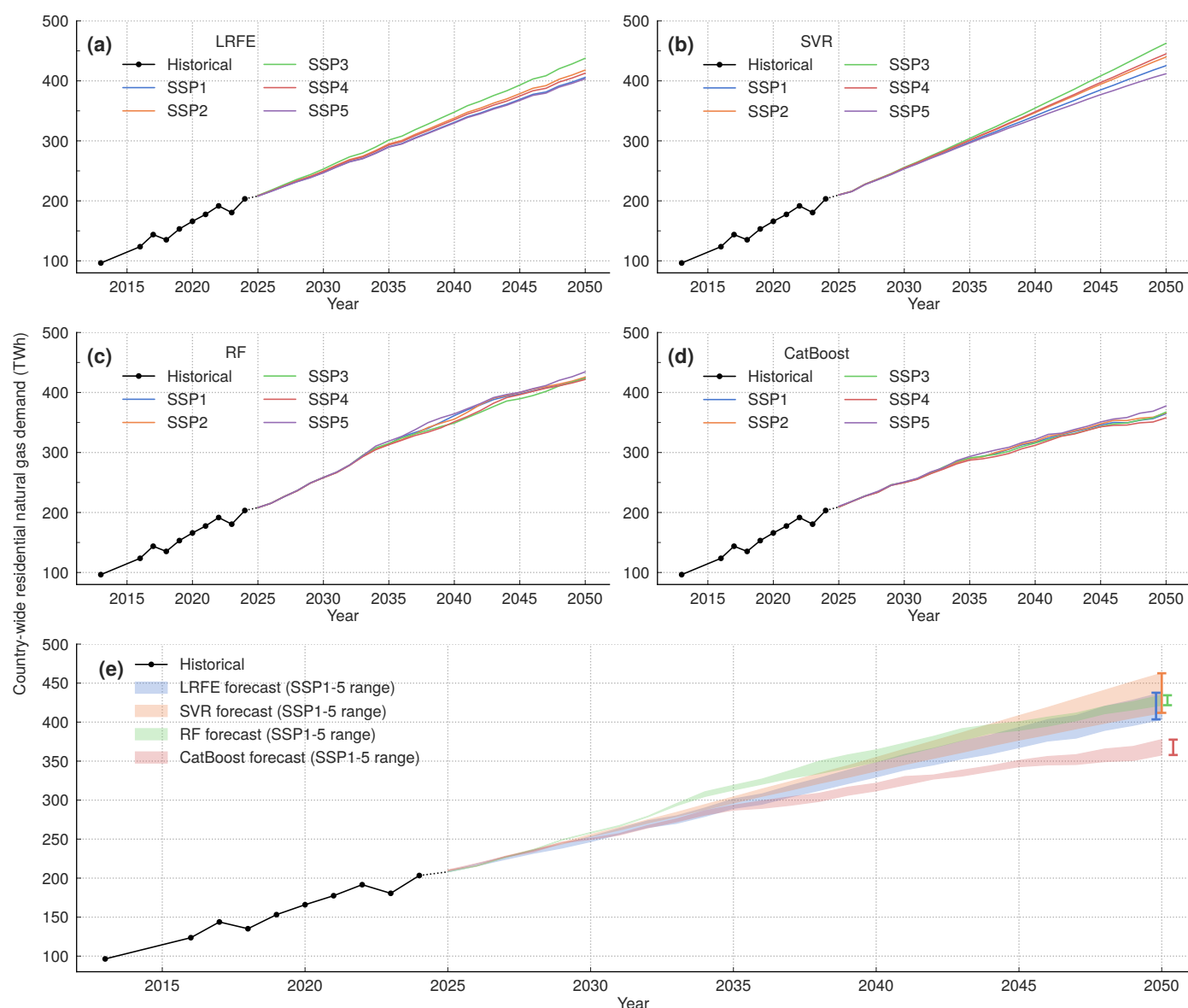


Figure 4. National residential natural gas demand projections to 2050. Panels (a–d) show projections from four machine learning algorithms (LRFE, SVR, RF, and CatBoost) under five SSP scenarios (SSP1–5), with historical observations shown as black dots (2013–2024). Panel (e) combines all model forecasts to show the full uncertainty envelope, with shaded ranges giving the SSP1–5 spread for each algorithm. Bars at 2050 indicate the scenario spread for each model.

Table 5. National residential natural gas demand projections. Gas demand in TWh is projected at five-year intervals from 2025 to 2050 under five SSP scenarios by four investigated algorithms: LRFE, SVR, RF and CatBoost. Mean and standard deviation values represent cross-scenario averages for each model–year combination.

Algorithm	Year	National Residential Gas Demand (TWh) in SSP Scenarios					Mean $\pm$ SD
		SSP1	SSP2	SSP3	SSP4	SSP5	
LRFE	2025	208.0	208.4	209.0	208.4	208.0	208.4 $\pm$ 0.3
	2030	247.1	249.7	253.0	248.9	246.9	249.1 $\pm$ 2.2
	2035	290.2	294.9	301.3	293.2	289.5	293.8 $\pm$ 4.2
	2040	330.8	337.9	347.9	335.2	329.7	336.3 $\pm$ 6.5
	2045	369.0	378.6	393.0	374.7	367.4	376.5 $\pm$ 9.1
	2050	405.7	418.0	437.7	412.8	403.5	415.5 $\pm$ 12.2

Table 5. Cont.

Algorithm	Year	National Residential Gas Demand (TWh) in SSP Scenarios					
		SSP1	SSP2	SSP3	SSP4	SSP5	Mean $\pm$ SD
SVR	2025	209.9	209.9	210.0	210.0	209.8	209.9 $\pm$ 0.1
	2030	253.9	254.7	255.8	254.9	253.4	254.5 $\pm$ 0.8
	2035	298.2	300.6	304.1	301.3	296.4	300.1 $\pm$ 2.6
	2040	341.6	347.0	354.6	348.5	337.5	345.9 $\pm$ 5.9
	2045	385.0	394.3	408.2	397.3	377.0	392.4 $\pm$ 10.7
	2050	425.3	439.8	462.6	444.9	411.9	436.9 $\pm$ 17.3
RF	2025	208.1	208.1	208.1	208.1	208.1	208.1 $\pm$ 0.0
	2030	258.3	258.4	258.1	257.9	258.4	258.2 $\pm$ 0.2
	2035	314.2	313.7	315.2	313.0	319.0	315.0 $\pm$ 2.1
	2040	361.4	355.5	349.0	351.2	364.4	356.3 $\pm$ 5.9
	2045	397.5	399.9	389.5	396.3	400.3	396.7 $\pm$ 3.9
	2050	424.2	425.6	423.5	421.7	434.4	425.9 $\pm$ 4.4
CatBoost	2025	209.2	209.2	209.2	209.2	210.4	209.4 $\pm$ 0.5
	2030	250.3	250.3	250.0	249.6	251.0	250.2 $\pm$ 0.4
	2035	289.8	289.9	291.0	287.2	293.4	290.2 $\pm$ 2.0
	2040	317.0	318.5	315.6	311.9	321.6	316.9 $\pm$ 3.2
	2045	345.9	347.8	343.2	342.9	350.8	346.1 $\pm$ 3.0
	2050	364.7	366.0	367.5	357.9	377.5	366.7 $\pm$ 6.3

Despite differences in projected levels, all four algorithms produce nearly linear trajectories for national residential gas demand through 2050. This linearity stems from the smooth evolution of the SSP-driven inputs, population and GDP, which contain no structural breaks or sudden shifts. Such consistency supports forecast stability but carries a caveat. Real-world gas demand can deviate from smooth trajectories under policy interventions such as efficiency standards, building regulations, and financial incentives [100]. Models in this study capture these influences only through their effects on GDP and population. International evidence also shows that mature gas markets can undergo technology-driven fuel switching in space heating [27]. Such transitions, should they occur, may produce departures from the trajectories presented here.

Scenario sensitivity increases over the forecast horizon (Figure 4). By 2030, within-model variation across SSPs is no more than 2.2 TWh for all algorithms; by 2050, this spread expands to 4.4–17.3 TWh depending on the model (Table 5). Because we varied only population and GDP while holding other drivers constant, these figures are likely lower bounds on true scenario uncertainty. Household counts, which weigh heavily in LRFE and SVR, as shown in Figure 3, are also fixed across scenarios. The direction in which scenarios push long-run projections is more informative than the magnitude of the spread. LRFE and SVR place SSP3 at the high end by 2050 (437.7 and 462.6 TWh respectively), while tree-based models reverse this ordering, with SSP5 generating the highest projections (434.4 and 377.5 TWh). These opposite sensitivities imply that algorithmic structure shapes the mapping from socioeconomic narratives to energy demand. The two linear models, LRFE and the linear-kernel SVR, tend to reflect demographic inertia as gradual, consistent increases in energy demand. Tree-based ensemble methods are more sensitive to complex interactions, such as those arising from accelerated economic growth and shifts in societal behaviours, and therefore produce more pronounced changes in projected outcomes [101].

Model differences at the national level are substantial even under a fixed scenario. Under SSP2 in 2050, SVR yields the highest projection ($\approx$ 440 TWh), followed by RF ($\approx$ 426 TWh) and LRFE ($\approx$ 418 TWh), while CatBoost is most conservative ($\approx$ 366 TWh). The gap between the highest and lowest models under SSP2 is 73.8 TWh, larger than the within-model spread

for any single algorithm. Model uncertainty therefore dominates scenario uncertainty in this study, in which the scenarios vary population and GDP only. These differences can be explained by the underlying model mechanics. The linear-kernel SVR extrapolates its fitted relationship, and its recursive lagged inputs carry recent growth forward, which can amplify gentle accelerations in recent data [102]. RF delivers comparatively high long-run national levels despite near-flat projections for Istanbul, as discussed in Section 5.2. In contrast, CatBoost's boosting with ordered statistics and regularisation tends to encode saturation-like behaviour when features contain weak trend breaks or plateauing signals [86]. LRFE's intermediate position suggests that once provincial fixed effects absorb spatial heterogeneity, linear extrapolation can yield a reasonable central tendency at the aggregate level. Adequacy at the aggregate level does not guarantee adequacy at finer scales [103], and multi-scale validation therefore remains essential for planning applications. The dominance of model uncertainty over scenario uncertainty is a methodological finding. Under data-scarce conditions, algorithmic structure shapes long-horizon projections at least as much as the socioeconomic narrative they embed, and reporting results from a single model risks understating the true range of plausible outcomes. This finding motivates the multi-model envelope reported in the remainder of this section, in preference to any individual algorithm as the central estimate.

The national projections indicate a sustained increase in residential natural gas demand through 2050, subject to the quantitative uncertainty described above. Policymakers and planners should therefore plan against a demand envelope of 358–463 TWh by mid-century when evaluating efficiency strategies and infrastructure investments [104]. The steady growth and limited scenario variation should be interpreted with caution, as both are shaped by the study's conservative SSP assumptions, which account only for changes in population and GDP. The models do not reflect policy measures, market price fluctuations, or technological innovation, any of which could alter future demand trajectories.

One caveat applies specifically to the tree-based projections. Because RF and CatBoost predictions stay largely within the range of target values seen during training, their national totals for 2050 are disproportionately shaped by conservative (near-flat) projections for Istanbul and other provinces at the top of the training distribution, which dominate the aggregate. The RF and CatBoost national envelopes should therefore be interpreted as lower bounds rather than central estimates, with SVR and LRFE providing more credible upper ends of the range where urbanisation-driven demand growth continues.

5.2. Provincial Forecasts and Spatial Heterogeneity

Provincial projections show that residential gas demand is concentrated in Turkey's western and northwestern metropolitan regions, which together make up most of the national total. Many smaller provinces contribute less to overall demand, although a few show higher growth rates in relative terms. Figure 5 illustrates that, while demand is expected to rise in most provinces through 2050, the pace and spread of this growth differ depending on the modelling approach used. Full details for each algorithm-SSP combination are provided in Appendix B. These differences are consistent with documented patterns of urbanisation, income levels, and infrastructure across Turkey [105,106]; capturing them is the reason for the bottom-up approach. Nationally, the overall increase comes from a mix of fast-growing metropolitan regions, steady gains in more developed areas, and smaller provinces that are gradually expanding from a lower starting point [12].

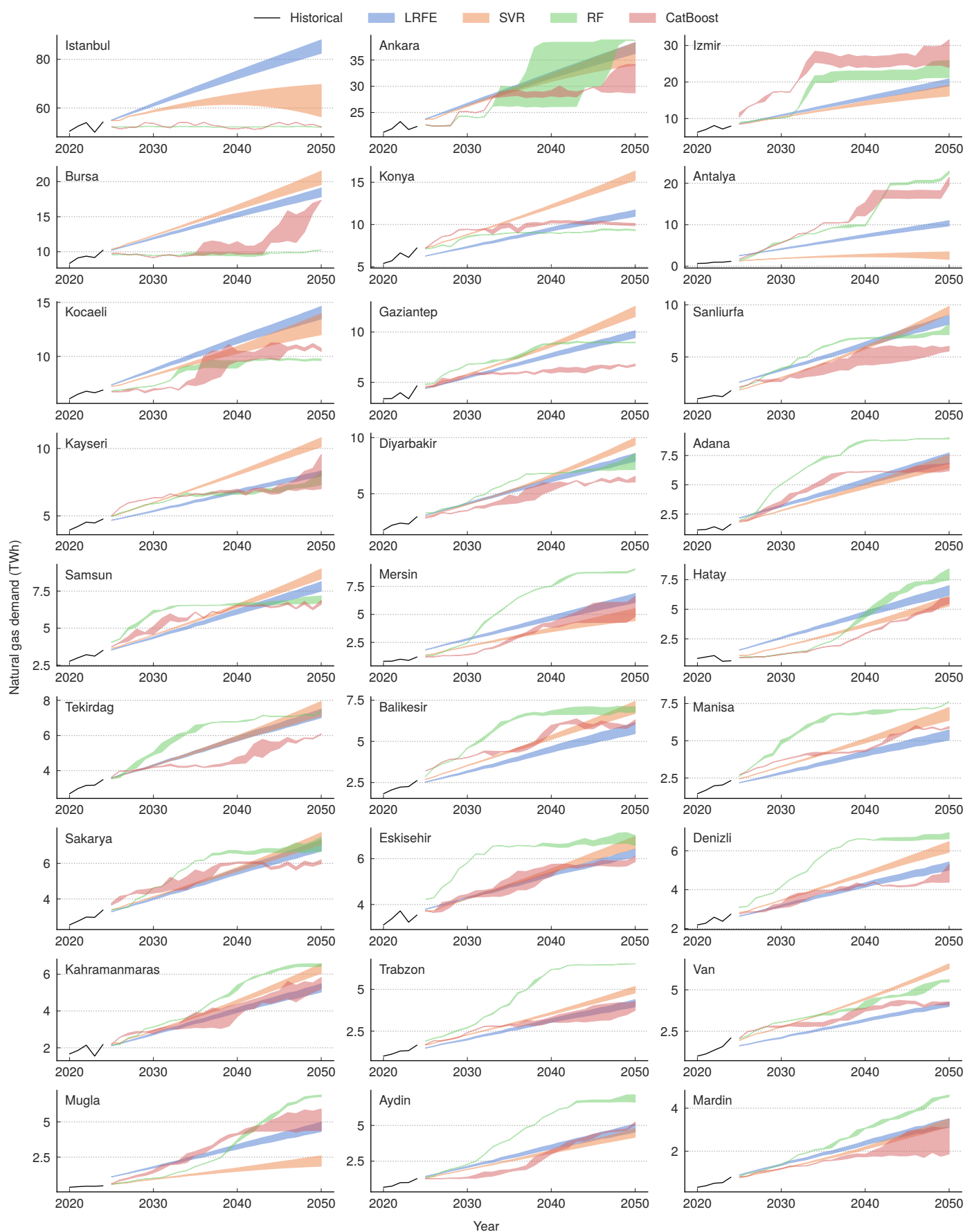


Figure 5. Residential natural gas demand projections to 2050 for 27 major provinces. Shaded ranges span the five SSP scenarios for each of the four ML algorithms.

Most of Turkey's residential gas demand is concentrated in the largest metropolitan areas of the Marmara, Aegean, Central Anatolia, and Mediterranean regions. Cities such as Istanbul, Ankara, Izmir, Bursa, Konya, and Antalya continue to account for a large share of total consumption, and Istanbul alone weighs heavily in the national figures. This regional distribution is similar to patterns observed in earlier studies of electricity demand [11], where consumption is also centred in the industrialised northwest, while areas with the best renewable energy potential are found elsewhere [21].

In provinces with high gas consumption, projections from the LRFE and SVR models tend to show a steady increase, in line with ongoing population growth and expansion of the building sector. By comparison, tree-based models often predict flatter demand trends, a difference that stands out in Istanbul, where both RF and CatBoost suggest nearly unchanged demand, which seems unlikely given the expected growth in that metropolitan area. This outcome relates to a documented limitation of tree-based ensemble models in long-term forecasting. Their predictions stay largely within the range of target values seen during training, so forecasts for provinces with unusually high demand often remain close to historical maximum values [84,107]. Since these provinces fall well outside the typical data range and the available historical period is relatively short, the models struggle to capture any acceleration specific to these locations. We include the tree-based projections for completeness but read them as lower bounds.

