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Probabilistic Evaluation of Methane Concentration Variability and Ventilation Sensitivity under Routine Operating Conditions in Underground Coal Mining

Ali Kemal Eyüboğlu[1] · Oznur Onel[2] · Muharrem Kemal Özfırat[3]

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Abstract
Routine monitoring of methane concentration in underground coal mines yields measurements that remain well below regulatory limits while exhibiting measurable variability influenced by environmental and operational conditions. This study presents a probabilistic modeling framework for examining methane concentration variability and ventilation sensitivity using routine monitoring data from an underground coal mine in the Soma region of Türkiye. Continuous measurements of methane concentration, air temperature, and relative humidity were recorded at five-minute intervals throughout 2023, yielding 105,120 observations. Probability distributions were assigned to each variable using maximum likelihood estimation, with family selection supported by information criteria and Kolmogorov-Smirnov evaluation. A multiple linear regression response model explained 54% of the variance in methane concentration and identified ventilation performance as the dominant predictor (standardized coefficient −0.621), followed by relative humidity (0.337) and air temperature (0.212). Monte Carlo simulation with 10,000 iterations propagated input uncertainty through the response model across three ventilation scenarios. Reducing ventilation to 80% of nominal raised the mean methane concentration by 9.3%, while improving it to 120% lowered the mean by 9.6%, with modest changes in dispersion. Quantile comparison between simulated and empirical distributions yielded a root mean square error of 1.3 ppm, confirming the internal consistency of the fitted response model and input distributions with the monitoring data. The framework provides an analytically rigorous basis for uncertainty-aware ventilation management and is transferable to other mining environments provided that distributions and the response model are re-estimated from local observations.

Keywords Methane concentration variability · Monte Carlo simulation · Ventilation sensitivity · Underground coal mining

1 Introduction

Underground coal mining continues to play a critical role in global energy production, particularly in regions where lignite and subbituminous coal resources remain economically significant [1]. Safe and efficient mine operation relies on continuous monitoring of environmental and operational parameters, among which methane concentration represents one of the most routinely measured variables [2, 3]. In many underground coal mines, methane concentrations recorded during normal operations remain well below regulatory limits; however, they still exhibit measurable temporal variability influenced by geological conditions, environmental factors, and ventilation performance [4].

A substantial proportion of methane released from underground coal mines is emitted as ventilation air methane, which is typically characterized by relatively low concentration ranges between approximately 0.1% and 1.5%. These emissions account for the majority of total methane released to the atmosphere from mining activities, with reported contributions exceeding 80% in major coal

✉ Oznur Onel
ozonel@vt.edu

[1] Department of Electricity and Energy, Bergama Vocational School, Dokuz Eylül University, Izmir, Türkiye

[2] Department of Mining and Minerals Engineering, Virginia Polytechnic Institute and State University, Blacksburg, VA, USA

[3] Engineering Faculty, Mining Engineering Department, Dokuz Eylül University, Izmir, Türkiye

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producing regions such as China, where concentrations frequently remain below 0.25% [5]. Consequently, modern underground mines increasingly rely on continuous atmospheric monitoring systems to capture subtle variations in methane concentration under routine operating conditions [6, 7]. Fixed sensor networks, remotely integrated monitoring systems, and advanced detection technologies provide extensive time series datasets that reflect the dynamic behavior of methane in mine air, even when absolute concentration values remain low [8].

Methane behavior in underground coal mines is fundamentally controlled by geological characteristics of the coal seam, including coal rank, maceral composition, cleat and fracture networks, and burial history. These factors govern gas generation, adsorption, desorption, and migration processes within the coal matrix and surrounding strata, leading to inherent spatial and temporal variability in methane emissions [9, 10]. As a result, methane concentrations measured in mine workings reflect not only ventilation performance but also the natural heterogeneity of the coal seam, producing observable fluctuations even under stable production conditions.

Temporal variability in methane concentration is further influenced by environmental and operational factors. Previous studies have demonstrated strong relationships between methane concentration and production rate, with increased output often associated with elevated methane release [2, 11]. Variations in atmospheric pressure represent another important driver of methane fluctuations over limited time scales, giving rise to the phenomenon commonly referred to as gob breathing, where pressure reductions promote enhanced gas release from mined out areas [7, 12]. Pressure variations in the mine atmosphere may lead to delayed and nonlinear methane release behavior, highlighting the complexity of methane concentration dynamics and the limitations of interpreting monitoring data using fixed values or static assumptions.

Despite the availability of extensive monitoring datasets, interpretation of routine methane measurements has traditionally emphasized compliance with safety thresholds and predefined alarm criteria. While such approaches are essential for hazard prevention, they offer limited insight into the underlying variability and sensitivity of methane concentration behavior when measured values consistently remain below critical limits. Recent research has therefore highlighted the importance of examining uncertainty, dispersion, and sensitivity in methane monitoring data in order to improve operational awareness and ventilation management [8, 13]. The prevailing focus on threshold exceedance, however, means that the distributional behavior of methane concentration under normal operating conditions has received comparatively limited systematic attention. Although probabilistic methods have been applied to methane-related risk assessment and groundwater contamination prediction [15, 16], their use as interpretive tools for routine underground monitoring data in which concentrations remain consistently within safe operating ranges has not been fully explored in the literature.

In parallel, probabilistic and statistical methods have gained increasing attention for representing uncertainty in complex mining systems. Time series modeling approaches, including ARIMA, VAR, and ARIMAX models, have been applied to methane concentration forecasting through analysis of autocorrelation structures and relationships with auxiliary variables such as barometric pressure [7, 11]. Machine learning techniques, including multilayer perceptron neural networks, have also demonstrated strong performance in methane concentration prediction using monitoring data [14]. In addition, Monte Carlo methods have been widely applied in geoscience and mining research to propagate uncertainty and explore system sensitivity without reliance on deterministic assumptions [15, 16]. These applications have predominantly addressed hazard quantification or predictive modeling, leaving a gap in the understanding of how Monte Carlo simulation can be used to characterize the natural variability and ventilation sensitivity of methane concentrations observed during routine mining operations. The present study addresses this gap by treating Monte Carlo simulation not as a risk estimation tool but as a framework for uncertainty propagation and sensitivity analysis within measured monitoring data collected under normal conditions.

Threshold based monitoring strategies evaluate whether measured concentrations exceed predefined safety limits, providing essential protection against acute hazards but offering limited interpretive capacity for data collected during normal operations. A probabilistic framework oriented toward variability rather than exceedance examines how methane concentration distributions respond to changes in ventilation performance and environmental parameters, supporting trend interpretation and uncertainty-aware assessment without reliance on hazard classifications. This distinction reflects a broader recognition that routine monitoring data contain operationally meaningful information beyond compliance status, and that probabilistic methods can serve as analytical instruments for understanding system behavior under everyday conditions rather than only under exceptional ones [2, 8].

The Soma coal basin, located in the western Aegean region of Türkiye, hosts some of the country's thickest lignite seams and has a long history of underground mining. Soma lignites are characterized by relatively low rank, high moisture content, and complex structural features, which

contribute to variable methane behavior during production [10]. These geological conditions, together with large scale ventilation systems, make the Soma basin an appropriate case study for examining how methane concentration variability responds to operational and environmental influences under routine mining conditions.

The objective of this study is to examine methane concentration variability in an underground coal mine located in the Soma coal basin using a probabilistic framework implemented through Monte Carlo simulation. In contrast to previous probabilistic studies that focus on methane explosion risk or exceedance of regulatory thresholds, the present work investigates the distributional behavior of methane concentration under routine operating conditions, where measured values remain well within safe limits yet exhibit meaningful variability driven by ventilation performance and environmental factors. By analyzing high frequency monitoring data collected throughout 2023, this study aims to improve interpretation of routine methane measurements and to support ventilation management through an uncertainty aware analytical perspective grounded in real field observations. Methodologically, Monte Carlo simulation is employed as an uncertainty propagation and sensitivity analysis tool for routine methane monitoring data, rather than as a risk or hazard prediction approach. This focus on operational variability rather than hazard scenarios distinguishes the present study from existing probabilistic methane assessments and reflects the methodological contribution of applying stochastic analysis to the interpretation of low level, subthreshold monitoring data in underground coal mining.

2 Site Description and Monitoring Framework

2.1 Geological and Mining Setting of the Soma Coal Mine

The Soma coal basin, located in western Turkey, hosts some of the thickest lignite seams in the country and represents one of the most important underground coal mining regions. As near surface reserves within the license areas of Turkish Coal Enterprises and other operators have been progressively depleted, underground mining has become increasingly significant. The spatial location of the Soma Eynez basin and its geological stratigraphic framework are presented in Fig. 1 [17].

The geological structure of the basin is characterized by a complex stratigraphic sequence that exerts strong control on seam continuity and mining conditions. The basement

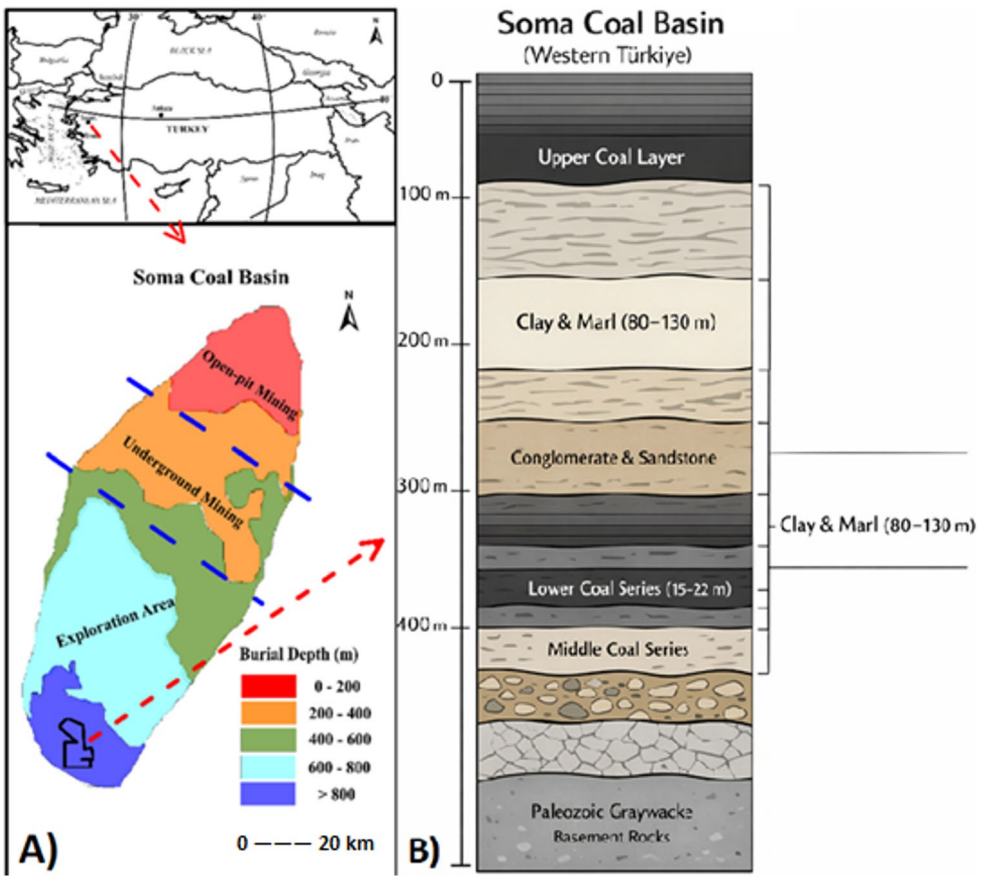


Fig. 1 Location (**a**) and simplified geological–stratigraphic framework (**b**) of the Soma coal basin, illustrating the major lithological units and lignite bearing horizons that control methane occurrence and migration in the study area

consists of Paleozoic aged graywackes composed predominantly of fine textured material. These units are locally overlain by Mesozoic crystalline limestones that are moderately thick, highly fractured, and structurally disturbed. Above this basement, Cenozoic Miocene aged sedimentary units composed of conglomerate, sandstone, clay, and marl form the immediate roof rocks of the coal seam [18]. The marl units, typically 80 to 130 m thick, are well stratified and locally fractured, providing important roof conditions for underground mining operations [19]. The lignite seam, located between these stratigraphic units, reaches thicknesses of up to approximately 30 m and constitutes the primary production horizon currently being mined, as illustrated in Fig. 1 [20].

