Contact Details

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Objective

The goal of this project is to develop a suite of probability density functions (PDFs) that describe Eruption Source Parameter (ESP) inputs required by the NAME model. These estimations are crucial for accurate volcanic ash dispersion modeling.

Key Tasks:

1. **Automated Retrieval and Parsing of Volcanic Advisory Reports (VAA):**
   - Implement a system to automatically retrieve and parse real-time Volcanic Advisory Reports (VAA) from the Tokyo Volcanic Ash Advisory Center (TVAAC).
2. **Annual VEI Probability Parsing:**
   - Utilize the methodology outlined in Whelley et al. (2015) to extract annual Volcanic Explosivity Index (VEI) probabilities for the volcano of concern using data from VAA reports.
3. **Bayesian Sampling for Total Eruption Mass (TEM):**
   - Estimate the range of Total Eruption Mass (TEM) for a known VEI level using Bayesian probability sampling. This estimation will account for a range of tephra particl densities.
4. **Mass Eruption Rate (MER) Estimation:**
   - Calculate the Mass Eruption Rate (MER) based on the derived Total Eruption Mass (TEM).
5. **Eruption Duration Calculation:**

- Derive the eruption duration by integrating the MER and TEM values.

6. **Plume Height Estimation from MER:**

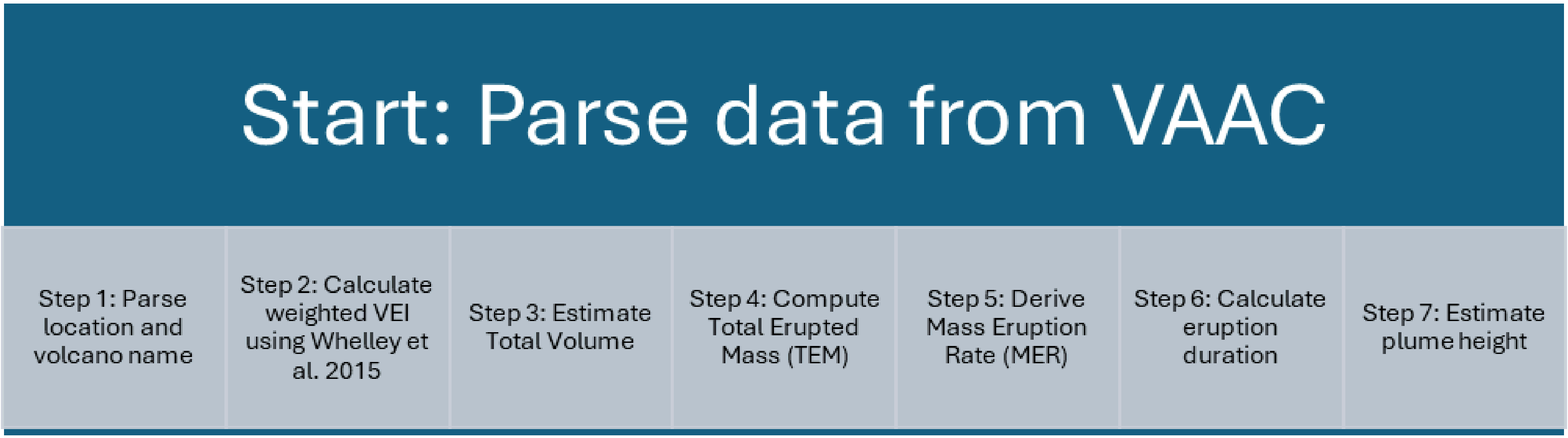
    - Estimate the volcanic plume height using the Mass Eruption Rate (MER).

7. **MER Estimation from Plume Height:**

    - Estimate the MER using observed Plume Height.

8. **Estimation of Mass fraction of ash particle size below 63 microns:**

    - Estimate the Mass fraction of ash particle size below 63 microns using the Mass Eruption Rate (MER).