Beyond the largest metropolitan areas, agreement among the models is generally stronger in provinces with moderate demand, such as Diyarbakir, Adana, Samsun, and Hatay. In these locations, all four modelling approaches point to a steady rise in demand, and the range of projected outcomes is relatively narrow. The historical data in these provinces likely give the models a clear basis for identifying stable links between demand and its drivers, without the complication of outlier behaviour. For most provinces, sensitivity to the SSP scenarios follows the national trend. Scenario differences are small up to 2030 and become more pronounced by 2050, although the pace and extent of this divergence vary across years.

Future modelling efforts could benefit from hybrid or global-plus-local frameworks that share information across provinces while still letting each province's characteristics influence its forecast [108,109]. Another option is to weight model validation towards provinces with higher demand or greater planning importance, which would discourage systematic underestimation of growth in major metropolitan areas [110].

At the provincial level, LRFE and SVR mostly continue recent trends in a nearly straight line out to 2050, whereas RF and CatBoost produce more variable trajectories. For each model, differences due to the SSP scenarios are generally smaller than the contrasts between the models themselves, a pattern that matches what is seen at the national level. While changes in population and GDP do shift the demand levels, they have little effect on the overall shape of the trajectories. LRFE and SVR therefore agree most closely with each other in provinces with moderate gas demand, while the greatest disagreements between models appear in the largest metropolitan areas, where total demand is highest.

Although nearly linear growth aligns with the evolution of population and households, it is unlikely to continue indefinitely, especially in regions nearing market saturation or exposed to new policies such as electrification of heating, updated efficiency standards, or large shifts in fuel prices [111,112]. The widening gap between model projections in high-demand provinces shows that uncertainty is greater in some areas than others. Planning should therefore use province-specific uncertainty ranges rather than a single national estimate, and should weigh the higher end of demand projections in large provinces, since tree-based models may underestimate future growth there.

5.3. Emissions Implications of Projected Natural Gas Demand

To assess the climate impact of residential natural gas use, we converted residential demand into direct end-use greenhouse gas emissions. We excluded emissions from upstream production, processing, and distribution losses to distinguish end-use effects from those of the broader supply chain. All residential gas is assumed fully combusted during end use, with non-combustion applications considered negligible.

For conversion, we apply an end-use emission factor of 0.2025594 kgCO₂e per kWh [113] on a lower heating value basis. This factor already includes the standard additions for CH₄ and N₂O and is the same value Turkey uses in its national inventory reporting under IPCC AR5 guidelines [114]. Demand in this paper is on the gross basis of the EMRA conversion. For emissions, it is converted to the net basis of the factor at 9.595 kWh/Sm³, equivalent to 8250 kcal/Sm³, the value at which the national energy balance tables record residential volumes [115]. Emissions for 2020–2023 are calculated from the same tables. Because the mapping from energy to emissions is linear, relative differences across models and scenarios are preserved in the emissions series. Figure 6 illustrates the resulting emissions envelope constructed from bottom-up provincial forecasts (by model and SSP) aggregated to the national level.

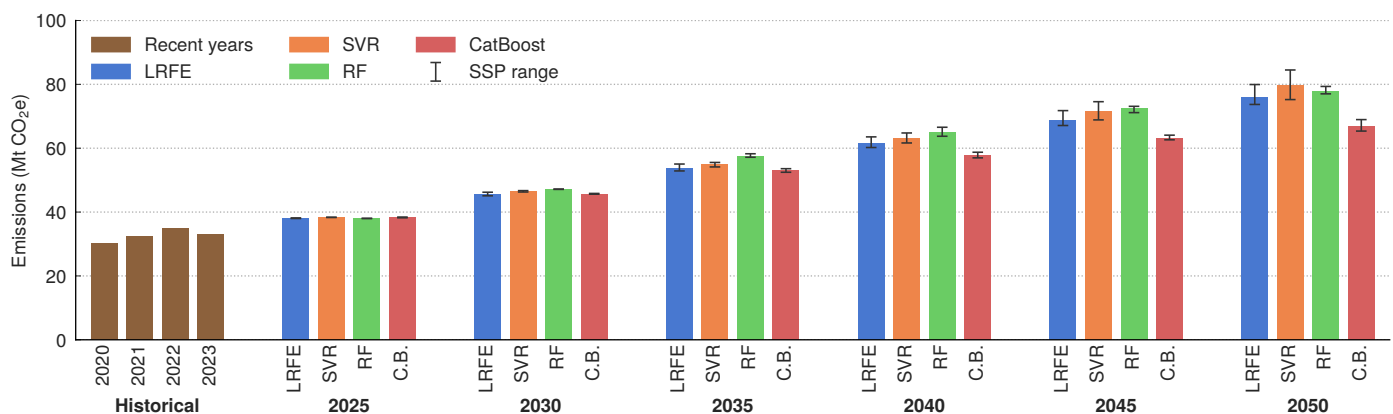


Figure 6. Direct residential CO₂ emissions implied by provincial natural gas demand projections under five SSPs and four modelling approaches. The envelope reflects within-model scenario spreads and cross-model differences; values represent end-use combustion only. Emissions for past years are calculated using annual energy balance tables [115].

At the national level, projected emissions remain closely grouped in the near term but diverge by mid-century. The mean of model SSP averages is 38.2 MtCO₂e in 2025 and rises to 46.2 MtCO₂e in 2030. After 2030, the spread among model means widens. By 2035, the range is 53.0–57.5 MtCO₂e; in 2040, it is 57.9–65.1 MtCO₂e; in 2045, it is 63.2–72.5 MtCO₂e; and by 2050, it is 67.0–79.8 MtCO₂e. On average, annual emissions increase by 1.48 MtCO₂e per year, an average annual growth rate of 2.75% across all scenarios.

Two patterns stand out. First, scenario spreads are modest in the early years and widen towards mid-century, consistent with our implementation that varies population and GDP by SSP while holding other drivers fixed. Second, the cross-model emission envelope by 2050 spans approximately 13 MtCO₂e, so model selection alone shifts carbon budget estimates by this margin.

The central climate-policy finding of this study is that residential natural gas emissions rise continuously through 2050 across every model-scenario combination examined, rather than peaking within the projection horizon. By mid-century, end-use emissions from residential gas alone reach 67.0–79.8 MtCO₂e on average across SSPs for each model, and 65.4–84.5 MtCO₂e across all model-scenario combinations, with no algorithm or scenario producing a turning point. This result holds despite the substantial inter-model

divergence documented earlier. Even the most conservative tree-based projections, which we treat as lower bounds, show monotonic growth through 2050.

By 2030, residential natural gas combustion alone would account for about 6.6% of Turkey's national emissions ceiling, from a single end-use category within one sector. Turkey's Updated First Nationally Determined Contribution (NDC) sets an economy-wide target of 695 MtCO₂e by 2030, including Land Use, Land-Use Change and Forestry (LULUCF), a 41% reduction against the business-as-usual scenario [26], and our projections put residential gas at 46.2 MtCO₂e in that year. Because the target counts the LULUCF sink, it is smaller than Turkey's emissions reported excluding LULUCF, so 6.6% is an upper bound on the share. Turkey's Second NDC, submitted in November 2025, sets a single-year target of 643 MtCO₂e for 2035, also including LULUCF [116].

The Updated First NDC further commits Turkey to peak total greenhouse gas emissions by 2038 and to achieve net-zero emissions by 2053 [26], and the Climate Law No. 7552 frames national climate policy around the net-zero emissions target [22]. The continuous upward trajectory documented above is a challenge for these economy-wide objectives. Residential gas emissions show no peak by 2038, and they continue rising through 2050, three years before the net-zero target year, rather than declining. Without targeted interventions in the building sector, rising residential gas emissions would require larger reductions in other sectors for the national targets to be met.

The NDC identifies several mitigation strategies for the building sector by 2030, including the adoption of heat pumps, expansion of district heating, retrofitting of existing buildings, implementation of Nearly Zero Energy Building (NZEB) standards, and enforcement of building performance codes [26]. These policy interventions are not incorporated into our modelling approach, which forecasts demand from demographic and economic trends alone, without technological transitions or regulatory measures. The contrast between our upward emissions projections and the policy aspirations articulated in the NDC reflects this omission. Should such mitigation measures be implemented at scale, they could change the demand pathways presented here and could produce the emissions peak that our models currently do not reflect. Our projections are therefore best interpreted as a no-new-policy baseline, a reference against which the impact of building sector decarbonisation strategies can be evaluated.

5.4. Limitations and Future Research

Tree-based ensembles such as Random Forest and CatBoost capture non-linear relationships well, but their predictions are constrained by the range of target values seen during training and in practice do not exceed historical maxima. The mechanism, noted earlier in the context of high-consumption provinces, is that observations with exceptionally large values dominate impurity reduction and split selection, so a small number of high-leverage points constrains the fitted response surface. For this reason, we treat the RF and CatBoost national totals as lower bounds. A target normalised by households or population, or a growth target, could relax this constraint.

Although we used the maximum available provincial historical data, the panel comprises only a decade of observations. The pooled panel design supplies sample size and cross-sectional variation, which mitigates but does not eliminate the limitations imposed by a short estimation window relative to the 25-year projection horizon, and heightens the risk of distributional shifts over time. A specific consequence, already noted in Section 4, is that annual pooled models cannot isolate the effect of climate variables because cross-province population variation dominates within-province year-to-year variation in heating degree-days; recovering this signal would require monthly or within-province specifications outside the scope of long-horizon planning forecasts. Furthermore, our analysis does

not explicitly account for technological transitions or policy interventions that could alter residential gas demand. The selection of variables was also restricted by the availability of provincial data, which prevented direct incorporation of factors such as connection rates, floor-area expansion, appliance and boiler composition, and retrofit intensity.

Network expansion enters only through population and households, and the direction of bias depends on network maturity. The proxy is closest in mature networks, where demographic growth translates into new connections. Where networks expanded during 2013–2024, past growth combines higher use per household with new connections, and projections may overstate demand once networks saturate. Provinces without access have no consumption history, and demand may be understated if they are connected before 2050. Consistent provincial connection data were not available for a robustness check.

Linking household projections to SSP population would widen the scenario spread, because households weigh heavily in LRFE and SVR. Historical GDP includes price and exchange-rate effects, whereas projected GDP reflects real growth; the difference matters most for RF and CatBoost, which give GDP more weight.

Scenarios vary population and GDP only; climate follows one pathway, and network expansion, prices, efficiency and fuel switching are held constant. Sensitivity cases that link households to SSP population, add a second climate pathway and separate mature from new networks would test whether model uncertainty still exceeds scenario uncertainty.

Given the constraints of a limited historical record and the omission of explicit technological and policy dynamics, future research should aim to expand the provincial evidence base. As more comprehensive data become available, modelling efforts could integrate characteristics such as dwelling stock (e.g., floor area per dwelling), heating technology composition and turnover rates, connection rates, appliance and boiler efficiencies, and retrofit intensity. Scenario development should also move beyond the current focus on GDP and population-based SSPs to include trajectories for variables such as natural gas prices and tariffs, efficiency standards, electrification pathways, and building code requirements, all aligned with SSP narratives. The framework could also be adapted to the commercial and industrial sectors and to interactions between different energy sources, enabling more complete assessments of provincial energy transitions.

6. Conclusions

This study shows that pooled panel data, combined with scenario-based projections under Shared Socioeconomic Pathways, make long-horizon energy demand forecasting feasible under training data scarcity by compensating for limited observations in one dimension with variation in another. In the Turkish case study, we combined cross-sectional variation across all 81 provinces with only a decade of annual observations and built models that performed consistently across cross-validation split counts and test window lengths. In year-ordered cross-validation, the machine learning models roughly halved the relative error of linear regression with provincial fixed effects, and SVR had the lowest absolute error, 33% below that model. The integration of SSP-aligned population and GDP projections enables demand forecasts that are consistent with the socioeconomic narratives widely used in IPCC assessments and national climate policy frameworks. The approach may be transferable to other contexts where spatially or sectorally disaggregated energy data are available but temporally shallow, a condition that arises wherever demand records have only recently been broken down by region, end use, or fuel type. Its transfer to other countries remains to be tested.

Three methodological findings emerge with implications beyond the Turkish case. First, the spread across forecasting models exceeds the variation introduced by socioeconomic scenarios that vary population and GDP only. Under a middle-of-the-road pathway

(SSP2), the gap between the highest and lowest model projections in 2050 is 73.8 TWh, while within-model scenario spreads range from 4.4 to 17.3 TWh. When historical records are too short for models to converge on a single learned relationship, algorithmic choice shapes long-term projections more than assumptions about future development pathways. The practical consequence for infrastructure planning is that scenario analysis alone is insufficient; multi-model comparisons are needed to capture the range of plausible outcomes.

Second, lagged consumption dominated the three machine learning models, and among exogenous drivers, population and household composition outweighed heating degree days in all four. This ranking is unexpected for a sector in which space heating accounts for 78% of residential energy use and natural gas supplies 58% of total household energy. The low importance of climate variables may well be an artefact of the pooled panel structure. At annual resolution, demographic differences across provinces are far larger than year-to-year climatic variation within any single province, and models trained on pooled data may preferentially assign predictive weight to the dimension with greater variance. Feature importance rankings in pooled panels should therefore be interpreted with the panel design in mind.

Third, tree-based ensemble methods, which under-predicted Istanbul in validation, stay largely within the range of historical consumption, which flattens projections for high-consumption provinces that appear as outliers in the training data. Because these provinces dominate national totals, this behaviour propagates directly into aggregate forecasts, so tree-based results are more reliable as lower bounds than as central estimates. More broadly, among the four methods selected from an initial screening of twelve algorithms, none performed best across all provincial consumption scales; multi-model envelopes are therefore preferable to any single selected method.

For Turkey, the projections have direct implications for energy security and climate policy. National residential gas demand is projected to nearly double from 209 TWh in 2025 to between 358 and 463 TWh by 2050, depending on the model and scenario. This growth implies sustained and increasing dependence on imported natural gas, with consequences for energy security, trade balances, and supply vulnerability. The implied direct emissions from residential gas combustion alone would account for 6.6% of Turkey's nationally determined emissions ceiling by 2030 and reach 67–80 MtCO₂e by 2050. Across every model and scenario combination examined, residential gas emissions continue to rise through 2050 without peaking, a trajectory that challenges Turkey's economy-wide commitments to peak national emissions by 2038 and achieve net-zero by 2053. These projections are a no-new-policy baseline; targeted interventions in the building sector, including heat pump adoption, efficiency retrofits, and building performance standards identified in Turkey's NDC, could alter these trajectories but are not captured in the current modelling framework.

Future research should extend the approach by incorporating explicit representations of infrastructure expansion, technology substitution pathways, and policy scenarios aligned with decarbonisation targets. As provincial data coverage expands, adding dwelling characteristics, heating technology composition, and retrofit rates would improve projection accuracy and policy relevance.

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Data Availability Statement: The provincial natural gas consumption data used in this study were extracted from publicly available annual sector reports of the Energy Market Regulatory Authority (EMRA). SSP-aligned population and GDP projections were derived from published global gridded datasets. Processed datasets and code will be made available upon reasonable request to the corresponding author.

Conflicts of Interest: The authors declare no conflicts of interest.

Appendix A. Review of Natural Gas Demand Forecasting Studies

Table A1 summarises the natural gas demand forecasting studies discussed in Section 2.

Table A1. A review of natural gas demand forecasting studies. Columns give the modelling approach, input features, geographical coverage, sector, forecast output, temporal resolution, the range of historical data used, and the prediction horizon.

Ref	Approach	Input Features	Coverage	Sector	Output	Resolution	Data Range	Prediction Range
[34]	JITL-GPR, SARIMA, ETS, STL, TBATS, AFTER	Lagged natural gas consumption, year and month indices	Regional	Residential	Natural gas demand	Monthly	2014–2024	21 months ahead
[44]	FSE	Natural gas consumption, temperature, day-ahead feedback	Regional	Residential, industry	Natural gas demand	Daily	2002–2017	Up to one year
[6]	MARS, CMARS, NN, LR	Lagged natural gas consumption, HDD, temperature, price, wind speed, pressure, precipitation, soil temperature, exchange rate, moisture, number of users	Regional	Residential	Natural gas demand	Daily	2009–2013	One-day ahead
[4]	LogR, LR, NLMR	Population, GDP per capita, inflation rate, average winter temperature, price of electricity generation and natural gas	National	Residential, energy	Natural gas demand	Annual	1986–2014	2015–2025
[5]	ABC, LR	GDP, population, import, export	National	Total	Natural gas demand	Annual	1998–2017	2018–2030
[7]	ABC, ANN	Past 7-day consumption	Regional	Residential, commercial	Natural gas demand	Day ahead	2011–2014	One-day ahead
[8]	MCS, OU process	HDD, CDD, time trend, holiday effects, daily temperature	Regional	Residential, commercial	Natural gas demand	Daily	2004–2011	Daily forecasts
[48]	TSD, Holt–Winters, ARIMA, SARIMA	Past monthly natural gas consumption	Regional	Residential, commercial	Natural gas demand	Monthly	2011–2014	One year ahead
[36]	SSM-TVP, OLS	Price of natural gas, GDP per capita	National	Residential	Price elasticity	Annual	1970–2016	N/A
[50]	PPA, GLS, GMM	Price of gas and electricity, household income, household demographics, education level, urbanisation, HDD	Regional	Residential	Elasticities of gas demand	Annual	2012–2019	N/A
[47]	Novel Approach	Temperature and holiday indicators, past natural gas consumption data	Regional	Residential, commercial	Natural gas demand	Daily	2016–2021	Up to 7 days

Table A1. Cont.