Coal seam thickness within the Soma Eynez field exhibits significant variability, ranging from approximately 1.8 m to 30 m. This variability has a direct influence on panel design, production planning, and operational control strategies. Due to the thick seam nature of the deposit, coal extraction is predominantly carried out using the Longwall Top Coal Caving (LTCC) method. This method enables the recovery of both the lower coal extracted at the face and the upper coal caved behind the face, thereby improving production efficiency under thick seam conditions [21].

Figure 2 illustrates the general layout of the longwall panel and the conceptual airflow pattern applied in the LTCC system. Clean intake air is supplied underground through dedicated intake roadways connected to the surface via the main ventilation system [22]. After entering the panel, airflow passes along the longwall face and adjacent roadways before being directed toward the return airway. This ventilation configuration ensures a clear separation between intake and returns air streams, supporting stable airflow circulation throughout the panel. The overall ventilation scheme is designed to maintain consistent air movement across production areas without intersecting clean and return air paths [23].

Within the longwall face, coal extraction is performed using a drum shearer loader, while powered roof supports provide immediate roof control along the face line. The extracted coal is transported from the face via armored chain conveyors to the panel roadways and subsequently transferred to the main haulage and shaft systems for transport to the surface. The combination of thick seam geometry, LTCC production method, and structured ventilation layout defines the geological and mining setting that governs routine underground operating conditions in the Soma coal mine, as schematically illustrated in Fig. 2.

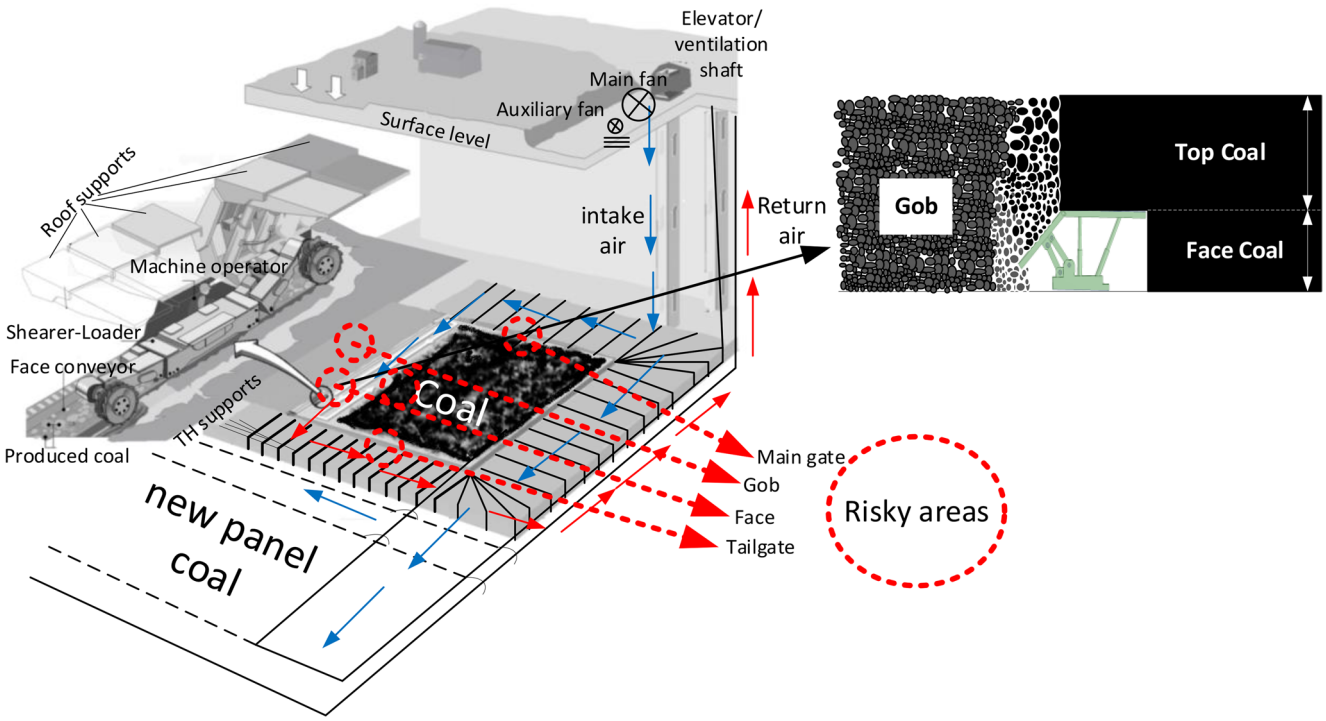


Fig. 2 Schematic illustration of the Longwall Top Coal Caving (LTCC) method and associated airflow pattern in the Soma coal basin, highlighting panel layout, ventilation routes, goaf zones, and potential methane accumulation areas

2.2 Methane Monitoring System and Data Acquisition

Methane concentration data used in this study were obtained through a routine underground monitoring system installed in the Soma coal mine, designed to support continuous environmental assessment under normal operating conditions. Modern underground methane monitoring systems typically rely on integrated sensor packages that simultaneously record gas concentration, airflow characteristics, and auxiliary environmental parameters, enabling comprehensive characterization of mine atmosphere behavior [24, 25]. Such systems emphasize data continuity and temporal resolution to capture natural variability rather than isolated peak events.

Fixed methane sensors were installed at strategically selected underground locations, including longwall return airways and main ventilation routes connected to the surface exhaust system. Sensor placement followed established principles based on methane buoyancy, expected airflow patterns, and spatial integration of emissions rather than localized accumulation zones [24, 26, 27]. Positioning sensors within return airways and near primary ventilation paths allows methane measurements to reflect combined geological emission and ventilation transport processes representative of routine production conditions.

Methane concentration measurements were recorded at a temporal resolution of 5 min throughout the entire year of 2023. High frequency monitoring has been shown to significantly improve the interpretation of methane concentration variability by resolving short term fluctuations and gradual trends that are often obscured in low resolution or averaged datasets [7, 25]. Continuous time series data also facilitate identification of systematic patterns, data gaps, and transient anomalies, supporting robust statistical and probabilistic analysis.

Methane concentrations were recorded in parts per million (ppm), which is appropriate for characterizing low level methane variability under normal ventilation conditions. Advances in sensor technologies, including infrared detection techniques and optical methods employing laser systems, enable reliable monitoring of methane concentrations within the tens to hundreds of ppm range, provided that environmental influences such as temperature, pressure, and relative humidity are properly considered [26, 28]. Simultaneous recording of air temperature and relative humidity was therefore incorporated to support interpretation of measurement stability and variability.

Consistent with these requirements, the methane sensors deployed in the monitoring system operate on the basis of infrared absorption detection, a measurement principle well suited to continuous monitoring within the tens to hundreds of ppm range characteristic of ventilation air methane and stable under the environmental conditions encountered in underground workings [26, 28]. Readings from the permanently installed sensors are transmitted continuously to a central surface monitoring station. Measurement consistency at the low concentrations typical of routine operation was maintained through the quality assurance protocol of the mine operator, comprising periodic zero and span calibration with certified reference gas mixtures at regular intervals, automated flagging of anomalous readings, exclusion of values recorded during documented sensor maintenance, and cross-checking of simultaneous measurements from adjacent monitoring points where applicable. Measurements falling outside physically plausible concentration ranges or associated with documented system faults were excluded from the dataset prior to analysis. In addition, the analyses of this study rest on distributional characteristics and regression relationships estimated from the full annual dataset of 105,120 observations rather than on individual readings; random instrument noise is therefore absorbed by the residual term of the response model, and the large sample size stabilizes the estimated distribution and model parameters, so that the systematic variability attributable to ventilation and environmental conditions is identified independently of instrument-level fluctuations.

The dataset used in this study comprises a total of 105,120 individual methane concentration measurements collected continuously throughout 2023. Measurements were recorded at a fixed temporal resolution of 5 min, resulting in a high frequency time series that reflects routine underground operating conditions. Along with methane concentration expressed in parts per million, the monitoring system simultaneously recorded air temperature, relative humidity, and ventilation related operational parameters expressed in relative terms. This dataset constitutes the empirical foundation of the study and is used consistently across all statistical analyses, probabilistic modeling, and sensitivity evaluations. Accordingly, the Monte Carlo simulations and subsequent interpretations rely solely on measured field observations rather than assumed, predefined, or design level values.

3 Methodology: Monte Carlo–Based Uncertainty and Sensitivity Analysis

The methodological framework adopted in this study treats the interpretation of routine methane monitoring data as a probabilistic modeling problem rather than a descriptive summary of recorded measurements. The monitored quantities are represented as random variables with parametric probability distributions estimated from the field data, and

Monte Carlo simulation is used as an uncertainty propagation mechanism through which the combined variability of these quantities is transmitted to the analytical outputs and quantified. Figure 3 summarizes the structure of the framework, showing how routinely collected underground monitoring data are converted into probabilistic inputs and processed through repeated stochastic sampling to obtain quantitative variability and sensitivity outputs that characterize methane concentration behavior under routine operating conditions.

The framework is organized into three sequential stages. In the first stage, methane concentration together with the associated operational and environmental parameters obtained from the routine monitoring system is characterized as a set of random variables. Each variable is assigned a parametric probability distribution whose parameters are estimated directly from the measured records using maximum likelihood estimation, so that the stochastic representation reflects the empirical variability and operational uncertainty present in the data rather than assumed or design level values [7, 8]. This stage establishes the probabilistic basis of the model and ensures that all subsequent computations are grounded in the statistical structure of the field observations.

In the second stage, Monte Carlo simulation propagates the characterized uncertainty through repeated random sampling of the fitted distributions. At each iteration, a complete set of values is drawn for the monitored variables according to their estimated distributions, representing one plausible realization of routine operating conditions. Repeating this procedure over a large number of iterations produces output probability distributions that capture the aggregated effect of input variability, rather than single point estimates or threshold-based classifications [15, 16]. Because the procedure samples the assigned distributions jointly and evaluates their combined effect, it provides information on the distributional behavior of the monitored system that cannot be recovered from descriptive statistics of any single variable considered in isolation.

In the third stage, the simulated output distributions are analyzed to quantify methane concentration variability and its sensitivity to ventilation performance. Variability is expressed through dispersion measures of the output distribution, and sensitivity is quantified as the relative change in these measures evaluated across defined ventilation scenarios. This formulation supports interpretation of monitoring trends and ventilation management from an uncertainty aware modeling perspective rather than a risk based or regulatory one, and provides a transparent and reproducible link between measured field data, probabilistic model inputs, and quantitative variability and sensitivity outputs.

3.1 Definition of Input Variables and Probability Distributions

This study represents methane concentration variability in underground coal mining through a limited and transparent set of input variables that reflect routine monitoring conditions and operational uncertainty. The variables were selected on the basis of direct measurability, physical relevance to methane behavior, and operational significance within the mine ventilation system. Parameters that would require assumptions beyond the measured field observations were intentionally excluded so that the probabilistic framework remains grounded in the empirical data.

Methane concentration measured in the mine air constitutes the primary variable of the framework. The monitoring records describe low level methane behavior under normal production and ventilation regimes and capture the natural fluctuations produced by operational and environmental influences. Methane concentration is treated as a stochastic representation of the observed system state rather than as a causal input, so that the Monte Carlo framework characterizes distributional stability and sensitivity under routine operating conditions instead of inferring predictive causation. The monitoring records fluctuate around a stable

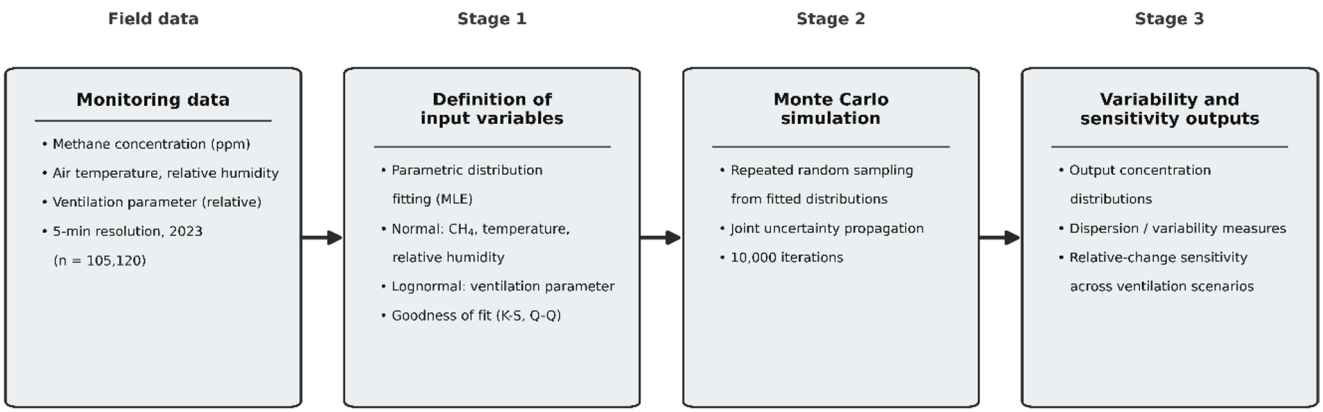


Fig. 3 Simplified workflow illustrating the transformation of monitoring data into variability and sensitivity analysis using Monte Carlo simulation

central tendency within a narrow range, with a coefficient of variation of approximately 9% (σ/μ = 9.8/107.5). This low and approximately symmetric dispersion supports representation of methane concentration by a normal distribution with probability density function (1).

$$f(x;\ \mu,\ \sigma) = \left(1/\left(\sigma\sqrt{(2\pi)}\right)\right) \cdot \exp\left(-(x-\mu)^2/\left(2\sigma^2\right)\right) \quad (1)$$

where μ and σ denote the mean and standard deviation estimated from the monitoring records.

Ventilation performance is introduced as the second variable and is expressed in relative terms to describe operational variability around the nominal system condition. Operationally, the relative ventilation parameter was derived from the air velocity recorded continuously by the anemometer of the same atmospheric monitoring system, installed in the return airway in accordance with the sensor placement principles described in Section 2.2. Each five-minute air velocity reading was normalized by the annual mean velocity at the same location, so that a value of 1.00 corresponds to the nominal ventilation state and deviations express proportional departures from it; the parameter mean of exactly 1.00 reported in Table 4 follows directly from this normalization, while the median of 0.98 and the positive skew of the values reflect the tendency for reduced-efficiency conditions to occur somewhat more frequently than proportionally elevated ones, consistent with the lognormal representation adopted below. This formulation renders the parameter dimensionless and site-independent while preserving the temporal variability of the effective ventilation condition experienced at the monitoring location. Absolute ventilation quantities are not imposed, because design airflows and panel specific values vary considerably with mining geometry, production stage, and layout. A relative representation allows ventilation scenarios to be compared systematically while remaining independent of assumptions tied to a particular site. Because the ventilation parameter is strictly positive and exhibits asymmetric operational variability, it is represented by a lognormal distribution with probability density function (2).

$$f(x;\ \mu_\ln,\ \sigma_\ln) = \left(1/\left(x\,\sigma_\ln\sqrt{(2\pi)}\right)\right) \cdot \exp\left(-(\ln x-\mu_\ln)^2/\left(2\sigma_\ln^2\right)\right),\ x>0 \quad (2)$$

where μ_ln and σ_ln are the mean and standard deviation in logarithmic space. The fitted parameters in Table 1 correspond to a real space median of exp(μ_ln) ≈ 0.99 and a mean of exp (μ_ln + σ_ln²/2) ≈ 1.00, in close agreement with the observed median (0.98) and mean (1.00) of the ventilation parameter reported in Table 4, and consistent with the tendency for reduced efficiency conditions to occur more frequently than proportionally elevated values.

Table 1 Fitted probability distributions and parameters used in Monte Carlo simulation

Variable	Distribution	Parameter 1	Parameter 2	Parameter definition
Methane concentration (ppm)	Normal	μ = 107.5	σ = 9.8	mean and standard deviation
Air temperature (°C)	Normal	μ = 24.6	σ = 2.3	mean and standard deviation
Relative humidity (%)	Normal	μ = 73.4	σ = 6.7	mean and standard deviation
Ventilation parameter (relative)	Lognormal	μ_ln = −0.0071	σ_ln = 0.1196	mean and standard deviation in logarithmic space

Air temperature and relative humidity are included as auxiliary variables, because both are routinely monitored and show measurable associations with methane behavior in underground coal mines. Under routine operating conditions their variations remain bounded and approximately symmetric, and they are therefore represented by normal distributions following Eq. (1), with parameters estimated from their respective monitoring records.

The distribution family for each variable was estimated by maximum likelihood, that is, by maximizing the log-likelihood (3).

$$\ell(\theta) = \sum \ln\ f(x_i;\ \theta),\ i = 1,\ldots,n \quad (3)$$

over the parameter vector θ for each candidate family. For methane concentration, the lognormal and gamma families were evaluated as alternatives to the normal distribution. The lognormal family, although suited to strictly positive right skewed variables, did not improve the representation of the methane records, which fluctuate symmetrically within a narrow range at low coefficient of variation. The gamma family, which accommodates a wider range of skewness, likewise offered no improvement over the normal distribution. The lognormal family was retained for the ventilation parameter on the basis of its strict positivity and the positive skewness of its operational deviations, while air temperature and relative humidity retained normal distributions consistent with their bounded, approximately symmetric variability. The selected distribution families and their fitted parameters are summarized in Table 1 and were used directly as the input definitions for the Monte Carlo simulations.

The adequacy of the selected distributions was assessed using the Kolmogorov-Smirnov statistic, defined as the

maximum absolute difference between the empirical and fitted cumulative distribution functions (4),

$$D_n = \sup |F_n(x) - F(x) \tag{4}$$

together with visual inspection of quantile-quantile plots comparing empirical and theoretical quantiles. The candidate distributions for methane concentration were compared quantitatively using the log-likelihood, the Akaike and Bayesian information criteria, and the Kolmogorov-Smirnov statistic, as summarized in Table 2. The normal distribution achieved the lowest Akaike and Bayesian information criteria, with the lognormal and gamma alternatives higher by ΔAIC values of approximately 1380 and 618, indicating a clear preference for the normal model. The Kolmogorov-Smirnov statistic was smallest for the normal fit ($D = 0.0013$), which was not rejected ($p = 0.996$), whereas the lognormal and gamma fits were rejected at $p < 0.001$. The near zero sample skewness of the methane records (-0.003) is consistent with the symmetric normal model and departs from the positive theoretical skewness of the lognormal (0.278) and gamma (0.183) candidates.

The selection of a normal distribution for methane concentration does not imply an underlying physical law governing gas generation or transport, it is a pragmatic characterization of the operational variability observed under stable ventilation and production conditions. Because the monitoring dataset is large ($n = 105{,}120$), the Kolmogorov-Smirnov test is highly sensitive and can indicate statistically significant deviations even when the practical differences are negligible. The normal fit for methane concentration was nevertheless not rejected, which reinforces its adequacy, and distribution adequacy was in all cases judged by considering the test outcome jointly with the quantile-quantile behavior and the empirical characteristics of the data, so that routine variability is captured without overinterpreting departures of limited magnitude. This formulation keeps the probabilistic framework aligned with the scale, resolution, and limitations of the available monitoring data, and represents routine operational variability rather than extreme events or hazard scenarios.

3.2 Monte Carlo Simulation Procedure

Monte Carlo simulation is used in this study to propagate the uncertainty associated with measured ventilation performance and environmental conditions into the resulting methane concentration, rather than to estimate hazardous events or regulatory exceedance. The procedure represents routine underground operating conditions by repeatedly sampling the probabilistic input variables, evaluating a fitted response relationship for methane concentration, and examining the variability of the resulting outcomes. This allows methane behavior to be interpreted as a continuous and dynamic process influenced by operational uncertainty rather than a phenomenon governed by fixed limits.