Ref	Approach	Input Features	Coverage	Sector	Output	Resolution	Data Range	Prediction Range
[51]	MDCEV	Location and household characteristics, HDD, CDD, appliance usage,	National	Residential	Usage by energy type	N/A	2015	N/A
[41]	ENET, NN, XGBoost	Electricity and gas consumption, temperature, solar irradiance, rainfall, time-related variables-covid	National	Residential	Electricity and gas demand	Daily	2019–2020	2020–2022
[45]	Bottom-up GIS	Temperature, global horizontal irradiation, building characteristics, appliance usage, HDD, CDD,	National	Residential	Total energy demand	Annual	2008–2021	2022–2100
[49]	LPRM	Daily pipeline gas deliveries, temperature, seasonal and daily weather forecast	National	Residential	Natural gas demand	Daily, weekly	2018–2019	2021
[52]	DT	Building characteristics, socio-demographic variables, psychological factors, household behaviour	National	Residential	Household gas consumption	N/A	2017–2018	N/A
[38]	MLP, SVM, VAR, M-GARCH	Air temperature, humidity, wind speed, number of users, gas price and consumption	Regional	Residential	Natural gas demand	Monthly	2003–2021	2019–2021
[55]	Statistical trend models, analyses	consumption data of coal, electricity, natural gas, and heating	National	Residential	Energy demand	Annual	2006–2021	Up to 2027
[33]	ARIMA, Holt–Winters	natural gas consumption by sectors	National	All	Natural gas demand	Annual	1992–2016	2016–2030
[54]	PSM, LS, LAD	price of gas (CG), household income, household size, gas consumption,	National	Residential	Natural gas demand	Monthly	2018	NA
[57]	JJ test, MCM, Unit-root test	GDP per capita, industrial GDP share, industry energy efficiency, population	Regional	All	Energy demand, CO ₂ emissions	Annual	1980–2016	2020–2035
[10]	ARIMA, LSTM	natural gas consumption, prices of primary fuels (crude oil, natural gas, thermal coal)	National	Total	Natural gas demand	Annual	1993–2020	Up to 2040
[42]	ARIMA, ETS, MA, LSTM, MLP, LightGBM, HRM	Population, households with gas access, number of dwellings	National	Residential	Natural gas demand	Annual	2000–2020	Up to 5-year ahead
[58]	AM, FDT, k-Means, CIM	GDP per capita, population, energy intensity of GDP, natural gas share in the energy mix, HDD, industry's share of GDP	International, adaptable	Total	Natural gas demand	Annual	1980–2019	Adaptable
[9]	MLR, LMLR, NARX-ANN	Population, GDP, natural gas price, electricity price, renewable energy share	National	Residential, commercial	Energy demand	Annual	1967–2017	Up to 2040

Table A1. *Cont.*

Ref	Approach	Input Features	Coverage	Sector	Output	Resolution	Data Range	Prediction Range
[56]	GCAM, Income decile modelling, Gompertz-type function	Income distribution, GDP per capita, population density, energy prices, building shell conductivity, HDD, CDD	Global and regional	Residential	Energy demand	5 yr interval	2015	Up to 2050
[35]	SMA, RWD, SES, ARIMA, TBATS	Monthly natural gas consumption data, seasonal variations	Regional	Residential	Natural gas demand	Monthly	2015–2020	12 months ahead

Abbreviations: ABC: Artificial Bee Colony; AFTER: Aggregated Forecast Through Exponential Reweighting; AM: Analog method; ANN: Artificial Neural Network; ARIMA: AutoRegressive Integrated Moving Average; CIM: Chain Increment Method; CMARS: Conic Multivariate Adaptive Regression Splines; DT: Decision Tree; ENET: Elastic Net Regression; ETS: Exponential Smoothing State Space Models; FDT: Fuzzy Decision Tree; FSE: Fourier Series Expansion; GCAM: Global Change Analysis Model; GLS: Generalized Least Squares (GLS); GMM: Generalized Method of Moments (GMM); Holt–Winters: Holt–Winters exponential smoothing; HRM: Hierarchical reconciliation methods; JITL-GPR: Just-in-Time-Learning-Gaussian Process Regression; JJ test: Johansen–Juselius cointegration test; k-Means: k-means Clustering; LAD: Least Absolute Deviations method; Light-GBM: Light Gradient Boosting Machine; LMLR: Logarithmic Multiple Linear Regression; LogR: Logarithmic Regression; LPRM: Linear-plus-plateau regression model; LR: Linear Regression; LS: Least Squares method; LSTM: Long Short-Term Memory; MA: Moving Average; MARS: Multivariate Adaptive Regression Splines; MCM: Markov Chain Model; MCS: Monte Carlo Simulation; MDCEV: Multiple Discrete Continuous Extreme Value; M-GARCH: Multivariate Generalized Autoregressive Conditional Heteroskedasticity; MLP: Multi-layer Perceptron; MLR: Multiple Linear Regression; NARX-ANN: Nonlinear Autoregressive with Exogenous Input—Artificial Neural Network; NLMR: Nonlinear Multiple Regression; NN: Neural Network; OLS: Ordinary Least Squares; OU process: Ornstein–Uhlenbeck stochastic process; PPA: Pseudo-panel approach; PSM: Price Sensitivity Measurement; RWD: Random Walk with Drift; SARIMA: Seasonal Autoregressive Integrated Moving Average; SES: Simple Exponential Smoothing; SMA: Simple Moving Average; SSM-TVP: State-space model with time-varying parameter framework; STL: Seasonal and Trend decomposition using LOESS; SVM: Support Vector Machine; TBATS: Trigonometric, Box–Cox, ARMA, Trend, Seasonal; TSD: Time Series Decomposition; Unit-root test: Unit-root test; VAR: Vector Autoregression; XGBoost: Extreme Gradient Boosting.

Appendix B. Provincial Residential Natural Gas Demand Projections

The following tables present the projected annual residential natural gas demand at the provincial level (in GWh) between 2025 and 2050 for all combinations of the four forecasting algorithms (LRFE, SVR, RF, and Catboost) and the five Shared Socioeconomic Pathway scenarios (SSP1–SSP5). Tables A2–A6 show the LRFE model under SSP1–SSP5; Tables A7–A11 the SVR model; Tables A12–A16 the RF model; and Tables A17–A21 the Catboost model. Each table lists provinces in alphabetical order and reports forecasts for the six key years (2025, 2030, 2035, 2040, 2045, and 2050) under the specified SSP scenario.

Table A2. Projected annual residential natural gas demand (GWh) in Turkish provinces between 2025 and 2050 under SSP1 scenario from LRFE algorithm.

Province	2025	2030	2035	2040	2045	2050	Province	2025	2030	2035	2040	2045	2050
Adana	2161	3115	4089	5053	5989	6874	K.maras	2112	2706	3328	3932	4508	5053
Adiyaman	1016	1320	1655	1961	2256	2501	Karabuk	827	960	1137	1315	1455	1604
Afyonk.	1293	1591	1942	2286	2583	2875	Karaman	657	737	879	1001	1105	1185
Agri	413	573	815	1015	1200	1355	Kars	474	524	665	758	854	893
Aksaray	923	1107	1348	1561	1761	1925	Kastamonu	840	1015	1261	1500	1693	1896
Amasya	944	1092	1307	1498	1672	1828	Kayseri	4670	5313	6034	6705	7377	7990
Ankara	23,715	26,382	29,047	31,612	34,081	36,446	Kilis	291	356	462	566	653	715
Antalya	2522	4041	5556	7016	8430	9804	Kirikkale	834	913	1059	1184	1275	1345

Table A2. Cont.

Province	2025	2030	2035	2040	2045	2050	Province	2025	2030	2035	2040	2045	2050
Ardahan	139	114	197	221	260	259	Kirklareli	1060	1217	1427	1626	1786	1991
Artvin	145	152	272	346	416	472	Kirsehir	624	673	787	881	954	999
Aydin	1420	2054	2709	3345	3965	4576	Kocaeli	7349	8663	9968	11,237	12,421	13,583
Balikesir	2519	3106	3723	4350	4924	5508	Konya	6271	7257	8279	9262	10,162	11,018
Bartin	401	498	637	781	876	1010	Kutahya	1506	1706	1956	2207	2404	2620
Batman	929	1249	1597	1918	2220	2469	Malatya	1988	2327	2733	3082	3445	3738
Bayburt	220	199	273	290	324	312	Manisa	2174	2769	3377	3973	4545	5097
Bilecik	735	832	963	1099	1197	1316	Mardin	888	1342	1831	2299	2731	3132
Bingol	491	647	868	1037	1187	1327	Mersin	1825	2709	3603	4475	5308	6118
Bitlis	511	683	920	1115	1293	1444	Mugla	1097	1731	2406	3081	3720	4353
Bolu	978	1124	1313	1510	1665	1846	Mus	455	607	837	1013	1189	1335
Burdur	585	679	816	949	1049	1147	Nevsehir	741	844	1017	1154	1285	1372
Bursa	10,211	11,827	13,434	14,997	16,490	17,955	Nigde	884	1004	1192	1364	1528	1653
Canakkale	1254	1495	1788	2074	2327	2611	Ordu	1417	1881	2430	2943	3427	3942
Cankiri	477	519	623	717	787	846	Osmaniye	691	981	1311	1638	1938	2236
Corum	1371	1566	1825	2061	2264	2446	Rize	667	802	1010	1199	1359	1542
Denizli	2629	3132	3643	4136	4595	5029	Sakarya	3278	3968	4686	5396	6052	6728
Diyarbakir	3069	4068	5084	6065	7020	7910	Samsun	3522	4303	5143	5954	6736	7526
Duzce	1150	1349	1595	1844	2046	2276	Sanliurfa	2570	3680	4829	5976	7106	8183
Edirne	900	1042	1235	1415	1567	1757	Siirt	460	605	804	973	1124	1239
Elazig	1717	2050	2436	2772	3100	3375	Sinop	328	433	608	763	870	1023
Erzincan	662	740	892	997	1104	1174	Sirnak	513	852	1258	1640	1994	2296
Erzurum	1862	2129	2483	2786	3079	3329	Sivas	1663	1862	2171	2391	2634	2834
Eskisehir	3787	4259	4762	5244	5684	6121	Tekirdag	3565	4255	4985	5707	6361	7051
Gaziantep	4378	5423	6492	7525	8530	9481	Tokat	1260	1510	1844	2140	2411	2654
Giresun	701	999	1374	1711	2016	2363	Trabzon	1481	1968	2523	3026	3491	3971
Gumushane	240	248	347	393	443	474	Tunceli	110	133	207	253	292	300
Hakkari	218	288	448	568	656	723	Usak	963	1151	1366	1585	1770	1952
Hatay	1552	2512	3483	4432	5345	6207	Van	1626	2068	2596	3091	3568	4005
Igdir	278	335	452	535	642	657	Yalova	1066	1226	1414	1602	1723	1900
Isparta	1169	1340	1555	1763	1944	2128	Yozgat	837	960	1155	1320	1462	1585
Istanbul	54,911	60,893	66,726	72,295	77,743	83,062	Zonguldak	1330	1601	1920	2233	2490	2780
Izmir	8536	10,757	12,930	15,033	17,084	19,091							

Table A3. Projected annual residential natural gas demand (GWh) in Turkish provinces between 2025 and 2050 under SSP2 scenario from LRFE algorithm.

Province	2025	2030	2035	2040	2045	2050	Province	2025	2030	2035	2040	2045	2050
Adana	2170	3187	4233	5266	6257	7225	K.maras	2117	2754	3405	4029	4634	5211
Adiyaman	1018	1341	1697	2026	2341	2613	Karabuk	828	968	1153	1338	1490	1654
Afyonk.	1296	1611	1987	2349	2670	2986	Karaman	658	743	890	1019	1131	1216
Agri	415	584	835	1046	1243	1413	Kars	475	529	676	775	878	922
Aksaray	924	1120	1365	1585	1796	1968	Kastamonu	841	1032	1290	1544	1761	1993
Amasya	945	1105	1331	1540	1736	1909	Kayseri	4675	5348	6087	6793	7483	8117
Ankara	23,744	26,537	29,341	32,063	34,674	37,198	Kilis	291	360	470	576	667	733
Antalya	2536	4125	5709	7268	8772	10,253	Kirikkale	835	923	1077	1214	1321	1409
Ardahan	139	117	200	226	267	268	Kirklareli	1061	1227	1449	1660	1836	2054
Artvin	146	158	282	361	440	503	Kirsehir	625	681	801	903	985	1041
Aydin	1426	2097	2787	3466	4138	4797	Kocaeli	7359	8732	10,117	11,476	12,711	13,960
Balikesir	2525	3154	3814	4492	5120	5750	Konya	6281	7315	8382	9404	10,374	11,298
Bartin	402	504	649	798	902	1045	Kutahya	1509	1721	1989	2258	2476	2714
Batman	932	1263	1622	1954	2269	2537	Malatya	1992	2348	2770	3134	3510	3824
Bayburt	220	200	275	295	330	322	Manisa	2181	2819	3474	4120	4745	5357
Bilecik	736	841	979	1124	1235	1367	Mardin	892	1372	1881	2381	2845	3290
Bingol	492	654	885	1062	1223	1375	Mersin	1833	2760	3701	4625	5521	6398
Bitlis	511	694	939	1141	1326	1485	Mugla	1103	1776	2483	3208	3908	4594
Bolu	979	1134	1334	1542	1711	1903	Mus	456	617	856	1036	1224	1385
Burdur	586	691	832	969	1077	1183	Nevsehir	743	852	1026	1173	1313	1407
Bursa	10,223	11,907	13,581	15,229	16,813	18,392	Nigde	885	1012	1207	1385	1555	1691
Canakkale	1256	1515	1821	2126	2402	2717	Ordu	1421	1909	2484	3021	3540	4091
Cankiri	478	526	635	740	820	882	Osmaniye	693	998	1338	1678	1994	2312
Corum	1372	1581	1851	2104	2319	2516	Rize	668	811	1028	1228	1400	1598
Denizli	2636	3167	3707	4229	4717	5183	Sakarya	3283	4006	4765	5524	6231	6961
Diyarbakir	3076	4124	5181	6213	7225	8172	Samsun	3529	4352	5237	6097	6927	7770
Duzce	1152	1365	1627	1892	2112	2359	Sanliurfa	2579	3746	4950	6146	7350	8499
Edirne	902	1053	1262	1454	1622	1829	Siirt	461	613	823	1002	1163	1290

Table A3. Cont.

Province	2025	2030	2035	2040	2045	2050	Province	2025	2030	2035	2040	2045	2050
Elazig	1719	2071	2471	2814	3155	3448	Sinop	329	442	622	784	903	1067
Erzincan	663	748	902	1012	1124	1198	Sirnak	515	878	1307	1709	2079	2407
Erzurum	1864	2147	2518	2831	3147	3415	Sivas	1665	1879	2192	2419	2668	2879
Eskisehir	3791	4292	4815	5315	5775	6237	Tekirdag	3571	4293	5054	5806	6487	7215
Gaziantep	4389	5485	6589	7665	8716	9711	Tokat	1263	1529	1884	2198	2490	2757
Giresun	704	1015	1400	1760	2090	2459	Trabzon	1486	2000	2576	3116	3611	4125
Gumushane	241	251	351	399	452	484	Tunceli	111	136	214	265	307	319
Hakkari	219	296	465	589	689	766	Usak	965	1161	1391	1620	1815	2010
Hatay	1559	2566	3587	4595	5581	6540	Van	1631	2098	2646	3150	3647	4106
Igdir	279	339	460	550	662	683	Yalova	1067	1238	1434	1633	1768	1968
Isparta	1171	1358	1584	1800	1987	2179	Yozgat	838	969	1171	1346	1499	1635
Istanbul	54,983	61,309	67,554	73,526	79,241	84,857	Zonguldak	1333	1621	1964	2297	2574	2892
Izmir	8561	10,864	13,158	15,393	17,579	19,726							

Table A4. Projected annual residential natural gas demand (GWh) in Turkish provinces between 2025 and 2050 under SSP3 scenario from LRFE algorithm.