The relationship between the operational and environmental inputs and methane concentration is represented by an empirically fitted response model. Methane concentration is expressed as a function of the relative ventilation parameter, air temperature, and relative humidity, estimated by least squares over the full dataset (5),

$$CH_4 = 99.64 - 50.72 \cdot V + 0.906 \cdot T + 0.495 \cdot RH + \varepsilon,\ \varepsilon \sim \text{Normal}\ (0,\ 6.64) \tag{5}$$

where V is the relative ventilation parameter, T is air temperature, RH is relative humidity, and ε is the residual term representing variability not explained by the included variables. The estimated coefficients, their standardized values, and the model fit statistics are reported in Table 3. The three predictors jointly explain approximately 54% of the variance in methane concentration ($R^2 = 0.542$), and their standardized coefficients reproduce the rank associations identified in Table 5: the ventilation parameter exerts the strongest and only negative effect (standardized coefficient -0.621), followed by relative humidity (0.337) and air temperature (0.212). The residual standard deviation of 6.64 ppm, combined with the variance contributed by the predictors, reproduces the observed methane standard deviation of 9.8 ppm and the normal marginal summarized in Table 1, confirming the internal consistency of the response model with the empirical data. Equation (5) provides the explicit analytical link through which changes in ventilation performance and environmental conditions propagate to methane concentration, distinguishing the present framework from a purely descriptive treatment of the monitoring data.

At each iteration, values of the relative ventilation parameter, air temperature, and relative humidity were drawn from their fitted distributions (Table 1) and a residual was drawn from Normal (0, 6.64). These values were substituted into Eq. (5) to generate one methane concentration realization,

Table 2 Goodness-of-fit comparison of candidate probability distributions for methane concentration ($n = 105{,}120$), estimated by maximum likelihood. ΔAIC is the difference from the best (lowest) AIC

Distribution	Log-likelihood	AIC	BIC	ΔAIC	K-S D	*p*-value
Normal	−389,082.9	778,169.7	778,188.8	0.0	0.0013	0.996
Lognormal	−389,772.8	779,549.5	779,568.7	1379.8	0.0193	< 0.001
Gamma	−389,392.0	778,788.0	778,807.2	618.3	0.0132	< 0.001

Table 3 Multiple linear regression of methane concentration on the relative ventilation parameter, air temperature, and relative humidity ($n = 105{,}120$)

Predictor	Coefficient (β)	Std. error	Standardized β	*p*-value
Intercept	99.643	0.357	-	< 0.001
Ventilation parameter (V)	−50.720	0.171	−0.621	< 0.001
Air temperature (T)	0.906	0.009	0.212	< 0.001
Relative humidity (RH)	0.495	0.003	0.337	< 0.001

Residual standard deviation $\sigma_\varepsilon = 6.64$ ppm; $R^2 = 0.542$; adjusted $R^2 = 0.542$

representing a plausible realization of routine operating conditions. Repeating this process over a large number of iterations produced the methane concentration output distribution, which therefore emerges from the combined influence of multiple uncertain inputs rather than from predefined or deterministic assumptions. By construction, the marginal distribution of the generated methane concentration reproduces the observed normal distribution summarized in Table 1, which is verified against the monitoring data in Section 3.5.

Because the response model of Eq. (5) is linear in its inputs and the inputs are sampled independently, the first two moments of the simulated methane concentration are available in closed form and provide an exact analytical benchmark for the Monte Carlo output. The expected value of the output follows from the fitted input means as $E[CH_4] = 99.64 - 50.72 \cdot E[V] + 0.906 \cdot E[T] + 0.495 \cdot E[RH] \approx 107.5$ ppm, and the output variance is the sum of the squared coefficient-weighted input variances and the residual variance, $Var[CH_4] = (50.72 \cdot \sigma_V)^2 + (0.906 \cdot \sigma_T)^2 + (0.495 \cdot \sigma_RH)^2 + \sigma_\varepsilon^2 = 37.0 + 4.3 + 11.0 + 44.1 = 96.5$ ppm², corresponding to a standard deviation of 9.82 ppm. The simulated baseline mean of 107.75 ppm and standard deviation of 9.82 ppm agree with these closed-form values to within approximately 0.2 ppm, consistent with Monte Carlo sampling variability, which verifies the correctness of the stochastic implementation. The decomposition additionally quantifies the share of output variance contributed by each input: the ventilation parameter accounts for approximately 38%, relative humidity 11%, air temperature 5%, and the residual term 46%, in agreement with the standardized coefficients of Table 3. Monte Carlo simulation is nevertheless retained as the propagation mechanism because it yields the full output distribution and its percentiles rather than the first two moments alone, accommodates the non-Gaussian log-normal input without approximation, and extends without modification to nonlinear response formulations; the closed-form moments thus serve as an independent analytical verification of the stochastic procedure rather than a substitute for it.

The ventilation parameter represents the relative operational state of the mine ventilation system with respect to its nominal performance level and is expressed as a dimensionless ratio rather than an absolute airflow quantity. The nominal state corresponds to the observed central condition of the monitoring dataset, where the ventilation parameter recorded a median of 0.98, a mean of 1.00, and a standard deviation of 0.12 (Table 4). This relative formulation reflects the combined influence of fan performance, airway resistance variations, and air leakage that together determine the effective ventilation state experienced at the monitoring location. Ventilation scenarios were defined by applying multiplicative factors to the sampled ventilation parameter, with a factor of 0.80 for the reduced state and 1.20 for the improved state, the baseline retaining the sampled values unchanged. These factors were calibrated to the observed operational range of the relative ventilation parameter, which extends from approximately the 5th percentile (0.80) to the 95th percentile (1.22) reported in Table 4, so that the scenarios reflect operationally realistic deviations rather than hypothetical extremes. Through the negative ventilation coefficient in Eq. (5), a reduction in the ventilation parameter raises the central tendency of the methane output distribution, while an improvement lowers it; the full effect of each scenario on the central tendency and dispersion of methane concentration is reported in Section 4.2.

A total of 10,000 simulation iterations were conducted to ensure statistical stability of the output distributions while preserving computational efficiency. The results are expressed as distributions of methane concentration outcomes rather than single point estimates, which supports examination of relative changes, dispersion characteristics, and sensitivity patterns, and enables direct comparison among ventilation scenarios without reliance on fixed thresholds or predefined safety limits.

The analytical value of this framework extends beyond what descriptive statistics alone can provide. Descriptive statistics characterize the distribution of a single variable

Table 4 Complete descriptive statistics of measured variables ($n = 105{,}120$)

Variable	Mean	Median	Std. dev.	Min	Q1	Q3	Max	5th perc.	95th perc.
Methane concentration (ppm)	107.5	106.9	9.8	89.4	100.8	114.2	126.1	90.0	125.0
Air temperature (°C)	24.6	24.4	2.3	19.8	22.9	26.1	28.7	21.2	27.9
Relative humidity (%)	73.4	72.8	6.7	58.3	69.1	78.2	86.5	62.0	84.1
Ventilation parameter (relative)	1.00	0.98	0.12	0.72	0.92	1.07	1.28	0.80	1.22

in isolation, summarizing central tendency and dispersion without accounting for the joint behavior of multiple uncertain inputs or their propagated effect on an output. The Monte Carlo procedure, by contrast, samples the distributions assigned to all input variables simultaneously and propagates them through Eq. (5), so that the methane output distribution reflects both the marginal variability of the individual inputs and the collective influence of their concurrent fluctuations. The scenario-based structure then allows systematic evaluation of how a controlled change in a single operational variable, the ventilation performance, alters the shape, spread, and central tendency of the methane distribution while all other inputs vary according to their fitted distributions. This controlled variation cannot be reproduced from the observed data alone, since the monitoring records reflect the inseparable combined influence of all variables at once. The theoretical basis follows the uncertainty propagation principles established in probabilistic risk and reliability analysis, adapted here for an interpretive rather than predictive purpose, namely to characterize the distributional response of a monitored quantity to operational variability rather than to forecast future states or estimate failure probabilities [15, 16].

It should be emphasized that the simulation framework does not address ignition mechanisms, combustion processes, or accident scenarios. Monte Carlo simulation is applied solely as a statistical tool to explore uncertainty propagation and sensitivity within routinely measured monitoring data, supporting interpretation of monitoring trends and ventilation management decisions within the realistic constraints of available field observations.

3.3 Definition of Concentration Variability and Sensitivity Indicators

In this study, concentration variability is defined as the statistical dispersion of the methane concentration outcomes obtained from Monte Carlo simulation, rather than as an indicator of hazard or threshold exceedance. Variability describes how methane concentration values fluctuate around their central tendency under routine operating conditions and under changes in ventilation performance, allowing methane behavior to be interpreted as a dynamic and uncertain process rather than a metric focused on regulatory compliance.

Methane concentration variability is quantified from the simulated output distribution using the standard deviation, the coefficient of variation, and selected percentile values. For an output distribution with mean μ_out and standard deviation σ_out, the coefficient of variation is (6).

$$\mathrm{CV} = \sigma_\mathrm{out}/\mu_\mathrm{out} \tag{6}$$

which provides a scale independent measure of dispersion, complemented by the 5th and 95th percentiles and the interquantile range to characterize the spread and asymmetry of the outcomes. These measures enable systematic comparison of methane concentration behavior across ventilation scenarios without implying safety limits, hazardous states, or decision thresholds.

Sensitivity is quantified through two complementary indicators. The first is the standardized regression coefficient of each input variable in the response model of Eq. (5),

$$\mathrm{SRC_j} = \beta_\mathrm{j} \cdot (\mathrm{s_j}/\mathrm{s_CH_4}) \tag{7}$$

where β_j is the regression coefficient of input j, and s_j and s_CH_4 are the standard deviations of input j and of methane concentration. The standardized coefficient expresses the change in methane concentration, in standard deviation units, produced by a one standard deviation change in input j while the other inputs are held constant, and therefore measures the relative influence of each input on methane concentration variability. The standardized coefficients are reported in Table 3 and identify the ventilation parameter as the dominant influence (SRC = −0.621), followed by relative humidity (0.337) and air temperature (0.212), a ranking consistent with the monotonic associations in Table 5.

The second indicator describes the response of the output distribution to controlled changes in ventilation performance. For a variability metric M evaluated under a

Table 5 Spearman correlation coefficients and sensitivity indicators

Variable pair	Spearman ρ	*p*-value	Direction	Sensitivity rank
Methane concentration vs. Ventilation parameter	−0.62	<0.001	Negative	1
Methane concentration vs. Relative humidity	0.34	<0.001	Positive	2
Methane concentration vs. Air temperature	0.21	<0.001	Positive	3
Relative humidity vs. Air temperature	0.18	<0.001	Positive	4
Ventilation parameter vs. Relative humidity	−0.15	<0.001	Negative	5
Ventilation parameter vs. Air temperature	−0.09	<0.001	Negative	6

Spearman correlation coefficients were calculated using the full dataset of 105,120 measurements. All reported correlations are statistically significant at the $p<0.001$ level, consistent with the large sample size. Sensitivity rank reflects the relative influence of each variable on methane concentration variability under routine operating conditions, determined by the absolute magnitude of the Spearman correlation coefficient

ventilation scenario s, the sensitivity is expressed as the relative change from the baseline condition (8),

$$\Delta_s = (M_s - M_0)/M_0 \tag{8}$$

where M_0 is the baseline value of the metric and M_s its value under scenario s. This indicator is applied to the mean, standard deviation, and percentile measures of the methane output distribution and is reported for the reduced, baseline, and improved ventilation scenarios in Section 4.2. Expressing sensitivity as a relative change isolates the direction and magnitude of the response while remaining independent of the absolute concentration level.

By defining variability and sensitivity through explicit quantitative indicators, the methodology establishes a consistent and reproducible framework for interpreting the Monte Carlo results within the context of ventilation management. The indicators support interpretation of routine monitoring data and provide operational insight under uncertainty, while remaining aligned with the scale, resolution, and limitations of the measured methane concentration data.

3.4 Implementation Parameters and Distribution Definitions

The Monte Carlo simulations were implemented to propagate measurement driven uncertainty through the response model defined in Eq. (5) and to characterize the resulting methane concentration variability under routine operating conditions. A total of 10,000 iterations were performed. At each iteration, values of the relative ventilation parameter, air temperature, and relative humidity were drawn from their fitted distributions, and a residual term was drawn from a normal distribution with zero mean and standard deviation $\sigma_\varepsilon = 6.64$ ppm. These sampled values were substituted into Eq. (5) to generate one methane concentration realization. Methane concentration was therefore obtained as the modeled response of the framework rather than sampled directly, which ensures that the simulated methane behavior is governed by the operational and environmental inputs and their estimated relationship.

The distribution families and parameter values used for the sampled inputs are summarized in Table 1. The relative ventilation parameter was represented by a lognormal distribution to ensure strictly positive samples and to reflect its asymmetric operational variability, while air temperature and relative humidity were represented by normal distributions consistent with their bounded variability during routine operation.

The three inputs were sampled independently, and this assumption is justified on three grounds. First, because the response model of Eq. (5) is linear, correlations among the inputs have no effect on the expected value of the output or on the scenario mean responses, which depend only on the input means and the regression coefficients; the central-tendency results of the sensitivity analysis are therefore exactly invariant to the independence assumption. Second, the influence of input correlations is confined to the output variance through the cross-covariance terms $2 \cdot \beta_i \cdot \beta_j \cdot \mathrm{Cov}(X_i, X_j)$, and this influence can be bounded empirically: the sum of the independent variance contributions and the residual variance (96.5 ppm², Section 3.2) reproduces the observed methane variance ($9.8^2 = 96.0$ ppm²) to within less than 1%, demonstrating that the net covariance contribution of the weakly associated inputs is negligible in the monitoring data. Third, the pairwise rank associations among the inputs are weak ($|\rho| \leq 0.18$, Table 5), consistent with this empirical bound. Independent sampling therefore introduces no material distortion of the output distribution, and the correspondence between the simulated and observed methane marginals is verified directly against the monitoring data in Section 3.5.

The relative ventilation parameter was treated as the primary operational lever in the sensitivity evaluation. Ventilation scenarios were generated by applying the multiplicative factors defined in Section 3.2 to the sampled ventilation parameter, representing reduced, nominal, and improved air exchange conditions within the observed operational envelope. This relative formulation avoids reliance on panel specific design airflows and allows the analysis to focus on comparative changes in methane behavior attributable to ventilation performance.

The number of iterations was selected on the basis of the convergence of the output statistics. For an output distribution with standard deviation σ_out, the Monte Carlo standard error of the estimated mean is (9).

$$SE_\mu = \sigma_out/\sqrt{N} \tag{9}$$

where N is the number of iterations. With $\sigma_out \approx 9.8$ ppm and $N = 10{,}000$, the standard error of the mean is approximately 0.10 ppm, so that the output mean is estimated to within about 0.1 ppm and the corresponding 95% confidence interval spans approximately ± 0.19 ppm. This level of precision confirms that 10,000 iterations provide stable estimates of central tendency and dispersion while preserving computational efficiency. The simulation outputs were summarized using mean values, percentile ranges, and confidence intervals, which are reported in the Results section.

All regression coefficients and distribution parameters were estimated by maximum likelihood from the full monitoring dataset, and all simulations were performed within the same temporal resolution context as the measurements.

This implementation structure provides a transparent link between the measured monitoring data, the probabilistic input definitions, the fitted response model, and the Monte Carlo outputs, thereby supporting reproducibility and avoiding black box modeling assumptions.

3.5 Model Verification and Internal Consistency Assessment

The adequacy of the framework was assessed through a model verification and internal consistency analysis, in which the methane concentration distribution generated by the response-model-based Monte Carlo simulation was compared with the empirical distribution obtained from the monitoring data. A terminological distinction is maintained deliberately: because the response model and the input distributions are estimated from the same monitoring dataset used in the comparison, the analysis verifies that the fitted framework reproduces the statistical characteristics of the data from which it was constructed, rather than validating its predictive performance against independent observations. This internal consistency requirement is the appropriate adequacy criterion for the interpretive purpose of the framework, namely uncertainty propagation and sensitivity analysis within the observed operational envelope, as opposed to forecasting future system states. The simulated output was produced using the response model of Eq. (5), the fitted input distributions, and the implementation parameters defined in Section 3.4, and the comparison focused on the consistency of central tendency, dispersion, and overall distributional shape rather than pointwise agreement.

The verification results indicate close agreement between the simulated and measured methane concentration. Under the baseline condition, the simulated output reproduced the observed mean of 107.5 ppm and standard deviation of 9.8 ppm, yielding a simulated mean of 107.75 ppm and a standard deviation of 9.82 ppm. The histogram comparison in Fig. 4a confirms this agreement, with the simulated and empirical distributions overlapping closely across the observed concentration range. The agreement is most pronounced within the central range, while minor discrepancies appear at the distribution tails, which is expected for a large monitoring dataset subject to natural variability.

To supplement the histogram comparison, quantile-quantile analysis was used to assess the agreement between empirical and theoretical quantiles across the full range of the distribution. The quantile-quantile plot of the measured methane concentration against the theoretical normal quantiles is presented in Fig. 4b, where the points align closely along the reference line throughout the central range, with only minor departures at the lower and upper extremes consistent with occasional short-term operational disturbances.

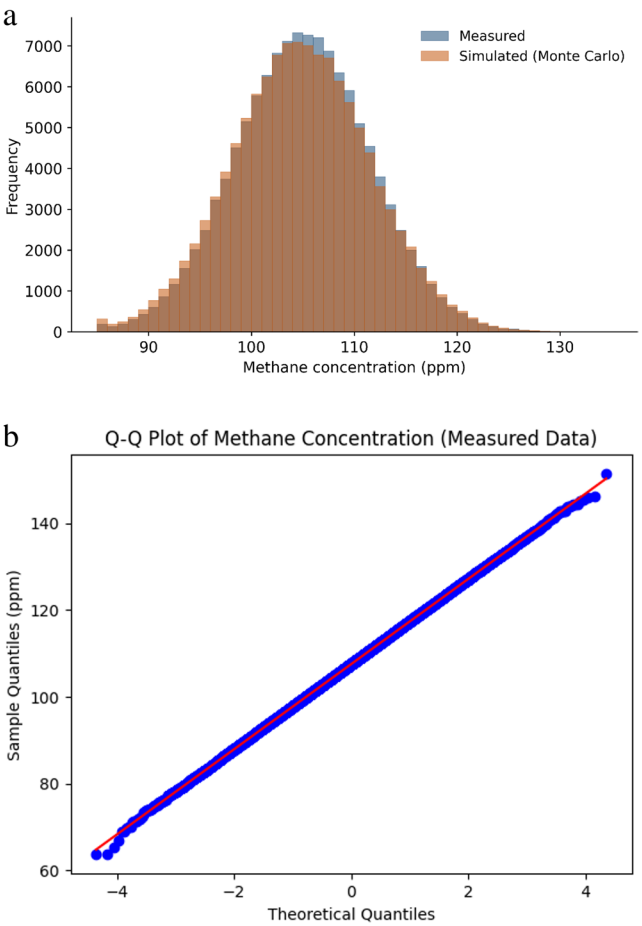


Fig. 4 **a** Comparison of measured and model-based Monte Carlo simulated methane concentration distributions. **b** Q-Q plot of measured methane concentration data against theoretical normal distribution quantiles

This visual agreement is reinforced by the goodness-of-fit comparison in Table 2, in which the normal distribution was not rejected ($D = 0.0013$, $p = 0.996$), confirming the adequacy of the normal marginal for methane concentration. For the ventilation parameter, the quantile-quantile plot of the lognormal fit similarly indicated good agreement across the central range, with minor tail deviations consistent with the asymmetric operational variability described in Section 3.1.

For the verification, the root mean square error between the empirical and simulated methane concentration quantiles was computed across equally spaced probability levels,

$$\mathrm{RMSE} = \sqrt{\left((1/\mathrm{m}) \cdot \sum (\mathrm{q_emp, i} - \mathrm{q_sim, i})^2\right)} \qquad (10)$$

where q_emp, i and q_sim, i are the empirical and simulated quantiles at m equally spaced probability levels. The resulting value of 1.3 ppm corresponds to approximately 1.2% of the observed mean concentration of 107.5 ppm, with the

central portion of the distribution showing closer agreement than the tails. This level of agreement confirms that the response-model-based Monte Carlo simulation reproduces the statistical characteristics of the measured data with sufficient accuracy for uncertainty propagation and sensitivity analysis under routine operating conditions.

These results confirm that the response model, the selected input distributions, and the implementation parameters together provide an adequate representation of routine methane concentration variability, and they support the use of the framework for the sensitivity and scenario analyses presented in the following section.

Predictive validation against temporally independent monitoring data, for example through estimation of the framework on one portion of the monitoring period and evaluation on another, represents a natural extension of the present approach but lies beyond the interpretive scope of this study.

The histogram comparison demonstrates close agreement in central tendency and dispersion, with minor deviations at the tails attributable to natural variability

4 Results and Discussion

4.1 Variability of Methane Concentration Under Environmental Conditions

Methane concentration recorded under routine underground operating conditions exhibits measurable variability in response to changes in environmental parameters, while remaining within a stable concentration range under normal ventilation operation. Variations in air temperature and relative humidity produce gradual and measurable changes in the methane concentration level rather than abrupt shifts or threshold type responses. This behavior reflects a progressive modulation of concentration driven by environmental conditions rather than sudden accumulation or depletion.

Table 4 summarizes the complete descriptive statistics derived from the full dataset of 105,120 measurements. Methane concentration is characterized by a mean of 107.5 ppm, with the majority of observations confined within a relatively narrow interval. The 5th and 95th percentiles define a range extending from 90 to 125 ppm, confirming that routine methane levels remain well below critical thresholds while exhibiting measurable dispersion. Air temperature and relative humidity display moderate variability over the monitoring period, whereas the ventilation parameter shows limited but systematic variation around its baseline value. These statistical characteristics establish the quantitative basis for the probabilistic analyses presented in the subsequent sections.

The probability distribution of methane concentration obtained from the monitoring dataset and the corresponding Monte Carlo simulation are illustrated in Fig. 5. The distribution shows a stable central tendency around the measured mean, accompanied by moderate dispersion attributable to routine variability. The 5th to 95th percentile interval indicated in the figure confirms that the dominant portion of the observed variability remains confined within the 90 to 125 ppm range, supporting the interpretation that the recorded concentrations represent routine operational fluctuations rather than anomalous events.