Province	2025	2030	2035	2040	2045	2050	Province	2025	2030	2035	2040	2045	2050
Adana	2186	3271	4391	5506	6611	7718	K.maras	2126	2796	3484	4162	4824	5470
Adiyaman	1022	1366	1740	2093	2445	2761	Karabuk	830	979	1170	1373	1549	1729
Afyonk.	1301	1637	2039	2432	2795	3162	Karaman	659	752	912	1053	1176	1275
Agri	417	600	861	1081	1288	1472	Kars	476	537	692	793	907	961
Aksaray	927	1137	1397	1635	1863	2051	Kastamonu	843	1049	1326	1609	1865	2138
Amasya	947	1121	1367	1598	1817	2028	Kayseri	4683	5390	6170	6903	7647	8335
Ankara	23,776	26,758	29,744	32,645	35,492	38,324	Kilis	292	365	482	597	694	770
Antalya	2552	4239	5946	7636	9292	10,984	Kirikkale	837	938	1105	1259	1384	1491
Ardahan	139	119	205	232	276	282	Kirklareli	1064	1243	1480	1711	1909	2162
Artvin	147	166	297	380	472	550	Kirsehir	626	690	817	927	1016	1083
Aydin	1434	2146	2887	3629	4366	5117	Kocaeli	7374	8852	10,345	11,788	13,180	14,623
Balikesir	2535	3211	3925	4685	5402	6136	Konya	6293	7401	8542	9640	10,703	11,718
Bartin	403	510	660	819	934	1092	Kutahya	1511	1746	2037	2327	2584	2869
Batman	935	1282	1666	2028	2370	2672	Malatya	1996	2376	2818	3211	3619	3970
Bayburt	220	201	278	299	339	330	Manisa	2191	2891	3597	4308	5012	5731
Bilecik	737	853	1001	1160	1293	1449	Mardin	897	1402	1943	2473	3001	3504
Bingol	493	668	900	1086	1261	1428	Mersin	1846	2839	3852	4861	5851	6870
Bitlis	513	703	960	1176	1375	1550	Mugla	1110	1825	2587	3387	4179	4978
Bolu	982	1149	1360	1585	1777	1996	Mus	458	632	883	1084	1278	1449
Burdur	588	701	850	1000	1118	1237	Nevsehir	744	864	1048	1202	1351	1460
Bursa	10,240	12,029	13,809	15,580	17,325	19,093	Nigde	887	1021	1226	1415	1604	1754
Canakkale	1261	1541	1873	2210	2532	2910	Ordu	1426	1950	2556	3141	3714	4324
Cankiri	479	535	654	769	863	937	Osmaniye	697	1017	1380	1746	2093	2447
Corum	1374	1599	1895	2159	2396	2622	Rize	671	825	1058	1277	1471	1694
Denizli	2644	3211	3783	4351	4894	5422	Sakarya	3290	4055	4870	5698	6485	7325
Diyarbakir	3087	4193	5317	6428	7525	8580	Samsun	3539	4405	5350	6277	7185	8138
Duzce	1155	1384	1666	1955	2200	2474	Sanliurfa	2592	3835	5120	6432	7741	9008
Edirne	905	1070	1294	1513	1708	1947	Siirt	463	626	845	1035	1208	1352
Elazig	1722	2094	2503	2871	3241	3567	Sinop	330	455	650	826	968	1166
Erzincan	664	755	921	1038	1162	1240	Sirnak	519	902	1357	1785	2201	2575
Erzurum	1868	2178	2568	2909	3241	3531	Sivas	1669	1893	2218	2457	2722	2956
Eskisehir	3797	4325	4871	5405	5905	6421	Tekirdag	3581	4341	5145	5945	6690	7495
Gaziantep	4400	5561	6736	7886	9020	10,122	Tokat	1266	1554	1934	2281	2614	2936
Giresun	706	1037	1451	1838	2205	2622	Trabzon	1493	2037	2651	3234	3790	4386
Gumushane	241	255	361	416	472	506	Tunceli	111	139	221	276	324	344
Hakkari	221	306	484	620	728	815	Usak	967	1176	1421	1669	1892	2122
Hatay	1570	2635	3723	4816	5928	6999	Van	1637	2125	2704	3237	3758	4249
Igdir	280	346	475	573	696	730	Yalova	1069	1253	1467	1689	1854	2085
Isparta	1175	1372	1614	1856	2065	2276	Yozgat	840	986	1198	1386	1555	1705
Istanbul	55,083	61,905	68,674	75,230	81,582	87,943	Zonguldak	1337	1649	2011	2375	2697	3074
Izmir	8588	11,041	13,523	15,940	18,385	20,845							

Table A5. Projected annual residential natural gas demand (GWh) in Turkish provinces between 2025 and 2050 under SSP4 scenario from LRFE algorithm.

Province	2025	2030	2035	2040	2045	2050	Province	2025	2030	2035	2040	2045	2050
Adana	2169	3166	4183	5190	6153	7073	K.maras	2116	2738	3372	3989	4575	5135
Adiyaman	1018	1335	1682	1998	2300	2555	Karabuk	828	965	1147	1328	1471	1626
Afyonk.	1296	1603	1971	2321	2630	2932	Karaman	658	742	886	1013	1121	1202
Agri	415	579	825	1029	1219	1381	Kars	475	527	671	766	866	906
Aksaray	924	1117	1357	1572	1779	1944	Kastamonu	841	1027	1278	1528	1733	1953
Amasya	945	1100	1321	1522	1703	1864	Kayseri	4674	5334	6065	6753	7436	8054
Ankara	23,742	26,495	29,251	31,909	34,465	36,930	Kilis	291	359	467	571	662	727
Antalya	2535	4098	5652	7171	8636	10,067	Kirikkale	835	919	1069	1197	1297	1375
Ardahan	139	116	199	224	264	264	Kirklareli	1061	1225	1440	1646	1815	2026
Artvin	146	156	279	355	429	487	Kirsehir	625	678	795	893	968	1017
Aydin	1425	2085	2758	3418	4063	4694	Kocaeli	7359	8714	10,071	11,377	12,593	13,803
Balikesir	2525	3141	3780	4434	5033	5640	Konya	6280	7296	8342	9339	10,278	11,158
Bartin	402	502	645	792	890	1029	Kutahya	1508	1716	1978	2238	2448	2676
Batman	931	1256	1609	1936	2241	2502	Malatya	1991	2340	2754	3110	3477	3777
Bayburt	220	200	274	292	327	315	Manisa	2181	2803	3435	4055	4649	5228
Bilecik	735	838	973	1114	1217	1337	Mardin	891	1362	1861	2345	2796	3221
Bingol	491	650	879	1051	1208	1351	Mersin	1832	2744	3665	4561	5422	6262
Bitlis	511	689	929	1128	1311	1465	Mugla	1102	1762	2455	3159	3827	4484
Bolu	979	1130	1324	1524	1685	1870	Mus	456	612	847	1026	1206	1358
Burdur	586	687	827	961	1066	1169	Nevsehir	742	849	1020	1164	1299	1391
Bursa	10,222	11,879	13,527	15,132	16,674	18,194	Nigde	885	1009	1201	1374	1542	1670
Canakkale	1256	1510	1809	2107	2372	2673	Ordu	1420	1899	2462	2988	3489	4025
Cankiri	478	524	631	732	809	869	Osmaniye	693	993	1327	1661	1967	2273
Corum	1372	1576	1839	2085	2292	2477	Rize	668	807	1021	1215	1380	1571
Denizli	2635	3155	3685	4188	4660	5105	Sakarya	3282	3993	4736	5470	6155	6853
Diyarbakir	3075	4104	5136	6143	7127	8043	Samsun	3528	4337	5199	6035	6841	7654
Duzce	1152	1361	1616	1873	2082	2321	Sanliurfa	2577	3721	4894	6068	7233	8340
Edirne	902	1049	1251	1438	1597	1794	Siirt	461	609	814	988	1142	1259
Elazig	1718	2064	2458	2790	3125	3407	Sinop	329	439	616	776	887	1044
Erzincan	663	746	898	1006	1115	1187	Sirnak	515	875	1302	1696	2058	2375
Erzurum	1864	2140	2504	2808	3112	3371	Sivas	1665	1872	2182	2404	2649	2854
Eskisehir	3791	4283	4800	5290	5738	6185	Tekirdag	3570	4278	5027	5768	6439	7149
Gaziantep	4387	5464	6550	7604	8628	9599	Tokat	1263	1522	1865	2168	2447	2697
Giresun	703	1010	1389	1744	2053	2417	Trabzon	1485	1991	2556	3081	3556	4052
Gumushane	241	250	349	395	449	477	Tunceli	111	135	212	260	300	309
Hakkari	219	293	458	578	672	739	Usak	965	1157	1381	1606	1791	1978
Hatay	1559	2550	3550	4527	5472	6375	Van	1630	2085	2622	3120	3608	4052
Igdir	279	337	456	543	652	670	Yalova	1067	1234	1426	1620	1748	1934
Isparta	1170	1352	1575	1787	1970	2159	Yozgat	838	965	1165	1335	1484	1611
Istanbul	54,981	61,195	67,347	73,232	78,905	84,491	Zonguldak	1333	1613	1949	2272	2536	2842
Izmir	8559	10,829	13,078	15,255	17,381	19,457							

Table A6. Projected annual residential natural gas demand (GWh) in Turkish provinces between 2025 and 2050 under SSP5 scenario from LRFE algorithm.

Province	2025	2030	2035	2040	2045	2050	Province	2025	2030	2035	2040	2045	2050
Adana	2159	3108	4074	5029	5952	6824	K.maras	2111	2703	3322	3920	4491	5030
Adiyaman	1015	1319	1651	1955	2248	2490	Karabuk	827	959	1135	1312	1451	1599
Afyonk.	1293	1589	1938	2279	2572	2862	Karaman	656	735	877	998	1100	1178
Agri	413	573	814	1013	1197	1351	Kars	474	523	663	757	852	890
Aksaray	922	1105	1345	1557	1755	1916	Kastamonu	839	1014	1259	1496	1687	1888
Amasya	944	1091	1305	1495	1668	1823	Kayseri	4668	5309	6025	6688	7352	7955
Ankara	23,708	26,359	28,996	31,521	33,944	36,255	Kilis	291	356	461	564	651	712
Antalya	2519	4032	5534	6980	8376	9726	Kirikkale	833	912	1058	1182	1271	1339
Ardahan	139	114	197	220	259	258	Kirklareli	1059	1216	1425	1620	1778	1980
Artvin	145	151	270	343	413	468	Kirsehir	624	673	786	879	950	993
Aydin	1419	2051	2701	3331	3947	4551	Kocaeli	7346	8650	9935	11,181	12,342	13,477
Balikesir	2518	3102	3713	4334	4901	5475	Konya	6270	7250	8264	9236	10,127	10,968
Bartin	401	498	636	779	873	1006	Kutahya	1506	1704	1953	2201	2395	2609
Batman	929	1248	1594	1913	2213	2460	Malatya	1987	2325	2730	3076	3435	3724
Bayburt	220	199	272	289	323	311	Manisa	2173	2764	3364	3952	4515	5059
Bilecik	734	831	961	1095	1192	1308	Mardin	888	1339	1825	2290	2718	3117
Bingol	490	646	867	1035	1185	1323	Mersin	1823	2702	3588	4448	5268	6063
Bitlis	510	682	917	1113	1290	1440	Mugla	1096	1727	2396	3064	3694	4318
Bolu	977	1123	1310	1505	1657	1835	Mus	455	606	836	1011	1185	1331
Burdur	585	678	814	945	1046	1142	Nevsehir	741	843	1016	1151	1281	1366

Table A6. Cont.

Province	2025	2030	2035	2040	2045	2050	Province	2025	2030	2035	2040	2045	2050
Bursa	10,208	11,814	13,404	14,945	16,415	17,854	Nigde	883	1003	1190	1360	1523	1646
Canakkale	1253	1494	1785	2068	2317	2597	Ordu	1417	1879	2427	2937	3420	3932
Cankiri	477	519	622	714	783	840	Osmaniye	691	980	1308	1633	1931	2226
Corum	1370	1565	1822	2056	2257	2437	Rize	667	801	1009	1197	1355	1538
Denizli	2628	3129	3636	4124	4581	5008	Sakarya	3277	3964	4677	5379	6029	6699
Diyarbakir	3068	4064	5075	6052	7001	7886	Samsun	3521	4301	5137	5945	6720	7506
Duzce	1149	1347	1592	1840	2040	2267	Sanliurfa	2569	3676	4819	5961	7083	8153
Edirne	900	1041	1233	1412	1563	1752	Siirt	460	604	803	970	1118	1231
Elazig	1716	2048	2432	2766	3093	3364	Sinop	328	433	607	760	866	1016
Erzincan	662	739	891	994	1101	1168	Sirnak	513	850	1252	1631	1982	2281
Erzurum	1861	2128	2481	2781	3072	3320	Sivas	1662	1860	2168	2386	2625	2823
Eskisehir	3786	4256	4755	5232	5666	6096	Tekirdag	3564	4249	4971	5683	6328	7009
Gaziantep	4376	5416	6476	7499	8492	9429	Tokat	1260	1509	1841	2135	2405	2645
Giresun	701	999	1373	1707	2012	2357	Trabzon	1481	1966	2520	3022	3484	3961
Gumushane	240	248	346	391	441	472	Tunceli	110	132	207	252	291	298
Hakkari	218	287	446	565	652	716	Usak	963	1150	1364	1580	1765	1945
Hatay	1551	2508	3474	4416	5322	6174	Van	1626	2066	2593	3085	3560	3994
Igdir	278	334	452	534	640	655	Yalova	1065	1225	1411	1597	1716	1890
Isparta	1169	1338	1553	1760	1939	2121	Yozgat	837	959	1153	1317	1457	1579
Istanbul	54,894	60,820	66,564	72,016	77,327	82,475	Zonguldak	1330	1600	1916	2228	2480	2767
Izmir	8533	10,741	12,897	14,976	16,997	18,971							

Table A7. Projected annual residential natural gas demand (GWh) in Turkish provinces between 2025 and 2050 under SSP1 scenario from SVR algorithm.

Province	2025	2030	2035	2040	2045	2050	Province	2025	2030	2035	2040	2045	2050
Adana	1811	2786	3775	4769	5754	6712	K.maras	2239	2913	3662	4463	5312	6181
Adiyaman	983	1329	1710	2123	2581	3024	Karabuk	786	996	1219	1440	1670	1882
Afyonk.	1462	1940	2434	2943	3483	4010	Karaman	710	906	1118	1332	1559	1756
Agri	573	932	1305	1710	2156	2624	Kars	539	743	958	1184	1422	1670
Aksaray	946	1211	1480	1754	2046	2301	Kastamonu	889	1194	1499	1810	2143	2467
Amasya	1018	1321	1650	1990	2366	2728	Kayseri	4986	5977	7023	8100	9216	10,335
Ankara	23,662	26,171	28,850	31,254	33,402	35,202	Kilis	296	370	442	519	605	670
Antalya	1304	1854	2225	2401	2369	2100	Kirikkale	887	1088	1295	1493	1709	1882
Ardahan	171	259	347	440	533	628	Kirklareli	1103	1385	1677	1966	2269	2557
Artvin	177	351	516	683	853	1022	Kirsehir	713	893	1072	1243	1429	1572
Aydin	1322	1912	2498	3093	3709	4304	Kocaeli	7209	8263	9385	10,498	11,610	12,679
Balikesir	2688	3520	4340	5175	6031	6875	Konya	7269	8806	10,395	12,057	13,788	15,542
Bartın	431	652	882	1123	1379	1635	Kutahya	1595	1972	2400	2823	3260	3679
Batman	906	1279	1637	2032	2477	2918	Malatya	1933	2333	2814	3311	3833	4324
Bayburt	222	322	418	516	619	712	Manisa	2439	3265	4090	4923	5777	6604
Bilecik	784	981	1189	1404	1641	1860	Mardin	758	1179	1623	2116	2662	3223
Bingol	550	765	989	1226	1487	1738	Mersin	1359	2125	2853	3549	4188	4764
Bitlis	620	910	1194	1505	1844	2188	Mugla	593	919	1248	1542	1813	2025
Bolu	1022	1273	1538	1804	2082	2353	Mus	549	836	1127	1442	1790	2138
Burdur	670	888	1120	1351	1595	1814	Nevsehir	815	1050	1279	1511	1758	1969
Bursa	10,349	12,288	14,228	16,196	18,189	20,169	Nigde	945	1238	1547	1868	2201	2525
Canakkale	1278	1652	2049	2446	2850	3241	Ordu	1441	2040	2695	3388	4131	4907
Cankiri	535	679	832	975	1136	1259	Osmaniye	553	924	1316	1744	2195	2661
Corum	1516	1919	2353	2793	3265	3717	Rize	741	1085	1414	1750	2103	2461
Denizli	2821	3448	4097	4748	5420	6050	Sakarya	3383	4113	4840	5599	6399	7212
Diyarbakir	2939	4041	5215	6513	7950	9469	Samsun	3629	4528	5460	6423	7429	8453
Duzce	1237	1569	1897	2232	2577	2919	Sanliurfa	1846	3020	4332	5810	7471	9262
Edirne	1002	1266	1523	1773	2030	2262	Siirt	431	619	817	1032	1272	1496
Elazig	1854	2272	2696	3137	3616	4070	Sinop	443	685	936	1195	1478	1767
Erzincan	680	874	1058	1246	1437	1620	Sirnak	261	526	824	1161	1539	1932
Erzurum	2257	2852	3405	3991	4604	5241	Sivas	1835	2314	2795	3297	3822	4340
Eskisehir	3730	4246	4834	5422	6022	6587	Tekirdag	3561	4292	5034	5792	6578	7366
Gaziantep	4488	5791	7140	8605	10,176	11,818	Tokat	1401	1873	2364	2878	3427	3976
Giresun	754	1161	1558	1976	2425	2886	Trabzon	1662	2276	2883	3509	4169	4840
Gumushane	294	421	548	677	805	933	Tunceli	137	186	227	259	304	307
Hakkari	206	382	550	734	926	1126	Usak	1024	1302	1611	1927	2273	2603
Hatay	1107	1798	2662	3568	4514	5476	Van	1947	2767	3554	4417	5352	6350
Igdir	312	468	630	790	973	1128	Yalova	1087	1251	1392	1504	1589	1633
Isparta	1274	1592	1936	2278	2633	2970	Yozgat	983	1291	1609	1931	2277	2597
Istanbul	54,822	58,613	61,323	62,533	62,170	60,065	Zonguldak	1564	2038	2519	3009	3515	4021
Izmir	8546	10,337	12,185	13,902	15,496	16,907							

Table A8. Projected annual residential natural gas demand (GWh) in Turkish provinces between 2025 and 2050 under SSP2 scenario from SVR algorithm.