The relationship between methane concentration and the environmental parameters is illustrated in Fig. 6, which presents the variation of methane concentration with air temperature and relative humidity. Both parameters show a positive association with methane concentration, quantified

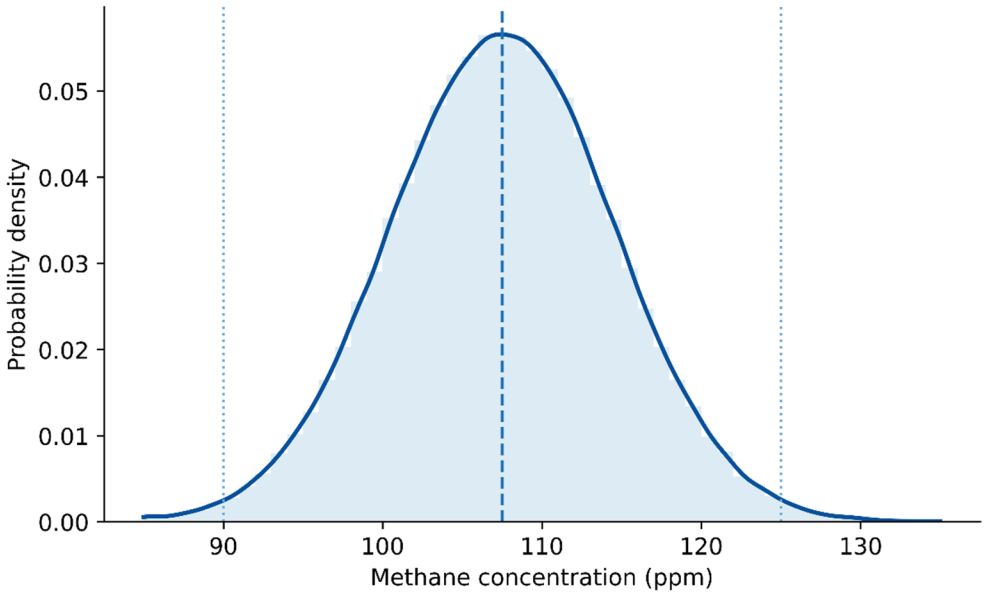


Fig. 5 Probability distribution of methane concentration from the monitoring data and the Monte Carlo simulation, showing the mean (dashed line) and the 5th and 95th percentiles (dotted lines)

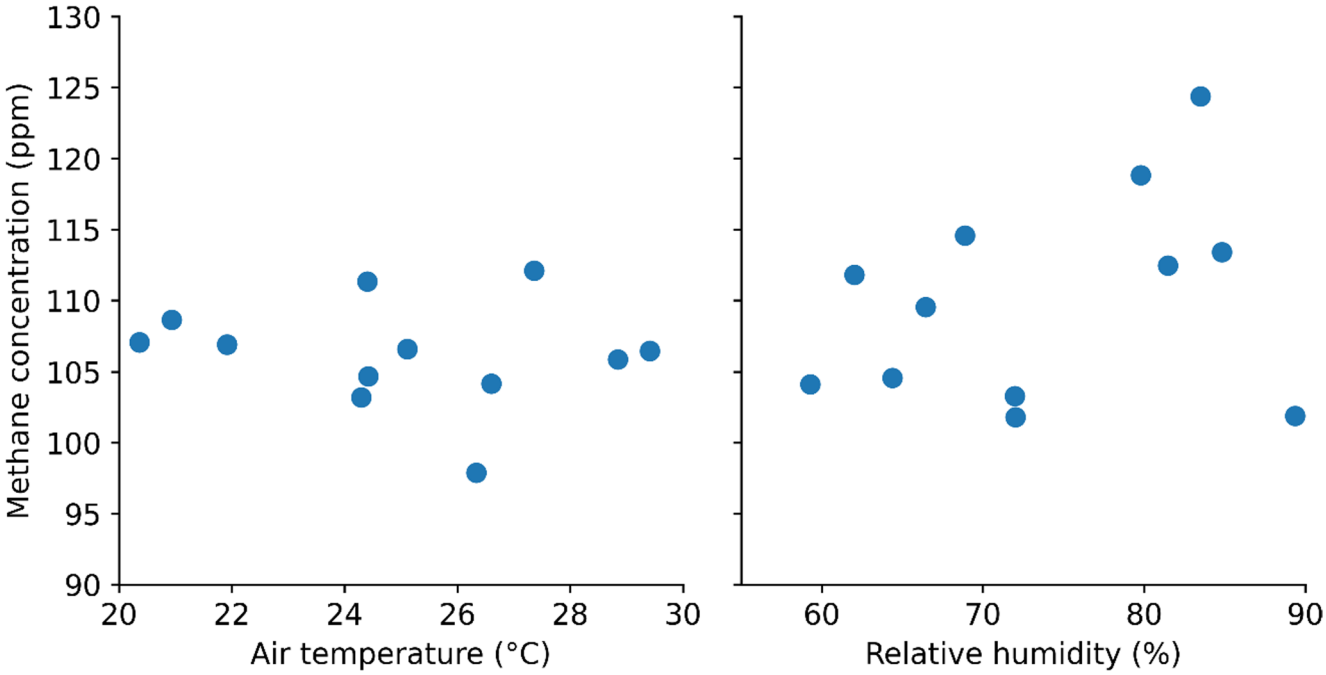


Fig. 6 Relationship between methane concentration and air temperature (left) and relative humidity (right)

through the response model (Eq. 5, Table 3). An increase in air temperature of approximately 3 °C, from 25 to 28 °C, raises the mean methane concentration by about 2.7 ppm (0.906 ppm per °C), while an increase in relative humidity of approximately 20% points, from 65 to 85%, raises it by about 9.9 ppm (0.495 ppm per percent). These effects are gradual and secondary to ventilation, with standardized coefficients of 0.212 for air temperature and 0.337 for relative humidity, indicating progressive changes in the methane concentration level rather than abrupt transitions.

The results demonstrate that air temperature and relative humidity contribute to methane concentration behavior under routine mining conditions as secondary drivers of the concentration level, modulating it gradually rather than abruptly. This finding emphasizes the importance of continuous environmental monitoring when interpreting methane concentration trends in underground coal mines, particularly for assessing behavior under stable operational and ventilation conditions.

These findings carry several analytically significant implications that extend beyond a descriptive characterization of methane behavior at the study site. First, the observation that environmental parameters exert measurable and quantifiable effects on the central tendency of methane concentration, secondary to ventilation, demonstrates that routine monitoring data contain distributional information that is not accessible through single-value or threshold-based interpretations. This supports the argument that probabilistic analysis of monitoring records provides a richer characterization of system behavior than conventional compliance-oriented approaches, even when absolute concentration levels remain within safe operating ranges. Second, the consistency between the Monte Carlo simulation outputs and the empirical monitoring data across varying environmental conditions confirms that the framework reproduces the operational reality of methane behavior at the study site, lending credibility to the ventilation sensitivity results presented in the following section. Third, the gradual and proportional nature of the observed responses to changes in temperature and humidity indicates that the monitoring system resolves environmentally driven variability at the temporal resolution used in this study, supporting its suitability for continuous uncertainty-aware interpretation rather than periodic or event-driven assessment.

4.2 Sensitivity of Methane Concentration to Ventilation Scenarios

Monte Carlo simulation results indicate that methane concentration exhibits a systematic and continuous sensitivity to variations in ventilation performance under routine operating conditions. This sensitivity is expressed through gradual shifts in the concentration level and accompanying changes in distributional characteristics, rather than through abrupt transitions or threshold type responses. The observed behavior reflects a proportional adjustment of methane concentration to operational changes in air exchange within the observed operational envelope, rather than evidence of direct causal escalation mechanisms.

The monotonic relationships between methane concentration and the operational and environmental parameters were quantified using Spearman correlation analysis, summarized in Table 5. The ventilation parameter exhibits the strongest association with methane concentration, a pronounced inverse relationship ($\rho = -0.62$), followed by relative humidity (0.34) and air temperature (0.21). Sensitivity ranks in Table 5 were assigned by the absolute magnitude of the Spearman coefficients, with rank 1 corresponding to the strongest association. This ranking is corroborated by the standardized regression coefficients of the response model (Table 3), which identify ventilation as the dominant influence (−0.621), followed by relative humidity (0.337) and air temperature (0.212). The agreement between the rank based and model-based measures provide consistent evidence that ventilation performance is the dominant operational influence on methane concentration, while air temperature and relative humidity make secondary contributions.

The effect of ventilation performance was quantified directly through the scenario analysis, with the resulting methane concentration output distributions summarized in Table 6. Relative to the baseline condition (mean 107.75 ppm), the reduced ventilation scenario raised the mean methane concentration to 117.80 ppm, an increase of 9.3%, while the improved ventilation scenario lowered it to 97.43 ppm, a decrease of 9.6%. The dominant effect of ventilation is therefore on the central tendency of the methane concentration distribution. The dispersion of the distribution changed more modestly and in the opposite direction to the mean: the standard deviation decreased from 9.82 ppm at baseline to 9.13 ppm under reduced ventilation and increased to 10.44 ppm under improved ventilation, while the coefficient of variation decreased to 0.078 under reduced ventilation and increased to 0.107 under improved ventilation. Expressed as relative changes from baseline (Eq. 8), the mean responded by +9.3 and −9.6% and the coefficient of variation by −14.9 and +17.7% across the reduced and improved scenarios respectively. The shift in the methane concentration distribution across the three scenarios is illustrated in Fig. 7.

The scenario responses summarized in Table 6 follow directly from the structure of the linear response model and admit closed-form verification. Because each scenario rescales the sampled ventilation parameter by a factor c, the scenario mean shifts by $\Delta E[CH_4] = -50.72 \cdot (c-1) \cdot E[V] \approx \mp 10.1$ ppm for $c = 0.80$ and 1.20, reproducing the simulated means of 117.80 and 97.43 ppm to within Monte Carlo sampling variability. The same rescaling multiplies the standard deviation of the ventilation input by c, so that its contribution to the output variance scales by c^2: the scenario variance is $Var_s[CH_4] = c^2 \cdot (50.72 \cdot \sigma_V)^2 + (0.906 \cdot \sigma_T)^2 + (0.495 \cdot \sigma_RH)^2 + \sigma_\varepsilon^2$, which evaluates to standard deviations of 9.12 and 10.62 ppm for the reduced and improved scenarios, in close agreement with the simulated values of 9.13 and 10.44 ppm. The modest dispersion changes reported in Table 6 are therefore a direct mathematical consequence of the multiplicative scenario definition, in which a proportional change in ventilation performance rescales the variability of the ventilation input together with its level, rather than an independent empirical finding about methane release physics. The changes in the coefficient of variation combine this dispersion effect with the opposite shift of the mean, which explains why relative variability decreases under reduced ventilation and increases under improved ventilation. The physically substantive outcome of the scenario analysis is accordingly the response of the central tendency, governed by the empirically estimated ventilation coefficient of Eq. (5), while the dispersion response characterizes the propagation behavior of the scenario formulation itself.

These results identify ventilation performance as the dominant operational control on methane concentration, acting primarily on the concentration level rather than on the dispersion of the distribution. Reduced ventilation shifts the entire distribution upward and improved ventilation shifts it downward; the accompanying slight narrowing and widening follow analytically from the c^2-scaling of the ventilation variance contribution inherent in the multiplicative scenario definition. The responses are gradual and proportional to the change in ventilation performance, with no abrupt transitions or threshold type behavior within the observed operational envelope. This monotonic and proportional adjustment is consistent across the Spearman correlation analysis, the standardized coefficients of the response model, and the scenario simulations, which together establish ventilation as the principal lever governing methane concentration behavior under routine conditions.

The results confirm that methane concentration in the Soma coal mine responds predictably and proportionally to operational changes in ventilation performance within the observed operational envelope. The absence of abrupt concentration shifts supports the interpretation that routine methane behavior is governed by gradual variability rather than escalation processes, reinforcing the role of ventilation as the key operational parameter for managing methane concentration under uncertainty.

Table 6 Methane concentration output distribution under the reduced, baseline, and improved ventilation scenarios (10,000 iterations per scenario)

Scenario	Mean (ppm)	Std (ppm)	P5 (ppm)	P95 (ppm)	CV
Reduced (×0.80)	117.80	9.13	102.53	132.63	0.0775
Baseline (×1.00)	107.75	9.82	91.24	123.65	0.0911
Improved (×1.20)	97.43	10.44	79.91	114.17	0.1072

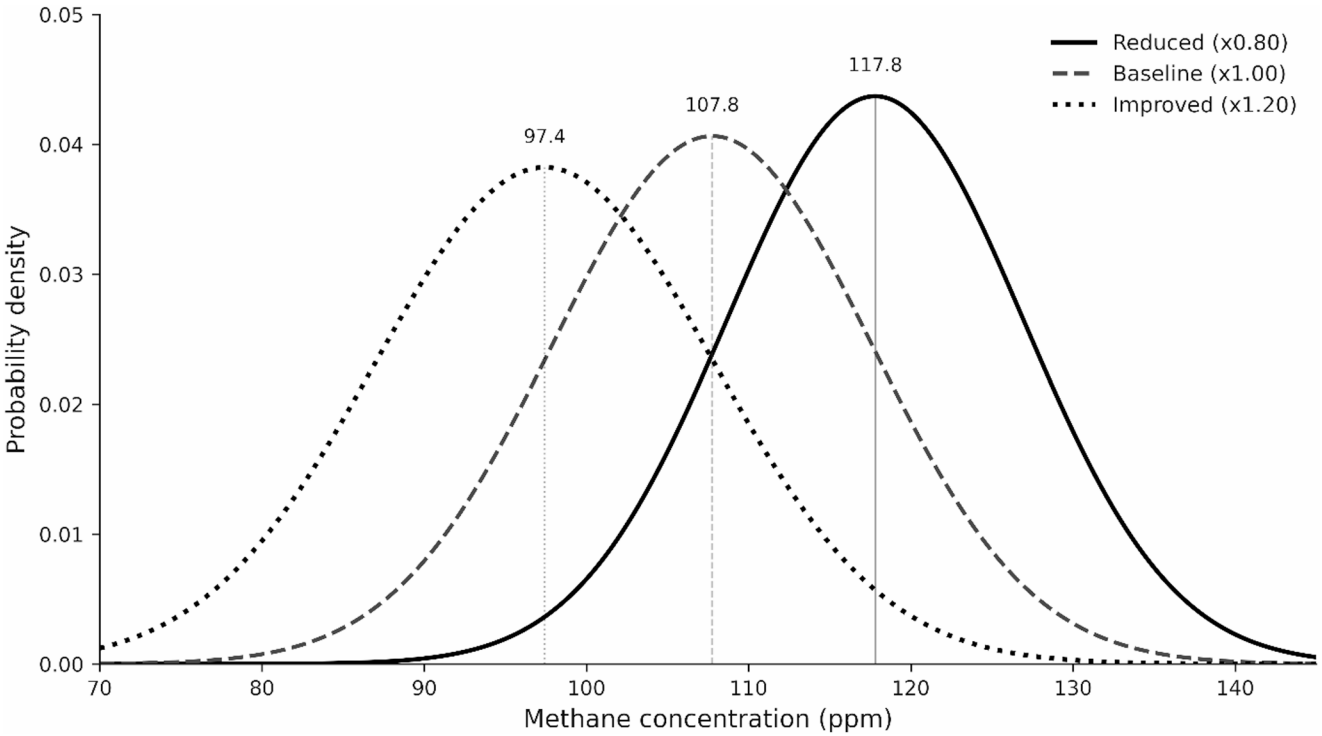


Fig. 7 Methane concentration output distributions under the reduced, baseline, and improved ventilation scenarios, shown as normal approximations based on the simulated means and standard deviations reported in Table 6. Reduced ventilation shifts the distribution toward higher concentrations and improved ventilation toward lower concentrations, while the dispersion changes only modestly

4.3 Implications for Ventilation Management and Monitoring

The findings of this study provide practical implications for ventilation management and methane monitoring in underground coal mining environments where methane concentrations remain at low levels while exhibiting measurable variability. The results demonstrate that ventilation performance is the dominant operational control on the methane concentration level during routine operations, with environmental conditions making secondary contributions, and that these influences act gradually rather than producing abrupt changes or exceedance type behavior.

The sensitivity of methane concentration to ventilation scenarios highlights the role of ventilation systems both in diluting gas and in setting the overall concentration level over time. Improved ventilation performance lowers the mean methane concentration, by approximately 9.6% in the improved scenario, while reduced ventilation performance raises it, by approximately 9.3%, with comparatively modest accompanying changes in dispersion. From an operational standpoint, controlling the mean concentration level through ventilation performance is therefore the primary lever, while the relative variability of the distribution represents a secondary consideration that can complicate interpretation of monitoring data even when absolute concentration levels remain within low ppm ranges.

The relative ventilation parameter employed in this study represents the combined effect of multiple operational factors influencing air distribution within the mine rather than a single fixed design quantity. Variations in fan performance, air leakage along roadways and stoppings, and temporary increases in airway resistance caused by operational activities are all reflected within this relative parameter. By aggregating these influences, the parameter captures the effective ventilation condition experienced by the working areas under routine operation, allowing comparative evaluation of ventilation performance without dependence on absolute airflow values or assumptions tied to a particular mining site.

These results emphasize the importance of continuous methane monitoring as an interpretive tool rather than a binary warning mechanism. Progressive changes in the level and distribution of methane concentration provide early indications of evolving ventilation performance or environmental influences, enabling potential deviations to be identified before critical conditions arise. Interpreting monitoring data through its distributional characteristics supports more proactive and informed ventilation management practices under routine operating conditions.

From a decision support perspective, the Monte Carlo framework applied in this study offers a transparent and flexible approach for integrating routine monitoring data into ventilation assessment. The methodology enables evaluation of how relative changes in ventilation performance influence methane concentration behavior without reliance on predefined safety limits or categorical hazard classifications. This capability supports operational planning, ventilation system optimization, and management strategies implemented over extended periods in underground coal mining.

The sensitivity analysis also carries practical implications for the selection of input variables in future probabilistic assessments of routine methane monitoring data. The standardized regression coefficients of the response model (Table 3) and the Spearman correlation analysis (Table 5) both identify ventilation performance as the dominant influence on methane concentration, with relative humidity a moderate secondary contributor (standardized coefficient 0.337, $\rho = 0.34$) and air temperature a weaker one (0.212, $\rho = 0.21$). From a monitoring system design perspective, ventilation performance is the primary parameter warranting continuous probabilistic assessment. Relative humidity contributes meaningfully to the explained variability and is therefore worth retaining, whereas air temperature plays a more limited role and could be deprioritized where monitoring resources are constrained. The inclusion of all three variables in the present study was justified by their routine availability in the monitoring dataset and their potential relevance under more variable environmental conditions than those observed during the 2023 monitoring period at the Soma coal mine.

The observed behavior of methane concentration is consistent with the geological and mining characteristics of the Soma coal basin. The low rank lignite seams exploited in the study area are characterized by high inherent moisture content, which promotes continuous but low intensity gas release rather than abrupt methane accumulation. In addition, the relatively thick coal seams mined using longwall top coal caving result in sustained exposure of freshly broken coal surfaces, enhancing short term fluctuations in methane release without producing persistent concentration build up.

High moisture conditions in low rank lignite reduce gas adsorption capacity and favor rapid desorption in response to minor environmental and operational changes. As a result, methane behavior is governed by gradual variability rather than threshold driven escalation, and the absence of sharp concentration transitions in the monitoring data is consistent with both the geological setting and the mining method employed. From a ventilation management perspective, these findings indicate that control strategies should prioritize stable airflow and continuous monitoring rather than reliance on threshold driven interventions, reinforcing the suitability of probabilistic approaches for assessing methane behavior in similar longwall operations.

4.4 Time Series Characteristics of Methane Concentration

Time series analysis of the methane concentration measurements indicates stable and continuous behavior throughout the monitoring period under routine underground operating conditions. The recorded values fluctuate around a consistent mean level without exhibiting persistent upward or downward trends, which suggests that methane concentration remains temporally stable when ventilation performance and operational conditions are maintained within their normal ranges.

Evaluation of the temporal continuity shows no evidence of abrupt discontinuities, step changes, or sustained accumulation events. Short term fluctuations are present and reflect routine operational variability rather than structural changes in the ventilation system or gas release mechanisms. These fluctuations remain bounded within the concentration range defined by the descriptive statistics and probabilistic analysis presented in the previous sections.

Inspection of the time series does not reveal a pronounced seasonal pattern in methane concentration. Although minor variations occur over the monitoring period, these changes do not follow a repeating or cyclical structure that could be attributed to seasonal effects. The absence of clear seasonality indicates that methane concentration variability is governed primarily by short term operational and environmental factors rather than long term temporal trends.

To characterize the temporal structure of the series, the autocorrelation function was examined. For a series X_t, the autocorrelation at lag k is defined as (11).

$$\rho_k = \mathrm{Cov}\left(X_t,\ X_\{t+k\}\right) / \mathrm{Var}\left(X_t\right) \tag{11}$$

The autocorrelation function of the methane concentration series indicates short term serial dependence, with statistically significant autocorrelation observed at lags up to approximately 12 measurement steps, corresponding to a temporal window of about one hour given the five-minute recording resolution. This short-term dependence is consistent with the gradual and continuous nature of methane release and ventilation transport processes, where concentration changes propagate over time rather than occurring instantaneously. Beyond this range, the autocorrelation function decays toward zero without periodically recurring peaks, confirming the absence of systematic diurnal or weekly cyclical patterns and reinforcing the earlier

observation that no pronounced seasonal structure is present. The absence of long-range temporal dependence or structural breaks further supports the interpretation that methane concentration variability during the 2023 monitoring period was governed primarily by short term operational and environmental fluctuations rather than by persistent trends or cyclic production schedules. These characteristics are consistent with weak (covariance) stationarity over the monitoring period, which supports the treatment of methane concentration as a stationary stochastic process within the Monte Carlo framework, since the assumption of distributional stability is consistent with the observed time series behavior.