Province	2025	2030	2035	2040	2045	2050	Province	2025	2030	2035	2040	2045	2050
Adana	1812	2805	3835	4902	5985	7067	K.maras	2240	2923	3692	4525	5416	6339
Adiyaman	984	1333	1723	2153	2634	3106	Karabuk	786	998	1225	1453	1694	1920
Afyonk.	1462	1945	2451	2981	3549	4114	Karaman	710	908	1123	1345	1582	1792
Agri	573	934	1313	1727	2186	2672	Kars	540	744	963	1196	1443	1702
Aksaray	947	1214	1489	1774	2081	2356	Kastamonu	889	1198	1510	1835	2187	2539
Amasya	1018	1323	1658	2010	2402	2786	Kayseri	4987	5987	7053	8166	9332	10,513
Ankara	23,668	26,231	29,047	31,698	34,178	36,391	Kilis	296	371	445	525	616	687
Antalya	1306	1882	2315	2604	2727	2657	Kirikkale	887	1091	1303	1510	1740	1932
Ardahan	171	260	350	446	542	642	Kirklareli	1103	1388	1688	1991	2314	2628
Artvin	177	352	522	695	875	1056	Kirsehir	713	894	1078	1255	1451	1607
Aydin	1322	1922	2529	3162	3832	4496	Kocaeli	7211	8284	9457	10,661	11,896	13,126
Balikesir	2689	3531	4376	5254	6172	7095	Konya	7270	8821	10,443	12,163	13,975	15,836
Bartin	432	654	886	1133	1397	1663	Kutahya	1596	1976	2414	2855	3318	3769
Batman	907	1282	1647	2054	2514	2977	Malatya	1933	2338	2830	3346	3892	4415
Bayburt	222	322	420	519	624	721	Manisa	2441	3278	4131	5014	5939	6858
Bilecik	785	983	1196	1419	1668	1904	Mardin	758	1185	1640	2155	2731	3333
Bingol	550	766	994	1239	1509	1773	Mersin	1360	2140	2899	3652	4372	5052
Bitlis	620	912	1201	1519	1869	2225	Mugla	594	931	1286	1627	1966	2265
Bolu	1022	1276	1548	1826	2121	2415	Mus	549	838	1133	1456	1815	2178
Burdur	671	891	1128	1367	1622	1856	Nevsehir	815	1052	1285	1524	1781	2006
Bursa	10,351	12,313	14,309	16,376	18,509	20,673	Nigde	945	1240	1555	1884	2230	2569
Canakkale	1278	1657	2066	2484	2917	3347	Ordu	1442	2046	2716	3431	4207	5027
Cankiri	536	681	837	986	1156	1292	Osmaniye	553	927	1328	1769	2237	2728
Corum	1516	1922	2364	2817	3307	3783	Rize	741	1088	1423	1771	2140	2518
Denizli	2822	3457	4127	4814	5533	6223	Sakarya	3384	4122	4872	5672	6529	7417
Diyarbakir	2940	4052	5250	6589	8083	9676	Samsun	3630	4541	5499	6509	7578	8684
Duzce	1237	1573	1911	2261	2629	2998	Sanliurfa	1847	3032	4370	5889	7611	9481
Edirne	1003	1270	1535	1800	2078	2337	Siirt	431	621	822	1045	1295	1534
Elazig	1854	2277	2710	3167	3667	4147	Sinop	443	687	942	1207	1500	1802
Erzincan	680	876	1064	1259	1459	1653	Sirnak	261	530	838	1191	1591	2011
Erzurum	2258	2856	3420	4023	4661	5330	Sivas	1835	2318	2807	3322	3864	4404
Eskisehir	3731	4255	4861	5480	6122	6741	Tekirdag	3562	4303	5070	5871	6716	7579
Gaziantep	4489	5807	7187	8705	10,350	12,084	Tokat	1402	1877	2377	2907	3477	4056
Giresun	754	1165	1569	2001	2471	2959	Trabzon	1663	2284	2908	3564	4266	4991
Gumushane	294	422	550	682	814	947	Tunceli	137	187	229	265	314	324
Hakkari	206	384	556	746	948	1161	Usak	1024	1305	1620	1948	2310	2659
Hatay	1107	1809	2700	3653	4666	5720	Van	1948	2773	3572	4454	5414	6444
Igdir	312	469	634	799	988	1153	Yalova	1087	1255	1402	1525	1626	1692
Isparta	1275	1596	1950	2307	2682	3042	Yozgat	983	1293	1616	1946	2305	2642
Istanbul	54,840	58,798	61,926	63,884	64,499	63,580	Zonguldak	1564	2044	2537	3049	3584	4129
Izmir	8551	10,379	12,325	14,218	16,054	17,767							

Table A9. Projected annual residential natural gas demand (GWh) in Turkish provinces between 2025 and 2050 under SSP3 scenario from SVR algorithm.

Province	2025	2030	2035	2040	2045	2050	Province	2025	2030	2035	2040	2045	2050
Adana	1814	2829	3911	5067	6286	7563	K.maras	2241	2934	3725	4600	5554	6566
Adiyaman	984	1339	1740	2189	2699	3215	Karabuk	786	1001	1233	1471	1728	1978
Afyonk.	1463	1953	2474	3031	3641	4266	Karaman	710	911	1133	1366	1621	1855
Agri	573	938	1323	1749	2223	2730	Kars	540	746	970	1210	1467	1742
Aksaray	947	1219	1504	1807	2140	2451	Kastamonu	889	1202	1524	1866	2247	2640
Amasya	1018	1327	1671	2037	2453	2870	Kayseri	4988	6001	7098	8262	9506	10,796
Ankara	23,677	26,325	29,344	32,343	35,349	38,308	Kilis	296	373	450	536	637	722
Antalya	1310	1918	2432	2864	3203	3441	Kirikkale	887	1094	1315	1536	1787	2009
Ardahan	172	261	352	450	551	656	Kirklareli	1104	1393	1704	2027	2379	2737
Artvin	177	354	527	705	893	1087	Kirsehir	714	897	1085	1271	1479	1654
Aydin	1324	1935	2570	3252	3997	4768	Kocaeli	7214	8324	9584	10,934	12,394	13,949
Balikesir	2690	3546	4424	5362	6371	7425	Konya	7272	8846	10,520	12,328	14,272	16,315
Bartin	432	656	892	1145	1419	1700	Kutahya	1596	1983	2435	2900	3399	3905
Batman	907	1286	1662	2089	2578	3081	Malatya	1934	2345	2851	3391	3976	4551
Bayburt	222	323	421	523	631	732	Manisa	2442	3297	4191	5142	6170	7235
Bilecik	785	987	1206	1442	1712	1977	Mardin	759	1192	1665	2209	2832	3502
Bingol	550	769	1002	1254	1535	1816	Mersin	1363	2162	2971	3808	4656	5522
Bitlis	621	914	1209	1536	1899	2275	Mugla	596	946	1334	1734	2164	2597
Bolu	1022	1280	1561	1856	2176	2506	Mus	549	842	1144	1478	1854	2239
Burdur	671	894	1137	1387	1658	1914	Nevsehir	815	1055	1295	1545	1818	2065

Table A9. Cont.

Province	2025	2030	2035	2040	2045	2050	Province	2025	2030	2035	2040	2045	2050
Bursa	10,355	12,354	14,437	16,655	19,018	21,511	Nigde	945	1243	1565	1905	2269	2633
Canakkale	1279	1665	2091	2537	3016	3512	Ordu	1443	2055	2741	3486	4308	5192
Cankiri	536	683	844	1002	1186	1341	Osmaniye	554	932	1344	1805	2304	2838
Corum	1517	1927	2380	2851	3367	3880	Rize	741	1091	1433	1795	2183	2590
Denizli	2823	3470	4165	4897	5685	6471	Sakarya	3385	4136	4917	5773	6715	7726
Diyarbakir	2941	4068	5299	6694	8274	9987	Samsun	3631	4555	5545	6612	7768	8997
Duzce	1237	1578	1927	2298	2696	3108	Sanliurfa	1849	3050	4428	6016	7840	9853
Edirne	1003	1275	1551	1834	2142	2442	Siirt	431	624	831	1064	1328	1587
Elazig	1855	2283	2727	3203	3733	4256	Sinop	443	689	951	1226	1535	1861
Erzincan	680	878	1072	1276	1491	1704	Sirnak	262	536	856	1231	1664	2134
Erzurum	2258	2863	3442	4069	4741	5456	Sivas	1836	2323	2822	3354	3923	4501
Eskisehir	3732	4267	4896	5557	6262	6971	Tekirdag	3564	4321	5125	5990	6933	7937
Gaziantep	4491	5829	7258	8861	10,631	12,544	Tokat	1402	1882	2395	2946	3549	4175
Giresun	755	1170	1584	2034	2532	3062	Trabzon	1664	2293	2935	3623	4376	5174
Gumushane	294	423	553	690	828	970	Tunceli	137	188	232	271	326	343
Hakkari	207	386	563	761	975	1204	Usak	1024	1309	1633	1976	2363	2749
Hatay	1109	1827	2755	3775	4895	6098	Van	1948	2779	3593	4499	5494	6572
Igdir	312	471	639	810	1008	1186	Yalova	1087	1259	1416	1556	1686	1791
Isparta	1275	1601	1964	2340	2742	3141	Yozgat	983	1297	1628	1971	2349	2712
Istanbul	54,869	59,085	62,841	65,900	68,185	69,618	Zonguldak	1565	2051	2558	3096	3670	4273
Izmir	8557	10,445	12,535	14,680	16,899	19,158							

Table A10. Projected annual residential natural gas demand (GWh) in Turkish provinces between 2025 and 2050 under SSP4 scenario from SVR algorithm.

Province	2025	2030	2035	2040	2045	2050	Province	2025	2030	2035	2040	2045	2050
Adana	1813	2809	3845	4925	6032	7151	K.maras	2240	2924	3693	4529	5426	6360
Adiyaman	984	1333	1724	2153	2634	3107	Karabuk	786	999	1226	1454	1696	1923
Afyonk.	1462	1946	2454	2986	3559	4131	Karaman	710	909	1126	1349	1590	1805
Agri	573	934	1313	1727	2185	2671	Kars	540	745	963	1197	1445	1705
Aksaray	947	1215	1492	1780	2092	2374	Kastamonu	889	1198	1511	1836	2190	2544
Amasya	1018	1324	1659	2010	2402	2786	Kayseri	4987	5990	7062	8186	9370	10,580
Ankara	23,672	26,260	29,135	31,889	34,546	37,031	Kilis	296	372	446	527	620	694
Antalya	1307	1889	2335	2649	2814	2812	Kirikkale	887	1091	1304	1512	1744	1938
Ardahan	171	260	350	446	543	644	Kirklareli	1103	1390	1691	1998	2327	2650
Artvin	177	352	521	694	873	1052	Kirsehir	714	895	1079	1257	1453	1612
Aydin	1323	1924	2533	3169	3846	4521	Kocaeli	7212	8298	9494	10,732	12,026	13,349
Balikesir	2689	3534	4382	5266	6193	7132	Konya	7271	8827	10,458	12,192	14,029	15,927
Bartın	432	654	887	1134	1399	1666	Kutahya	1596	1977	2417	2861	3329	3790
Batman	907	1282	1647	2055	2518	2983	Malatya	1933	2339	2832	3350	3901	4430
Bayburt	222	322	420	520	625	722	Manisa	2441	3281	4140	5032	5970	6912
Bilecik	785	984	1198	1423	1675	1915	Mardin	758	1186	1643	2160	2740	3349
Bingol	550	766	994	1239	1509	1774	Mersin	1361	2145	2913	3679	4422	5137
Bitlis	620	912	1201	1518	1868	2225	Mugla	595	933	1292	1640	1989	2307
Bolu	1022	1277	1550	1830	2128	2427	Mus	549	838	1134	1457	1816	2181
Burdur	671	891	1129	1370	1628	1866	Nevsehir	815	1052	1286	1527	1787	2017
Bursa	10,353	12,324	14,340	16,439	18,626	20,873	Nigde	945	1241	1556	1887	2236	2579
Canakkale	1278	1659	2070	2493	2934	3375	Ordu	1442	2046	2715	3429	4205	5025
Cankiri	536	681	838	988	1160	1298	Osmaniye	553	928	1329	1772	2244	2739
Corum	1516	1923	2365	2820	3312	3792	Rize	741	1087	1423	1771	2139	2518
Denizli	2822	3459	4132	4825	5555	6262	Sakarya	3385	4125	4878	5684	6551	7456
Diyarbakir	2940	4053	5250	6589	8085	9683	Samsun	3630	4542	5502	6515	7592	8711
Duzce	1237	1574	1913	2265	2636	3012	Sanliurfa	1847	3032	4370	5888	7610	9483
Edirne	1003	1270	1537	1803	2085	2349	Siirt	431	621	823	1045	1295	1534
Elazig	1854	2278	2712	3169	3673	4158	Sinop	443	687	942	1207	1500	1802
Erzincan	680	876	1065	1261	1464	1662	Sirnak	262	531	841	1197	1601	2029
Erzurum	2258	2857	3422	4026	4667	5342	Sivas	1835	2319	2810	3328	3876	4425
Eskisehir	3731	4258	4869	5498	6156	6800	Tekirdag	3563	4308	5083	5900	6771	7676
Gaziantep	4490	5811	7199	8732	10,403	12,180	Tokat	1402	1877	2377	2905	3475	4052
Giresun	754	1165	1569	2000	2468	2956	Trabzon	1663	2284	2907	3563	4265	4991
Gumushane	294	422	550	682	815	949	Tunceli	137	187	230	265	315	324
Hakkari	206	384	556	746	947	1159	Usak	1024	1305	1622	1951	2316	2669
Hatay	1108	1812	2706	3665	4688	5754	Van	1948	2773	3571	4452	5414	6446
Igdir	312	469	633	798	987	1152	Yalova	1087	1255	1404	1529	1634	1705
Isparta	1275	1597	1951	2311	2690	3058	Yozgat	983	1293	1618	1950	2311	2651
Istanbul	54,852	58,886	62,210	64,531	65,775	65,837	Zonguldak	1564	2044	2538	3053	3592	4143
Izmir	8553	10,394	12,372	14,322	16,254	18,120							

Table A11. Projected annual residential natural gas demand (GWh) in Turkish provinces between 2025 and 2050 under SSP5 scenario from SVR algorithm.

Province	2025	2030	2035	2040	2045	2050	Province	2025	2030	2035	2040	2045	2050
Adana	1809	2774	3735	4677	5579	6416	K.maras	2239	2908	3643	4421	5231	6044
Adiyaman	983	1326	1701	2104	2545	2963	Karabuk	785	995	1215	1430	1652	1851
Afyonk.	1461	1937	2424	2918	3435	3930	Karaman	710	905	1112	1318	1533	1712
Agri	573	931	1302	1702	2141	2599	Kars	539	742	956	1179	1413	1654
Aksaray	946	1209	1472	1735	2010	2241	Kastamonu	889	1192	1493	1795	2114	2419
Amasya	1018	1319	1645	1979	2345	2693	Kayseri	4985	5969	6995	8033	9090	10,123
Ankara	23,657	26,124	28,694	30,890	32,705	34,015	Kilis	296	370	439	512	593	651
Antalya	1302	1836	2165	2262	2102	1644	Kirikkale	887	1087	1290	1481	1686	1843
Ardahan	171	259	346	438	529	621	Kirklareli	1103	1382	1668	1946	2231	2494
Artvin	177	350	513	677	841	1002	Kirsehir	713	891	1068	1234	1411	1542
Aydin	1321	1907	2480	3051	3631	4171	Kocaeli	7206	8237	9296	10,286	11,208	12,012
Balikesir	2687	3513	4315	5117	5921	6691	Konya	7267	8794	10,353	11,958	13,599	15,225
Bartin	431	652	879	1117	1367	1614	Kutahya	1595	1969	2391	2803	3221	3613
Batman	906	1277	1629	2015	2445	2864	Malatya	1932	2329	2803	3287	3787	4246
Bayburt	222	322	418	514	615	706	Manisa	2439	3256	4059	4850	5639	6372
Bilecik	784	979	1182	1389	1612	1811	Mardin	757	1175	1610	2087	2606	3128
Bingol	550	764	986	1219	1473	1715	Mersin	1358	2113	2810	3448	3996	4441
Bitlis	620	909	1191	1496	1827	2159	Mugla	593	913	1226	1490	1714	1857
Bolu	1022	1271	1530	1787	2048	2296	Mus	549	835	1123	1433	1773	2110
Burdur	670	887	1116	1340	1575	1779	Nevsehir	815	1048	1274	1500	1736	1933
Bursa	10,347	12,265	14,150	16,011	17,838	19,580	Nigde	944	1236	1542	1856	2178	2486
Canakkale	1277	1648	2038	2420	2801	3157	Ordu	1441	2038	2688	3371	4099	4852
Cankiri	535	678	828	965	1118	1230	Osmaniye	553	921	1308	1725	2158	2598
Corum	1516	1917	2346	2777	3233	3664	Rize	741	1084	1410	1743	2089	2435
Denizli	2820	3442	4080	4709	5345	5922	Sakarya	3383	4106	4817	5547	6298	7042
Diyarbakir	2938	4035	5197	6471	7870	9334	Samsun	3628	4523	5442	6382	7350	8318
Duzce	1236	1567	1890	2215	2546	2865	Sanliurfa	1846	3013	4310	5758	7373	9097
Edirne	1002	1265	1518	1760	2006	2220	Siirt	431	618	811	1020	1248	1457
Elazig	1854	2270	2688	3117	3579	4007	Sinop	443	684	934	1188	1464	1744
Erzincan	680	873	1054	1236	1418	1588	Sirnak	261	523	814	1137	1494	1857
Erzurum	2257	2849	3397	3971	4567	5178	Sivas	1834	2311	2786	3275	3781	4271
Eskisehir	3730	4240	4814	5375	5932	6435	Tekirdag	3560	4282	4999	5709	6421	7103
Gaziantep	4487	5780	7101	8513	10,003	11,525	Tokat	1401	1871	2358	2864	3400	3932
Giresun	754	1160	1553	1965	2404	2851	Trabzon	1662	2274	2875	3491	4134	4780
Gumushane	294	421	546	673	798	922	Tunceli	137	186	225	255	296	294
Hakkari	206	381	546	723	906	1093	Usak	1024	1300	1605	1913	2247	2558
Hatay	1106	1790	2635	3506	4396	5277	Van	1947	2764	3544	4395	5311	6280
Igdir	312	467	628	785	963	1112	Yalova	1087	1249	1384	1485	1553	1571
Isparta	1274	1590	1930	2265	2607	2925	Yozgat	982	1289	1604	1919	2254	2558
Istanbul	54,807	58,467	60,838	61,404	60,017	56,412	Zonguldak	1563	2036	2510	2990	3478	3957
Izmir	8543	10,308	12,091	13,683	15,077	16,193							

Table A12. Projected annual residential natural gas demand (GWh) in Turkish provinces between 2025 and 2050 under SSP1 scenario from RF algorithm.

Province	2025	2030	2035	2040	2045	2050	Province	2025	2030	2035	2040	2045	2050
Adana	1960	5033	7195	8702	8819	8913	K.maras	2147	3129	3819	5410	6314	6415
Adiyaman	945	1407	1919	1862	1817	1937	Karabuk	768	980	1298	1514	1671	1814
Afyonk.	1475	2066	2920	3363	3874	5007	Karaman	679	856	954	1120	1309	1439
Agri	609	894	1154	1328	1603	1918	Kars	542	707	857	929	998	1272
Aksaray	938	1319	1589	1897	1969	1891	Kastamonu	892	1245	1427	1619	1823	1858
Amasya	944	1154	1322	1435	1581	1615	Kayseri	4917	5903	6538	6770	7085	8276
Ankara	22,553	24,278	26,151	37,379	38,377	38,722	Kilis	315	386	490	662	770	866
Antalya	1357	5718	8511	9967	20,009	22,947	Kirikkale	918	1156	1368	1616	1804	1820
Ardahan	142	204	302	376	436	458	Kirklareli	1111	1365	1624	1805	1831	1895
Artvin	206	414	582	728	911	1154	Kirsehir	696	858	1014	1299	1526	1784
Aydin	1341	2270	3989	5827	6642	6740	Kocaeli	6812	7270	9139	9594	9597	9615
Balikesir	2865	4582	6212	6779	7098	7105	Konya	7114	8628	8998	9030	9138	9286
Bartin	395	583	729	920	1174	1302	Kutahya	1599	1870	1956	2071	2890	3692
Batman	976	1332	1857	1846	1926	2040	Malatya	1916	2021	2646	3296	4389	5599
Bayburt	225	296	334	374	433	464	Manisa	2621	5035	6591	6951	7115	7633
Bilecik	761	860	944	1124	1330	1474	Mardin	825	1395	2093	3065	3824	4589
Bingol	576	825	1002	1294	1405	1622	Mersin	1282	2426	5915	7494	8700	9000
Bitlis	625	855	947	1158	1330	1494	Mugla	547	1009	1832	3698	5764	6898
Bolu	1016	1330	1596	1901	1848	1856	Mus	582	820	940	1128	1306	1394
Burdur	688	917	1160	1333	1499	1606	Nevsehir	839	1073	1365	1628	1841	1796

Table A12. Cont.

Province	2025	2030	2035	2040	2045	2050	Province	2025	2030	2035	2040	2045	2050
Bursa	9588	9418	9514	9848	9819	10,248	Nigde	880	1056	1313	1453	1613	1781
Canakkale	1313	1804	2003	2460	3741	4909	Ordu	1413	2102	3264	4178	5872	6283
Cankiri	551	710	899	1151	1347	1615	Osmaniye	558	1053	1498	1881	1878	1950
Corum	1497	1838	1834	1916	1961	1940	Rize	744	1036	1329	1552	1694	1808
Denizli	3075	4161	5787	6601	6634	6762	Sakarya	3403	4631	6141	6672	6743	7476
Diyarbakir	3282	4222	6053	6812	7077	7265	Samsun	4034	6019	6545	6565	6735	7162
Duzce	1289	1514	1650	1865	1860	1969	Sanliurfa	1984	3866	5917	6760	6823	7299
Edirne	1029	1367	1591	1793	1844	1833	Siirt	470	705	859	905	982	1246
Elazig	1845	1800	1886	1967	2002	2519	Sinop	424	681	870	1086	1296	1456
Erzincan	670	868	1058	1315	1394	1588	Sirnak	305	772	1192	1797	1906	1903
Erzurum	2306	3028	3354	3825	4414	4520	Sivas	1931	1851	2028	2662	3277	3643
Eskisehir	4221	5821	6511	6528	6695	7001	Tekirdag	3543	4956	6584	6788	7081	7362
Gaziantep	4845	6800	7292	8779	8923	8923	Tokat	1355	1898	1930	1979	2073	3174
Giresun	795	1160	1520	1911	1864	1877	Trabzon	1899	2716	4148	6193	6453	6532
Gumushane	317	438	574	674	763	857	Tunceli	158	266	399	475	624	702
Hakkari	250	475	692	895	984	1264	Usak	1010	1311	1510	1615	1658	1878
Hatay	921	1216	2082	4523	6811	8041	Van	2043	3048	3564	4311	4812	5595
Igdir	313	401	546	686	790	876	Yalova	1170	1460	1777	2153	3089	3987
Isparta	1299	1516	1632	1861	1924	1892	Yozgat	967	1299	1482	1616	1771	1749
Istanbul	52,162	52,474	52,222	52,222	52,474	52,162	Zonguldak	1584	1929	1982	2268	3435	4753
Izmir	8974	10,115	19,866	20,593	20,593	21,201							

Table A13. Projected annual residential natural gas demand (GWh) in Turkish provinces between 2025 and 2050 under SSP2 scenario from RF algorithm.

Province	2025	2030	2035	2040	2045	2050	Province	2025	2030	2035	2040	2045	2050
Adana	1960	5053	7411	8810	8819	8913	K.maras	2147	3132	3813	5401	6314	6415
Adiyaman	945	1412	1925	1795	1856	1932	Karabuk	768	975	1302	1529	1709	1801
Afyonk.	1475	2069	2920	3429	4098	5493	Karaman	679	861	952	1094	1291	1430
Agri	609	894	1163	1327	1603	1918	Kars	541	705	859	926	994	1261
Aksaray	936	1316	1572	1872	1973	1884	Kastamonu	892	1237	1424	1617	1735	1848
Amasya	944	1163	1319	1430	1587	1638	Kayseri	4917	5903	6444	6651	7071	8276
Ankara	22,553	24,278	26,151	29,845	38,377	38,722	Kilis	315	381	483	634	750	860
Antalya	1357	5721	8513	9677	19,977	22,947	Kirikkale	913	1156	1361	1622	1814	1787
Ardahan	142	186	272	345	417	454	Kirklareli	1111	1365	1605	1792	1818	1885
Artvin	206	413	578	722	890	1097	Kirsehir	696	863	1009	1301	1527	1789
Aydin	1341	2270	3989	5827	6642	6645	Kocaeli	6812	7287	8748	9594	9597	9615
Balikesir	2865	4582	6232	6746	6772	7105	Konya	7114	8628	8998	9030	9138	9286
Bartin	395	584	730	919	1149	1314	Kutahya	1605	1870	1958	2072	2943	3684
Batman	976	1333	1804	1929	1934	1991	Malatya	1916	1988	2659	3284	4397	5630
Bayburt	225	296	334	374	432	464	Manisa	2621	4979	6482	6941	7115	7633
Bilecik	761	860	944	1128	1325	1467	Mardin	825	1395	2096	3061	3671	4522
Bingol	576	826	1012	1295	1451	1634	Mersin	1282	2439	5915	7494	8765	9065
Bitlis	625	856	944	1160	1322	1483	Mugla	547	1009	1832	3621	5692	6909
Bolu	1016	1326	1596	1875	1860	1850	Mus	582	820	940	1151	1305	1360
Burdur	688	922	1169	1328	1504	1615	Nevsehir	839	1069	1365	1628	1845	1802
Bursa	9588	9418	9514	9848	9798	10,227	Nigde	880	1056	1312	1446	1616	1735
Canakkale	1290	1820	2005	2462	3735	4893	Ordu	1413	2111	3249	4535	6018	6283
Cankiri	551	710	888	1122	1347	1568	Osmaniye	558	1061	1583	1831	1886	1947
Corum	1497	1838	1862	1872	1912	1942	Rize	744	1034	1317	1523	1669	1807
Denizli	3105	4161	5777	6601	6527	6728	Sakarya	3403	4622	6141	6565	6739	6978
Diyarbakir	3282	4222	6053	6812	7091	7155	Samsun	4034	6148	6545	6565	6686	6818
Duzce	1289	1514	1641	1860	1870	1971	Sanliurfa	1984	3922	6057	6849	7050	7362
Edirne	1029	1368	1591	1689	1888	1832	Siirt	470	705	858	906	982	1244
Elazig	1849	1800	1883	1967	2011	2761	Sinop	424	682	883	1083	1297	1456
Erzincan	670	868	1058	1315	1391	1595	Sirnak	305	771	1193	1803	1906	1888
Erzurum	2313	3028	3325	3731	4378	4528	Sivas	1935	1828	2015	2528	3192	3651
Eskisehir	4221	5821	6511	6528	6662	6732	Tekirdag	3543	4947	6531	6788	7093	7362
Gaziantep	4754	6794	7310	8843	8979	8979	Tokat	1355	1898	1936	1974	2595	3392
Giresun	794	1157	1520	1917	1867	1869	Trabzon	1898	2716	4128	6193	6453	6532
Gumushane	320	438	574	674	726	802	Tunceli	158	266	390	475	618	685
Hakkari	250	476	691	890	994	1268	Usak	1010	1311	1514	1634	1656	1841
Hatay	922	1216	2091	4523	6806	8045	Van	2043	3048	3483	4170	4665	5587
Igdir	313	401	535	678	786	870	Yalova	1170	1448	1777	2098	2919	3621
Isparta	1299	1510	1632	1793	1924	1897	Yozgat	967	1299	1480	1622	1778	1748
Istanbul	52,162	52,474	52,222	52,222	52,474	52,162	Zonguldak	1590	1929	1982	2260	3435	4753
Izmir	8974	10,115	19,866	23,011	23,011	23,692							

Table A14. Projected annual residential natural gas demand (GWh) in Turkish provinces between 2025 and 2050 under SSP3 scenario from RF algorithm.

Province	2025	2030	2035	2040	2045	2050	Province	2025	2030	2035	2040	2045	2050
Adana	1960	5053	7411	8810	8819	9012	K.maras	2147	3132	3813	5127	6220	6434
Adiyaman	945	1415	1932	1768	1866	2008	Karabuk	768	981	1302	1529	1707	1809
Afyonk.	1475	2102	2940	3432	4114	5493	Karaman	677	856	962	1150	1306	1435
Agri	609	891	1167	1319	1556	1912	Kars	541	707	865	933	991	1262
Aksaray	936	1315	1570	1850	1909	1875	Kastamonu	895	1236	1411	1627	1816	1823
Amasya	944	1157	1316	1436	1585	1645	Kayseri	4917	5903	6444	6603	6738	7309
Ankara	22,553	24,278	26,151	26,129	29,867	38,722	Kilis	315	372	466	601	716	856
Antalya	1357	5750	8658	9677	19,661	22,314	Kirikkale	912	1152	1361	1615	1815	1784
Ardahan	142	184	269	339	404	454	Kirklareli	1111	1360	1607	1755	1836	1899
Artvin	201	403	573	720	886	997	Kirsehir	696	858	1007	1301	1529	1786
Aydin	1341	2279	3989	5838	6661	6652	Kocaeli	6812	7287	8748	8921	9720	9764
Balikesir	2865	4603	6267	6639	6661	6771	Konya	7114	8506	8998	9030	9262	9385
Bartin	395	580	728	926	1210	1381	Kutahya	1605	1852	1898	2033	2938	3652
Batman	976	1331	1850	1906	1971	2072	Malatya	1916	2026	2680	3346	4395	5630
Bayburt	225	296	334	374	432	464	Manisa	2621	4775	6244	6846	7115	7641
Bilecik	762	860	945	1132	1319	1443	Mardin	825	1386	2108	3062	3685	4530
Bingol	576	826	1002	1295	1433	1634	Mersin	1282	2439	5902	7537	8757	9057
Bitlis	626	856	950	1161	1317	1479	Mugla	547	1009	1836	3556	5643	6786
Bolu	1014	1321	1590	1843	1835	1832	Mus	582	825	949	1156	1291	1334
Burdur	688	922	1167	1326	1507	1626	Nevsehir	839	1069	1359	1626	1840	1799
Bursa	9588	9418	9514	9431	9798	10,227	Nigde	879	1062	1312	1446	1622	1806
Canakkale	1284	1829	1996	2453	3740	4881	Ordu	1413	2143	3307	4468	5872	6283
Cankiri	549	710	880	1079	1344	1555	Osmaniye	558	1061	1561	1795	1908	1948
Corum	1497	1838	1880	1870	1886	1881	Rize	744	1024	1303	1523	1667	1815
Denizli	3105	4156	5777	6601	6527	6633	Sakarya	3403	4622	6141	6584	6622	6657
Diyarbakir	3282	4222	6081	6824	7114	7914	Samsun	4060	6207	6545	6565	6605	6715
Duzce	1289	1521	1644	1833	1832	1973	Sanliurfa	1984	3955	6059	6851	7053	7276
Edirne	1031	1363	1597	1701	1822	1828	Siirt	470	713	862	906	985	1249
Elazig	1849	1796	1849	1916	2000	2761	Sinop	424	681	883	1084	1325	1504
Erzincan	670	865	1026	1304	1391	1595	Sirnak	305	771	1193	1759	1915	1971
Erzurum	2313	3028	3266	3534	4159	4483	Sivas	1935	1829	1981	2127	2964	3378
Eskisehir	4221	5821	6511	6528	6555	6576	Tekirdag	3543	4897	6193	6788	7093	7375
Gaziantep	4760	6767	7388	8843	8987	8979	Tokat	1356	1894	1936	2409	3055	3626
Giresun	794	1157	1520	1915	1923	1935	Trabzon	1898	2688	4060	6188	6453	6532
Gumushane	320	442	575	673	723	795	Tunceli	158	264	360	469	591	681
Hakkari	250	475	688	899	1010	1271	Usak	1010	1308	1521	1645	1789	1811
Hatay	922	1219	2091	4261	6516	7698	Van	2043	3054	3503	3867	4665	5470
Igdir	313	400	521	653	744	846	Yalova	1170	1450	1777	2015	2115	2972
Isparta	1299	1518	1653	1776	1845	1853	Yozgat	967	1296	1480	1629	1790	1766
Istanbul	52,162	52,474	52,222	52,222	52,474	52,162	Zonguldak	1593	1929	1951	2262	3408	4749
Izmir	8974	10,115	21,787	23,011	23,273	24,307							

Table A15. Projected annual residential natural gas demand (GWh) in Turkish provinces between 2025 and 2050 under SSP4 scenario from RF algorithm.