5 Conclusion

This study developed and verified a probabilistic modeling framework for the interpretation of routine methane concentration monitoring data in an underground coal mine operating under normal ventilation conditions. The framework integrates maximum likelihood distribution fitting, a multiple linear regression response model, and Monte Carlo simulation into a structured three-stage procedure that propagates input uncertainty through an empirically estimated response relationship and evaluates the distributional sensitivity of methane concentration to controlled changes in ventilation performance, with the internal consistency of the framework established against the full annual monitoring dataset.

Distribution fitting by maximum likelihood, with selection among normal, lognormal, and gamma candidates evaluated through Akaike and Bayesian information criteria and the Kolmogorov-Smirnov statistic, established that methane concentration is adequately represented by a normal distribution with mean 107.5 ppm and standard deviation 9.8 ppm, while the relative ventilation parameter is represented by a lognormal distribution consistent with its strictly positive and asymmetrically variable nature. The multiple linear regression response model estimated from 105,120 monitoring records explains approximately 54% of the variance in methane concentration and identifies ventilation performance as the dominant predictor, with a standardized coefficient of -0.621, followed by relative humidity at 0.337 and air temperature at 0.212. This model provides the explicit analytical mechanism through which changes in operational and environmental conditions propagate to methane concentration within the Monte Carlo framework, distinguishing the present approach from descriptive statistical summaries of monitoring records.

Monte Carlo simulation with 10,000 iterations, whose precision was confirmed by a standard error of the mean of approximately 0.10 ppm, produced output distributions under reduced, baseline, and improved ventilation scenarios. Relative to the baseline mean of 107.75 ppm, the reduced ventilation scenario raised the mean concentration by 9.3% to 117.80 ppm, while the improved scenario lowered it by 9.6% to 97.43 ppm. Changes in dispersion were comparatively modest and directionally opposite to the mean response, with the coefficient of variation decreasing from 0.091 at baseline to 0.078 under reduced ventilation and increasing to 0.107 under improved ventilation. These results establish that ventilation performance governs the central tendency of the methane concentration distribution as the primary operational lever, while the accompanying dispersion response follows analytically from the multiplicative scenario formulation, in which the variance contribution of the ventilation input scales with the square of the scenario factor. The scenario-based relative change index introduced in this study provides a scale-independent quantitative basis for comparing distributional responses across ventilation conditions, which cannot be recovered from descriptive analysis of the observed monitoring records alone.

Model verification through quantile comparison between the simulated baseline output and the empirical monitoring data yielded a root mean square error of 1.3 ppm, corresponding to 1.2% of the observed mean concentration, confirming the internal consistency of the response model and the fitted input distributions with the statistical characteristics of the field measurements, at a level of accuracy sufficient for uncertainty propagation and sensitivity analysis.

The findings of this study are specific to the geological and operational characteristics of the Soma coal basin, where low-rank lignite seams with high inherent moisture content promote continuous but low-intensity gas release under stable ventilation conditions. Caution is therefore required when extending these results to higher-rank coal seams or gassy hard coal mines, where methane emission mechanisms and ventilation responses may differ substantially. Nevertheless, the probabilistic framework presented here is methodologically transferable to other underground coal mining environments where routine atmospheric monitoring data are available, provided that site-specific distributional characterizations are applied and the response model is re-estimated from local field observations.

The methodological contribution of this study lies in demonstrating that Monte Carlo simulation, when applied to routine monitoring data through an empirically fitted response model rather than assumed inputs or hazard scenarios, yields interpretive capabilities that extend beyond those of descriptive statistical analysis. By propagating uncertainty across multiple input variables simultaneously and evaluating distributional responses to controlled operational

changes, the framework reveals sensitivity patterns that are not recoverable from the observed data alone and provides a transparent and reproducible basis for uncertainty-aware ventilation management in underground coal mining.

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Declarations

Conflict of interest The authors declare that, they have no conflict of interest.

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References

1. Flores RM (1998) Coalbed methane: from hazard to resource. Int J Coal Geol 35(14):326. https://doi.org/10.1016/S01665162(97)000438
2. Karacan CÖ, Ruiz FA, Cotè M, Phipps S (2011) Coal mine methane: a review of capture and utilization practices with benefits to mining safety and to greenhouse gas reduction. Int J Coal Geol 86(23):121156. https://doi.org/10.1016/j.coal.2011.02.009
3. Karakurt I, Aydin G, Aydiner K (2011) Mine ventilation air methane as a sustainable energy source. Renew Sustain Energy Rev 15(2):1042–1049. https://doi.org/10.1016/j.rser.2010.11.030
4. Eyüboglu AK, Özfırat MK, Yetkin ME (2025) Methane Risk Analysis for Sustainable Occupational Safety in Underground Coal Mines. Rudarskogeološkonaftni zbornik 40(2):173184. https://doi.org/10.17794/rgn.2025.2.12
5. Cheng YP, Wang L, Zhang XL (2011) Environmental impact of coal mine methane emissions and responding strategies in China. Int J Greenh Gas Control 5(1):157–166. https://doi.org/10.1016/j.ijggc.2010.07.007
6. Karacan CÖ (2008) Modeling and prediction of ventilation methane emissions of US longwall mines using supervised artificial neural networks. Int J Coal Geol 73(34):371–387. https://doi.org/10.1016/j.coal.2007.09.003
7. Diaz J, Agioutantis Z, Hristopulos DT, Schafrik S, Luxbacher K (2022) Time series modeling of methane gas in underground mines. Min Metall Explor 39(5):19611982. https://doi.org/10.1007/s42461022006545
8. Swolkień J, Fix A, Gałkowski M (2022) Factors influencing the temporal variability of atmospheric methane emissions from Upper Silesia coal mines: a case study from the CoMet mission. Atmos Chem Phys 22(24):1603116052. https://doi.org/10.5194/acp22160312022
9. Flores RM (2013) Coal and coalbed gas: fueling the future. Newnes
10. Esen O, Özer SC, Soylu A, Rend AR, Fişne A (2020) Geological controls on gas content distribution of coal seams in the Kınık coalfield, Soma Basin, Turkey. Int J Coal Geol 231:103602. https://doi.org/10.1016/j.coal.2020.103602
11. Diaz J, Agioutantis Z, Hristopulos DT, Luxbacher K, Schafrik S (2023) Forecasting of methane gas in underground coal mines: univariate versus multivariate time series modeling. Stoch Env Res Risk Assess 37(6):20992115. https://doi.org/10.1007/s00477023023828
12. Niewiadomski AP, Koch N (2025) Analysis of the Influence of Atmospheric Pressure Variations on Methane Emission. Appl Sci 16(1):154. https://doi.org/10.3390/app16010154
13. Qu Q, Xu J, Wu R, Qin W, Hu G (2015) Threezone characterisation of coupled strata and gas behavior in multiseam mining. Int J Rock Mech Min Sci 78:9198. https://doi.org/10.1016/j.ijrmms.2015.04.018
14. Tutak M, Krenicky T, Pirník R, Brodny J, Grebski WW (2024) Predicting methane concentrations in underground coal mining using a multilayer perceptron neural network based on mine gas monitoring data. Sustainability 16(19):8388. https://doi.org/10.3390/su16198388
15. Shi L, Wang J, Zhang G, Cheng X, Zhao X (2017) A risk assessment method to quantitatively investigate the methane explosion in underground coal mine. Process Saf Environ Prot 107:317–333. https://doi.org/10.1016/j.psep.2017.02.023
16. Humez P, Osselin F, Wilson LJ, Nightingale M, Kloppmann W, Mayer B (2019) A probabilistic approach for predicting methane occurrence in groundwater. Environ Sci Technol 53(21):12914–12922. https://doi.org/10.1021/acs.est.9b03981
17. Esen O, Fişne A (2024) A comprehensive study on methane adsorption capacities and pore characteristics of coal seams: Implications for efficient coalbed methane development in the Soma Basin, Türkiye. Rock Mech Rock Eng 57(8):63556375. https://doi.org/10.1007/s00603024038541
18. Hokerek S, Ozcelik O (2015) Organic facies characteristics of the miocene soma formation (lower lignite successionKM2), Soma Coal Basin, Western Turkey. Energy Procedia 76:2732. https://doi.org/10.1016/j.egypro.2015.07.836
19. Karayigit AI, Oskay RG, Bulut Y, Mastalerz M (2020) Mesoand microporosity characteristics of Miocene lignite and subbituminous coals in the Kınık coalfield (Soma Basin, W. Turkey). Int J Coal Geol 232:103624. https://doi.org/10.1016/j.coal.2020.103624
20. Ünver B, Hindistan MA, Tercan AE, Ertunç G, Ünal MS, Kıllıoğlu SY, Atalay F (2017) A new production method proposal for Soma eynez coal field. Sci Min J 56(1):512
21. Simsir F, Ozfirat MK (2008) Determination of the most effective longwall equipment combination in longwall top coal caving (LTCC) method by simulation modelling. Int J Rock Mech Min Sci 45(6):1015–1023. https://doi.org/10.1016/j.ijrmms.2007.11.005
22. Alehossein H, Poulsen BA (2010) Stress analysis of longwall top coal caving. Int J Rock Mech Min Sci 47(1):3041. https://doi.org/10.1016/j.ijrmms.2009.07.004
23. Wang J, Yang S, Wei W, Zhang J, Song Z (2021) Drawing mechanisms for top coal in longwall top coal caving (LTCC): A review of two decades of literature. Int J Coal Sci Technol 8(6):11711196. https://doi.org/10.1007/s40789021004531
24. Cohen AF, Fisher TJ, Watson RA, Kohler JL (1987) Location strategy for methane, air velocity, and carbon monoxide fixed-point mine-monitoring transducers. IEEE Trans Ind Appl IA-23(2):375–381. https://doi.org/10.1109/TIA.1987.4504916

25. Kozielski M, Sikora M, Wróbel Ł (2021) Data on methane concentration collected by underground coal mine sensors. Data Br 39:107457. https://doi.org/10.1016/j.dib.2021.107457
26. Baris K, Aydin Y (2020) Atmospheric monitoring systems in underground coal mines revisited: a study on sensor accuracy and location. Int J Oil Gas Coal Technol 23(3):325–350. https://doi.org/10.1504/IJOGCT.2020.105777
27. Kruczkowski J, Ostrogórski P (2018), August New Method for Ventilation Methane Content Monitoring. In *Proceedings of the 11th International Mine Ventilation Congress* (p. 269279). Singapore: Springer Singapore. https://doi.org/10.1007/9789811314209_23
28. Deng J, Chen WL, Wang WF, He Y, Zhang BL (2018), August Study on online detection method of methane gas in coal mine based on TDLAS technology. In *Proceedings of the 11th International Mine Ventilation Congress* (p. 318332). Singapore: Springer Singapore. https://doi.org/10.1007/9789811314209_27

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