Province	2025	2030	2035	2040	2045	2050	Province	2025	2030	2035	2040	2045	2050
Adana	1960	5053	7411	8810	8819	8913	K.maras	2147	3132	3813	5388	6220	6415
Adiyaman	945	1412	1941	1840	1813	1911	Karabuk	768	975	1299	1529	1709	1796
Afyonk.	1475	2059	2917	3363	3861	5007	Karaman	677	862	951	1094	1292	1383
Agri	609	894	1156	1320	1564	1912	Kars	541	705	857	904	974	1212
Aksaray	938	1315	1572	1872	1953	1886	Kastamonu	895	1237	1414	1617	1735	1847
Amasya	944	1156	1320	1429	1584	1645	Kayseri	4917	5903	6444	6635	6856	7746
Ankara	22,553	24,278	26,151	29,845	38,377	38,722	Kilis	315	376	475	629	750	856
Antalya	1357	5721	8503	9677	19,661	22,895	Kirikkale	913	1155	1361	1622	1815	1795
Ardahan	142	187	272	341	406	454	Kirklareli	1111	1362	1607	1792	1820	1896
Artvin	206	413	578	722	890	1032	Kirsehir	696	863	1009	1296	1523	1778
Aydin	1341	2270	3989	5811	6642	6633	Kocaeli	6812	7287	8748	9312	9597	9615
Balikesir	2865	4582	6224	6639	6756	6775	Konya	7114	8506	8998	9030	9138	9286
Bartin	395	580	728	919	1135	1302	Kutahya	1599	1873	1942	2069	2884	3679
Batman	976	1332	1803	1929	1926	1952	Malatya	1916	1992	2540	3193	4397	5630
Bayburt	225	296	334	374	432	464	Manisa	2621	4775	6511	6941	7115	7641
Bilecik	761	860	942	1127	1323	1450	Mardin	825	1385	2095	3058	3681	4522
Bingol	576	826	1002	1295	1437	1628	Mersin	1282	2427	5915	7494	8700	9000
Bitlis	626	855	945	1160	1317	1483	Mugla	547	1009	1832	3554	5664	6782
Bolu	1014	1326	1596	1861	1829	1856	Mus	582	822	940	1122	1295	1358
Burdur	688	919	1169	1326	1507	1626	Nevsehir	839	1073	1364	1626	1845	1811

Table A15. Cont.

Province	2025	2030	2035	2040	2045	2050	Province	2025	2030	2035	2040	2045	2050
Bursa	9588	9418	9514	9848	9819	10,227	Nigde	879	1056	1312	1446	1620	1735
Canakkale	1287	1820	2003	2462	3732	4881	Ordu	1413	2111	3220	4170	5698	6283
Cankiri	551	710	885	1117	1344	1568	Osmaniye	558	1059	1541	1859	1903	1945
Corum	1497	1838	1840	1879	1909	1878	Rize	744	1034	1314	1523	1667	1814
Denizli	3105	4156	5777	6601	6527	6621	Sakarya	3403	4622	6141	6565	6603	6762
Diyarbakir	3282	4222	6053	6812	7077	7155	Samsun	4034	6140	6545	6565	6592	6809
Duzce	1289	1517	1641	1854	1893	1971	Sanliurfa	1984	3922	6034	6832	7026	7144
Edirne	1029	1368	1591	1656	1847	1864	Siirt	470	705	861	907	982	1243
Elazig	1849	1796	1849	1940	2014	2764	Sinop	424	676	882	1079	1298	1452
Erzincan	670	865	1036	1307	1389	1597	Sirnak	305	771	1193	1773	1888	1879
Erzurum	2313	3028	3275	3620	4159	4493	Sivas	1935	1828	1983	2390	3086	3503
Eskisehir	4221	5821	6511	6528	6555	6683	Tekirdag	3543	4906	6264	6788	7093	7362
Gaziantep	4754	6774	7310	8851	8987	8987	Tokat	1356	1894	1936	1993	2115	3095
Giresun	794	1157	1520	1917	1873	1889	Trabzon	1898	2686	4060	6188	6453	6532
Gumushane	320	438	574	674	726	798	Tunceli	158	265	380	475	618	683
Hakkari	250	475	687	888	995	1267	Usak	1010	1309	1518	1640	1656	1806
Hatay	922	1216	2091	4383	6482	7484	Van	2043	3048	3483	3946	4665	5587
Igdir	313	401	534	673	786	870	Yalova	1170	1450	1777	2041	2411	3205
Isparta	1299	1512	1632	1774	1879	1890	Yozgat	967	1296	1480	1622	1781	1755
Istanbul	52,162	52,474	52,222	52,222	52,474	52,162	Zonguldak	1590	1929	1977	2262	3427	4760
Izmir	8974	10,115	19,866	20,593	23,011	23,692							

Table A16. Projected annual residential natural gas demand (GWh) in Turkish provinces between 2025 and 2050 under SSP5 scenario from RF algorithm.

Province	2025	2030	2035	2040	2045	2050	Province	2025	2030	2035	2040	2045	2050
Adana	1960	5033	7411	8810	8819	8913	K.maras	2147	3136	3832	5410	6314	6562
Adiyaman	945	1408	1916	1889	1802	1960	Karabuk	768	980	1296	1531	1673	1801
Afyonk.	1475	2066	2922	3376	3880	5033	Karaman	679	856	955	1123	1320	1468
Agri	609	888	1157	1328	1603	1917	Kars	546	707	857	914	1008	1275
Aksaray	938	1319	1589	1894	1955	1896	Kastamonu	892	1245	1467	1626	1868	1872
Amasya	944	1157	1322	1430	1576	1623	Kayseri	4917	5903	6580	6802	7085	8276
Ankara	22,553	24,278	29,867	38,377	38,377	38,722	Kilis	316	389	514	672	791	897
Antalya	1357	5700	8511	9967	20,092	22,947	Kirikkale	918	1156	1373	1619	1828	1837
Ardahan	142	204	305	375	442	468	Kirklareli	1111	1365	1624	1832	1844	1895
Artvin	206	414	584	772	950	1194	Kirsehir	696	859	1015	1314	1525	1768
Aydin	1341	2270	3989	5827	6782	7137	Kocaeli	6812	7270	9139	9594	9597	9615
Balikesir	2865	4582	6212	6860	7098	7100	Konya	7114	8628	8998	9030	9138	9286
Bartin	395	586	732	943	1201	1302	Kutahya	1599	1877	1957	2041	2975	3728
Batman	976	1329	1796	1874	1949	2071	Malatya	1916	2028	2663	3358	4389	5630
Bayburt	225	296	334	374	434	464	Manisa	2621	5059	6591	6951	7103	7633
Bilecik	762	881	957	1131	1351	1538	Mardin	825	1395	2127	3072	3827	4614
Bingol	576	827	1011	1294	1440	1629	Mersin	1282	2427	5915	7494	8700	9000
Bitlis	625	855	943	1164	1332	1493	Mugla	547	1009	1832	3716	5788	6898
Bolu	1016	1330	1626	1913	1855	1862	Mus	582	820	941	1129	1311	1423
Burdur	686	914	1160	1338	1526	1620	Nevsehir	838	1077	1367	1621	1828	1820
Bursa	9588	9418	9886	9848	9819	10,248	Nigde	882	1056	1319	1456	1621	1859
Canakkale	1313	1801	2010	2628	3882	5590	Ordu	1414	2102	3296	4698	6018	6283
Cankiri	551	714	917	1169	1352	1608	Osmaniye	558	1053	1506	1881	1902	1955
Corum	1497	1832	1836	1932	1972	1938	Rize	744	1036	1333	1548	1654	1833
Denizli	3075	4161	5787	6601	6680	6936	Sakarya	3403	4631	6141	6718	6810	7476
Diyarbakir	3282	4222	6053	6812	7183	8604	Samsun	4034	6019	6545	6685	6828	7176
Duzce	1289	1516	1680	1842	1861	1974	Sanliurfa	1984	3866	5983	6760	7105	8157
Edirne	1029	1367	1603	1803	1847	1831	Siirt	470	704	858	904	986	1265
Elazig	1845	1802	1909	1964	2007	2772	Sinop	419	683	878	1117	1305	1456
Erzincan	670	879	1061	1315	1465	1600	Sirnak	305	772	1202	1830	1892	1907
Erzurum	2306	3028	3364	3835	4403	4541	Sivas	1928	1857	2024	2663	3276	3799
Eskisehir	4221	5821	6511	6652	6779	7015	Tekirdag	3543	5046	6591	6775	7081	7337
Gaziantep	4845	6800	7292	8779	8923	8923	Tokat	1355	1898	1911	2011	2642	3537
Giresun	796	1160	1520	1900	1866	1972	Trabzon	1899	2716	4148	6193	6453	6532
Gumushane	317	438	574	679	805	877	Tunceli	158	277	408	499	649	708
Hakkari	249	485	705	895	986	1277	Usak	1010	1311	1508	1640	1807	1849
Hatay	921	1216	2082	4733	7069	8408	Van	2049	3048	3566	4318	4804	5611
Igdir	313	404	561	702	805	876	Yalova	1170	1460	1819	2266	3227	4052
Isparta	1299	1508	1641	1868	1922	1887	Yozgat	969	1299	1482	1608	1643	1827
Istanbul	52,162	52,474	52,222	52,222	52,474	52,162	Zonguldak	1584	1933	1982	2289	3537	4772
Izmir	8974	10,115	19,866	20,593	20,593	25,790							

Table A17. Projected annual residential natural gas demand (GWh) in Turkish provinces between 2025 and 2050 under SSP1 scenario from CatBoost algorithm.

Province	2025	2030	2035	2040	2045	2050	Province	2025	2030	2035	2040	2045	2050
Adana	1909	3185	5035	6128	6061	6210	K.maras	2181	2941	3657	4372	5097	5634
Adiyaman	961	1351	1708	1657	1618	1709	Karabuk	795	1028	1306	1561	1773	1862
Afyonk.	1537	1947	2490	2860	3162	3979	Karaman	717	852	900	999	1332	1471
Agri	601	798	950	1047	1470	1714	Kars	498	582	743	863	912	991
Aksaray	952	1257	1570	1674	1786	1780	Kastamonu	961	1352	1522	1680	1726	1748
Amasya	938	1056	1392	1658	1685	1527	Kayseri	5004	6340	6673	6872	6752	8457
Ankara	22,683	25,181	28,121	29,186	29,791	28,756	Kilis	317	323	335	360	332	351
Antalya	1660	5619	10,429	12,402	18,167	21,418	Kirikkale	923	1089	1338	1559	1668	1672
Ardahan	178	200	227	286	317	320	Kirklareli	1175	1509	1713	1649	1755	1763
Artvin	258	441	470	520	822	988	Kirsehir	714	939	1116	1290	1482	1522
Aydin	1275	1309	1891	3296	4348	5203	Kocaeli	6722	6878	7295	10,471	10,971	10,458
Balikesir	3200	4012	4386	5591	5843	6242	Konya	7170	9422	10,183	10,208	10,052	9877
Bartin	407	359	470	631	746	799	Kutahya	1504	1784	1894	1996	2718	2746
Batman	957	1177	1528	1700	1668	1721	Malatya	1783	1839	2040	2796	3074	3066
Bayburt	205	214	206	221	221	295	Manisa	2729	3694	4205	4306	5619	5936
Bilecik	748	797	873	921	1319	1567	Mardin	805	1181	1544	1855	2505	2894
Bingol	542	804	1008	1326	1479	1568	Mersin	1195	1416	2526	3853	4304	4825
Bitlis	619	767	869	1158	1516	1690	Mugla	608	1382	2620	4157	4684	5886
Bolu	1033	1327	1485	1713	1665	1749	Mus	575	793	958	985	1186	1273
Burdur	677	919	1272	1504	1670	1498	Nevsehir	828	1094	1338	1489	1642	1630
Bursa	9788	9163	9505	11,438	13,902	17,352	Nigde	891	1153	1506	1705	1633	1684
Canakkale	1356	1588	1679	1747	1840	2469	Ordu	1333	1623	1801	1923	2771	3162
Cankiri	513	777	911	992	1276	1251	Osmaniye	470	791	929	994	1265	1213
Corum	1514	1555	1804	1793	1853	1877	Rize	829	1115	1515	1520	1681	1701
Denizli	2752	3283	3967	4206	4174	4715	Sakarya	3653	4603	5628	6010	5804	6086
Diyarbakir	2831	3515	4624	5854	6029	6062	Samsun	3739	5116	6089	6518	6477	6757
Duzce	1274	1482	1568	1684	1716	1769	Sanliurfa	2134	2641	3325	4259	4639	5571
Edirne	1029	1325	1529	1631	1581	1794	Siirt	440	623	740	873	887	886
Elazig	1646	1654	1709	1642	1734	1705	Sinop	432	348	535	788	849	994
Erzincan	668	828	1047	1372	1464	1498	Sirnak	417	838	1186	1668	1668	1712
Erzurum	2373	2633	2692	2717	2759	3051	Sivas	1817	1717	1910	2159	2632	2717
Eskisehir	3731	4440	5160	5712	5737	5959	Tekirdag	3627	4179	4303	4766	5620	6086
Gaziantep	4573	5616	5910	5941	6200	6651	Tokat	1455	1696	1809	1811	1863	1884
Giresun	779	860	826	825	883	972	Trabzon	1689	2408	2904	3162	3741	4129
Gumushane	253	287	374	419	417	472	Tunceli	180	206	287	287	344	481
Hakkari	259	472	762	928	1260	1397	Usak	1028	1335	1596	1526	1655	1623
Hatay	943	1179	1804	2967	4216	5574	Van	2073	2739	2798	3717	4229	4270
Igdir	337	433	466	488	520	658	Yalova	1150	1199	1248	1457	1484	1537
Isparta	1307	1520	1685	1725	1651	1740	Yozgat	996	1408	1657	1599	1648	1597
Istanbul	52,394	53,709	52,846	51,409	54,119	52,251	Zonguldak	1562	1721	1695	1808	1980	2564
Izmir	10,395	17,385	25,148	24,172	24,734	24,032							

Table A18. Projected annual residential natural gas demand (GWh) in Turkish provinces between 2025 and 2050 under SSP2 scenario from CatBoost algorithm.

Province	2025	2030	2035	2040	2045	2050	Province	2025	2030	2035	2040	2045	2050
Adana	1909	3320	5024	6122	6049	6213	K.maras	2181	2763	3117	4201	5085	5572
Adiyaman	961	1352	1708	1657	1709	1704	Karabuk	795	1028	1306	1513	1813	1860
Afyonk.	1537	1947	2463	2775	3160	3441	Karaman	717	852	900	999	1332	1471
Agri	601	792	950	1026	1470	1714	Kars	498	582	689	786	908	976
Aksaray	952	1257	1570	1674	1781	1757	Kastamonu	961	1352	1522	1680	1706	1748
Amasya	938	1056	1392	1658	1685	1527	Kayseri	5004	6351	6643	6831	6711	7710
Ankara	22,683	25,181	28,121	29,186	29,791	28,756	Kilis	317	323	343	354	332	349
Antalya	1660	5641	10,429	12,141	16,578	21,418	Kirikkale	923	1090	1336	1557	1666	1670
Ardahan	178	200	200	236	297	320	Kirklareli	1175	1509	1713	1644	1734	1672
Artvin	258	440	470	516	808	988	Kirsehir	735	925	1116	1275	1480	1522
Aydin	1275	1326	1778	2995	4113	5103	Kocaeli	6722	7012	7295	10,473	11,232	10,719
Balikesir	3200	4012	4395	5510	5804	6210	Konya	7170	9422	9725	10,205	10,040	9880
Bartin	407	359	479	614	731	798	Kutahya	1504	1784	1894	1976	2634	2739
Batman	957	1177	1528	1700	1648	1693	Malatya	1783	1842	2035	2783	2870	3063
Bayburt	205	224	222	225	222	248	Manisa	2729	3694	4166	4273	5588	5936
Bilecik	748	820	873	921	1319	1561	Mardin	805	1181	1547	1761	2015	2670
Bingol	542	803	1007	1326	1479	1472	Mersin	1195	1416	2751	3855	4951	6480
Bitlis	619	766	869	1158	1488	1690	Mugla	608	1448	2620	4078	4387	5314
Bolu	1033	1327	1485	1694	1665	1726	Mus	575	780	934	986	1221	1274
Burdur	677	919	1228	1507	1685	1512	Nevsehir	828	1094	1364	1575	1667	1630

Table A18. Cont.

Province	2025	2030	2035	2040	2045	2050	Province	2025	2030	2035	2040	2045	2050
Bursa	9788	9163	9505	9910	13,902	17,352	Nigde	891	1153	1506	1696	1633	1684
Canakkale	1356	1588	1778	1758	1774	1970	Ordu	1333	1643	1753	1918	2638	3072
Cankiri	513	750	903	992	1247	1251	Osmaniye	470	791	929	973	1237	1193
Corum	1514	1555	1804	1793	1789	1807	Rize	829	1115	1507	1520	1681	1701
Denizli	2752	3185	3967	4206	4174	4388	Sakarya	3653	4603	5628	6010	5779	6097
Diyarbakir	2831	3515	4624	5841	6029	6062	Samsun	3739	4734	6086	6529	6437	6649
Duzce	1274	1482	1568	1684	1711	1748	Sanliurfa	2134	2854	4391	5733	6022	6022
Edirne	1029	1325	1529	1612	1581	1769	Siirt	440	623	740	873	887	886
Elazig	1646	1654	1689	1642	1708	1705	Sinop	432	349	533	822	887	1041
Erzincan	668	833	1027	1372	1562	1699	Sirnak	417	838	1186	1669	1669	1689
Erzurum	2373	2633	2720	2746	2751	2836	Sivas	1817	1719	1934	1999	2633	2618
Eskisehir	3731	4440	5147	5712	5697	5908	Tekirdag	3627	4179	4303	4433	5532	6086
Gaziantep	4573	5616	5876	6271	6632	6815	Tokat	1455	1696	1801	1875	2350	2684
Giresun	779	860	826	825	883	972	Trabzon	1689	2408	2859	3093	3165	3851
Gumushane	253	287	356	419	409	462	Tunceli	180	206	282	284	335	470
Hakkari	259	470	762	928	1213	1397	Usak	1028	1335	1596	1526	1655	1623
Hatay	943	1166	1804	2949	4229	5575	Van	2073	2818	3039	3883	4187	4140
Igdir	337	433	458	479	507	630	Yalova	1150	1199	1248	1384	1488	1588
Isparta	1307	1520	1685	1706	1651	1715	Yozgat	996	1408	1657	1599	1648	1597
Istanbul	52,394	53,709	52,846	51,409	54,119	52,251	Zonguldak	1562	1701	1695	1789	1804	1891
Izmir	10,395	17,385	25,148	27,165	27,727	27,025							

Table A19. Projected annual residential natural gas demand (GWh) in Turkish provinces between 2025 and 2050 under SSP3 scenario from CatBoost algorithm.

Province	2025	2030	2035	2040	2045	2050	Province	2025	2030	2035	2040	2045	2050
Adana	1909	3604	5495	6094	6306	6834	K.maras	2181	2763	3105	3688	4552	5305
Adiyaman	961	1352	1708	1657	1689	1775	Karabuk	795	977	1305	1559	1771	1865
Afyonk.	1537	1947	2457	2730	2928	3022	Karaman	717	852	900	999	1332	1486
Agri	600	791	922	1011	1328	1678	Kars	498	584	677	773	857	926
Aksaray	952	1257	1570	1654	1762	1752	Kastamonu	961	1352	1522	1680	1706	1729
Amasya	938	1060	1366	1658	1685	1527	Kayseri	5004	6351	6643	6791	6647	7021
Ankara	22,683	25,181	28,121	28,171	29,791	28,756	Kilis	317	323	343	378	323	323
Antalya	1660	5641	10,429	12,141	16,317	19,568	Kirikkale	923	1104	1362	1557	1666	1674
Ardahan	178	200	200	200	207	287	Kirklareli	1175	1509	1693	1644	1730	1646
Artvin	258	440	470	503	746	934	Kirsehir	735	925	1012	1269	1357	1520
Aydin	1275	1375	1874	3207	4185	5082	Kocaeli	6722	6965	7297	9557	9700	10,753
Balikesir	3200	4016	4406	5975	5764	6075	Konya	7170	9422	9681	10,465	10,294	10,128
Bartın	407	359	479	605	747	897	Kutahya	1504	1784	1894	1972	2458	2614
Batman	957	1177	1529	1720	1745	1701	Malatya	1783	1822	1970	2588	2798	2979
Bayburt	205	224	224	225	224	248	Manisa	2729	3694	4126	4286	5612	5838
Bilecik	748	820	873	936	1332	1561	Mardin	805	1181	1541	1741	1783	1873
Bingol	533	803	1009	1320	1481	1563	Mersin	1195	1429	2815	4258	5986	6599
Bitlis	613	753	858	1123	1488	1649	Mugla	608	1576	2905	4132	4931	5731
Bolu	1033	1327	1485	1694	1649	1728	Mus	575	780	934	986	1153	1273
Burdur	677	919	1210	1517	1682	1511	Nevsehir	828	1094	1338	1489	1642	1631
Bursa	9788	9163	9505	9649	11,360	17,352	Nigde	891	1156	1575	1703	1629	1688
Canakkale	1356	1597	1654	1680	1687	1880	Ordu	1333	1643	1753	1898	2647	2900
Cankiri	513	747	890	992	1255	1262	Osmaniye	470	791	929	973	1126	1197
Corum	1514	1555	1804	1793	1770	1728	Rize	829	1115	1430	1525	1685	1705
Denizli	2752	3079	3833	4229	4161	4392	Sakarya	3660	4335	4861	6077	5749	6016
Diyarbakir	2831	3490	4115	5257	6017	6550	Samsun	3739	4590	6074	6516	6437	6609
Duzce	1274	1482	1568	1662	1688	1744	Sanliurfa	2134	2865	4255	5939	6012	6025
Edirne	1029	1325	1529	1612	1558	1495	Siirt	440	610	740	863	903	917
Elazig	1646	1656	1689	1619	1708	1800	Sinop	432	349	559	809	846	1002
Erzincan	668	828	1027	1343	1563	1699	Sirnak	417	838	1182	1649	1744	1809
Erzurum	2373	2652	2691	2746	2701	2764	Sivas	1817	1719	1914	1999	2372	2574
Eskisehir	3731	4305	4454	5236	5779	6100	Tekirdag	3627	4179	4281	4401	5271	6062
Gaziantep	4573	5686	5978	6206	6626	6799	Tokat	1455	1696	1801	2021	2658	2664
Giresun	779	857	826	825	884	968	Trabzon	1689	2408	2854	3048	3185	3858
Gumushane	253	287	343	406	409	453	Tunceli	180	206	263	284	335	459
Hakkari	266	458	749	893	1161	1313	Usak	1028	1335	1596	1526	1655	1603
Hatay	943	1166	1793	2909	4201	5998	Van	2073	2818	3019	3883	4261	4169
Igdir	337	433	458	475	498	502	Yalova	1150	1199	1248	1388	1441	1529
Isparta	1307	1521	1685	1706	1629	1695	Yozgat	996	1340	1587	1542	1623	1597
Istanbul	52,394	53,709	52,846	51,409	54,119	52,251	Zonguldak	1562	1701	1696	1813	1793	1747
Izmir	10,395	17,385	28,179	27,165	27,727	31,513							

Table A20. Projected annual residential natural gas demand (GWh) in Turkish provinces between 2025 and 2050 under SSP4 scenario from CatBoost algorithm.

Province	2025	2030	2035	2040	2045	2050	Province	2025	2030	2035	2040	2045	2050
Adana	1909	3320	5024	6122	6042	6198	K.maras	2181	2763	3124	4067	4548	5200
Adiyaman	961	1352	1708	1657	1686	1704	Karabuk	795	1014	1306	1482	1707	1833
Afyonk.	1537	1947	2457	2775	2955	3100	Karaman	717	852	900	999	1332	1471
Agri	601	791	922	1011	1423	1714	Kars	498	584	677	778	878	976
Aksaray	952	1257	1570	1654	1781	1752	Kastamonu	961	1352	1522	1680	1706	1729
Amasya	938	1056	1366	1658	1685	1527	Kayseri	5004	6340	6633	6821	6644	7549
Ankara	22,683	25,181	28,121	29,186	29,791	28,756	Kilis	317	323	343	354	323	326
Antalya	1660	5641	10,429	12,141	16,317	19,829	Kirikkale	923	1090	1338	1557	1666	1670
Ardahan	178	200	200	198	287	301	Kirklareli	1175	1509	1693	1644	1730	1650
Artvin	258	440	470	503	773	951	Kirsehir	735	925	1116	1275	1472	1522
Aydin	1275	1323	1768	2995	4109	5103	Kocaeli	6722	7012	7295	9572	10,971	10,458
Balikesir	3200	4012	4395	5510	5764	6115	Konya	7170	9422	9722	10,205	10,034	9868
Bartin	407	359	479	613	717	793	Kutahya	1504	1784	1894	1971	2460	2659
Batman	957	1177	1529	1700	1648	1673	Malatya	1783	1842	2035	2738	2870	2979
Bayburt	205	214	206	221	222	246	Manisa	2729	3694	4166	4286	5599	5905
Bilecik	748	820	873	922	1319	1483	Mardin	805	1181	1541	1761	1783	2201
Bingol	542	803	995	1313	1479	1472	Mersin	1195	1416	2808	3939	4285	4813
Bitlis	619	753	856	1158	1488	1658	Mugla	608	1448	2620	4078	4347	4397
Bolu	1033	1327	1485	1694	1665	1721	Mus	575	780	934	982	1132	1267
Burdur	677	919	1229	1493	1670	1498	Nevsehir	828	1094	1338	1489	1642	1631
Bursa	9788	9163	9505	9649	13,902	17,352	Nigde	891	1152	1506	1696	1625	1684
Canakkale	1356	1597	1679	1679	1755	1874	Ordu	1333	1625	1782	1918	2647	2905
Cankiri	513	750	903	992	1232	1251	Osmaniye	470	791	929	973	1175	1202
Corum	1514	1555	1804	1793	1769	1746	Rize	829	1115	1507	1520	1681	1701
Denizli	2752	3073	3884	4229	4174	4388	Sakarya	3660	4335	4861	6010	5725	5983
Diyarbakir	2831	3515	4190	5444	6017	6062	Samsun	3739	4715	6086	6529	6437	6609
Duzce	1274	1482	1568	1662	1711	1744	Sanliurfa	2134	2865	4117	5378	5888	5888
Edirne	1029	1325	1529	1612	1558	1746	Siirt	440	610	740	863	899	886
Elazig	1646	1654	1689	1639	1708	1682	Sinop	432	349	526	782	818	955
Erzincan	668	833	1027	1346	1540	1576	Sirnak	417	838	1186	1649	1669	1683
Erzurum	2373	2633	2692	2712	2687	2784	Sivas	1817	1719	1934	1998	2371	2618
Eskisehir	3731	4305	4454	5248	5697	5868	Tekirdag	3627	4179	4281	4401	5397	6080
Gaziantep	4573	5616	5843	5910	6194	6639	Tokat	1455	1696	1801	1875	1945	2645
Giresun	779	860	826	825	884	972	Trabzon	1689	2408	2854	3093	3103	3748
Gumushane	253	287	350	417	409	453	Tunceli	180	206	272	284	335	459
Hakkari	259	458	749	928	1197	1350	Usak	1028	1335	1596	1526	1655	1603
Hatay	943	1166	1804	2909	4050	5470	Van	2073	2818	2940	3718	4179	4091
Igdir	337	433	458	479	504	617	Yalova	1150	1199	1248	1384	1456	1529
Isparta	1307	1520	1685	1706	1629	1715	Yozgat	996	1355	1646	1599	1648	1597
Istanbul	52,394	53,709	52,846	51,409	54,119	52,251	Zonguldak	1562	1701	1695	1783	1803	1737
Izmir	10,395	17,385	25,148	24,172	27,727	27,025							

Table A21. Projected annual residential natural gas demand (GWh) in Turkish provinces between 2025 and 2050 under SSP5 scenario from CatBoost algorithm.

Province	2025	2030	2035	2040	2045	2050	Province	2025	2030	2035	2040	2045	2050
Adana	1909	3175	5055	6140	6061	6210	K.maras	2181	2966	3910	4350	5097	5816
Adiyaman	961	1350	1708	1676	1623	1729	Karabuk	795	1028	1310	1561	1773	1862
Afyonk.	1537	1947	2501	2859	3559	4273	Karaman	717	852	900	999	1332	1556
Agri	601	798	965	1047	1470	1720	Kars	498	582	743	863	955	1002
Aksaray	952	1257	1589	1674	1807	1954	Kastamonu	960	1352	1522	1680	1726	1774
Amasya	938	1071	1439	1658	1685	1527	Kayseri	5004	6340	6673	6980	7329	9551
Ankara	22,683	25,181	29,136	29,186	29,791	34,135	Kilis	317	323	335	363	358	355
Antalya	1660	5619	10,429	15,350	18,167	21,418	Kirikkale	923	1089	1338	1559	1668	1601
Ardahan	178	200	234	286	317	339	Kirklareli	1175	1509	1713	1670	1851	1783
Artvin	258	446	484	535	822	1045	Kirsehir	714	939	1116	1289	1482	1522
Aydin	1275	1372	1874	3296	4388	5229	Kocaeli	6722	6878	7978	10,471	10,971	10,458
Balikesir	3200	4025	4386	5630	6011	6307	Konya	7170	9450	10,183	10,221	10,052	9877
Bartin	407	351	479	649	754	845	Kutahya	1504	1803	1899	1996	2720	3170
Batman	955	1177	1528	1719	1668	1750	Malatya	1783	1959	2229	2856	3101	4017
Bayburt	205	214	206	221	258	318	Manisa	2729	3694	4192	4371	5626	5954
Bilecik	748	797	873	921	1339	1569	Mardin	805	1194	1567	1847	2915	3091
Bingol	542	804	1008	1326	1563	1578	Mersin	1195	1368	2526	3865	4304	4825
Bitlis	619	769	869	1178	1580	1690	Mugla	608	1382	2620	4184	5325	5917
Bolu	1033	1327	1485	1713	1690	1882	Mus	575	795	958	997	1243	1283
Burdur	677	934	1272	1504	1670	1518	Nevsehir	828	1109	1338	1489	1642	1650

Table A21. Cont.

Province	2025	2030	2035	2040	2045	2050	Province	2025	2030	2035	2040	2045	2050
Bursa	9788	9163	9766	11,438	13,902	17,352	Nigde	891	1225	1571	1708	1633	1703
Canakkale	1356	1587	1760	1741	1942	2870	Ordu	1333	1623	1801	1944	2904	3213
Cankiri	513	777	930	1008	1276	1250	Osmaniye	470	791	929	1016	1277	1294
Corum	1514	1555	1804	1877	1887	2258	Rize	829	1115	1580	1580	1709	1701
Denizli	2752	3287	3967	4206	4214	5292	Sakarya	3766	4603	5628	6050	5860	6194
Diyarbakir	2831	3515	4892	5926	6029	6141	Samsun	3739	5116	6089	6558	6516	6863
Duzce	1274	1482	1588	1684	1736	1943	Sanliurfa	2134	2851	3730	4395	4699	5597
Edirne	1029	1325	1529	1631	1571	1794	Siirt	440	619	751	873	887	885
Elazig	1646	1654	1712	1646	1734	1781	Sinop	432	348	535	790	851	993
Erzincan	668	833	1094	1477	1548	1659	Sirnak	417	838	1186	1727	1696	1808
Erzurum	2373	2633	2692	2776	2858	3187	Sivas	1817	1717	1910	2179	2725	2713
Eskisehir	3731	4440	5160	5752	5788	6081	Tekirdag	3627	4218	4335	4766	5627	6098
Gaziantep	4573	5603	5941	5947	6212	6651	Tokat	1455	1696	1809	1811	1882	1888
Giresun	779	859	826	825	883	1077	Trabzon	1689	2408	2904	3326	4019	4265
Gumushane	253	316	386	419	435	475	Tunceli	180	235	287	287	357	493
Hakkari	265	472	762	948	1259	1463	Usak	1028	1335	1596	1526	1713	1628
Hatay	943	1179	1804	2954	4205	5606	Van	2073	2739	2798	3764	4331	4253
Igdir	337	433	476	500	669	721	Yalova	1150	1199	1248	1521	1496	1684
Isparta	1307	1520	1685	1725	1677	1827	Yozgat	996	1407	1657	1599	1648	1617
Istanbul	52,394	53,709	52,846	51,409	54,119	52,251	Zonguldak	1562	1721	1686	1924	2640	2878
Izmir	11,551	17,385	25,148	24,172	24,734	24,000							

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