Parsing of Volcanic Advisory Reports (VAA)

In [40]:

```
# Using Whelley et al., 2015  paper that calculated VEI Level eruption for 750 volcanoes in southeast Asia we start estimating

# first we load Whelley 2015 Volcano Database later will be use to filter Volcanish Ash Advisory reports from Tokyo Volcanic A

import vei
```

```
data_loader=vei.LOADDATA()


whelley_data=data_loader.whelley_2015(as_geodataframe=True)
```

In [41]:
```
# import Libraries and classes required to parse VAA reports and filter dataset for later use.

import vep_vaa_text
from vep_vaa_text import VEP_TVAAC_VAAText
scraper = VEP_TVAAC_VAAText()
scraper.fetch_webpage()
tables = scraper.extract_all_tables()
tables
# Perform a search Note: for realtime operation set all parameters to None to retrive the latest report VAA report
search_results = scraper.search(query='SINABUNG', date_time=None, advisory_number='2020')  # Replace with your query string, s
downloaded_VAA_report, latest_VAA_report , latest_date_data=scraper.download_vaa_text(output_dir="./vaa_texts_2", filtered_res

downloaded_VAA_report.head(2)
```

Out[41]:

	DTG	VAAC	VOLCANO	VOLCANO CODE	PSN	AREA	SUMMIT ELEV	ADVISORY NR	INFO SOURCE	AVIATION COLOUR CODE	...	FCST VA CLD +6 HR	FC CL
0	20200810/1635Z	DARWIN	SINABUNG	261080	N0310 E09824	INDONESIA	2460M	2020/12	HIMAWARI-8, CVGHM, PIREP, WEBCAM	RED	...	10/2235Z NO VA EXP	11/
1	20200810/1030Z	DARWIN	SINABUNG	261080	N0310 E09824	INDONESIA	2460M	2020/10	HIMAWARI-8, CVGHM, PIREP, WEBCAM	RED	...	10/1630Z SFC/FL140 N0303 E09852 - N0337	10/ SFC/ E1

2 rows × 23 columns

In [42]:

```
latest_date_data
```

Out[42]:

	DTG	VAAC	VOLCANO	VOLCANO CODE	PSN	AREA	SUMMIT ELEV	ADVISORY NR	INFO SOURCE	AVIATION COLOUR CODE	...	FCST VA CLD +12 HR	FCS CLD
0	20200810/1635Z	DARWIN	SINABUNG	261080	N0310 E09824	INDONESIA	2460M	2020/12	HIMAWARI-8, CVGHM, PIREP, WEBCAM	RED	...	11/0435Z NO VA EXP	11/1 N

1 rows × 24 columns

In [43]:

```
# Retrive data from the latest report date
from rich.console import Console
from rich.table import Table

# Initialize the console
console = Console()

# Create a table for a professional and structured output
table = Table(title="Volcanic Activity Observations", show_lines=True, title_style="bold blue")

# Define table columns
table.add_column("Parameter", style="dim", width=25)
table.add_column("Value", style="bold white", justify="center")

# Populate the table with data, if available
if 'VOLCANO' in latest_date_data.columns:
    volcano_name = latest_date_data['VOLCANO'].to_list()[0]
    table.add_row("Site of Volcanic Activity", volcano_name)

if 'Altitude_Meters' in latest_date_data.columns:
    observed_ash_altitude_meter = latest_date_data['Altitude_Meters'].to_list()[0]
    table.add_row("Observed Ash Altitude (m ASL)", str(observed_ash_altitude_meter))
```

```python
if 'Latitude' in latest_date_data.columns:
    latitude = latest_date_data['Latitude'].to_list()[0]
    table.add_row("Latitude", str(latitude))

if 'Longitude' in latest_date_data.columns:
    longitude = latest_date_data['Longitude'].to_list()[0]
    table.add_row("Longitude", str(longitude))



# Call the search_whelley_2015 method on the instance
search_results, vei_range = data_loader.search_whelley_2015(Volcano=volcano_name, max_vei_returns=2)

# View the search results
#print(f"Potential VEI Levels for  Volcano site {volcano_name} is based on Whelley et al. 2015 paper   {vei_range}")
#print(search_results)

table.add_row(f"Potential VEI Levels for  Volcano  {volcano_name}  based on Whelley et al. 2015 paper", str(vei_range))

# Render the table
console.print(table)
```

Volcanic Activity Observations

Parameter	Value
Site of Volcanic Activity	SINABUNG
Observed Ash Altitude (m ASL)	4267.2
Latitude	3.09
Longitude	9.92
Potential VEI Levels for Volcano SINABUNG based on Whelley et al. 2015 paper	[2, 3]

Step 1: Define Total Eruption Mass (TEM) from VEI

This cell initializes the `VEI_BulkVolume_Mass` class to perform probabilistic calculations of total eruption mass based on known VEI values.

Key Parameters:

- `use_default_densities=True` : Applies default density values for tephra deposits.
- `density_min=800` and `density_max=1700` (kg/m^3): Define the density range for volcanic materials.
- `num_samples=1000` : Specifies the number of Monte Carlo samples for probabilistic calculations.

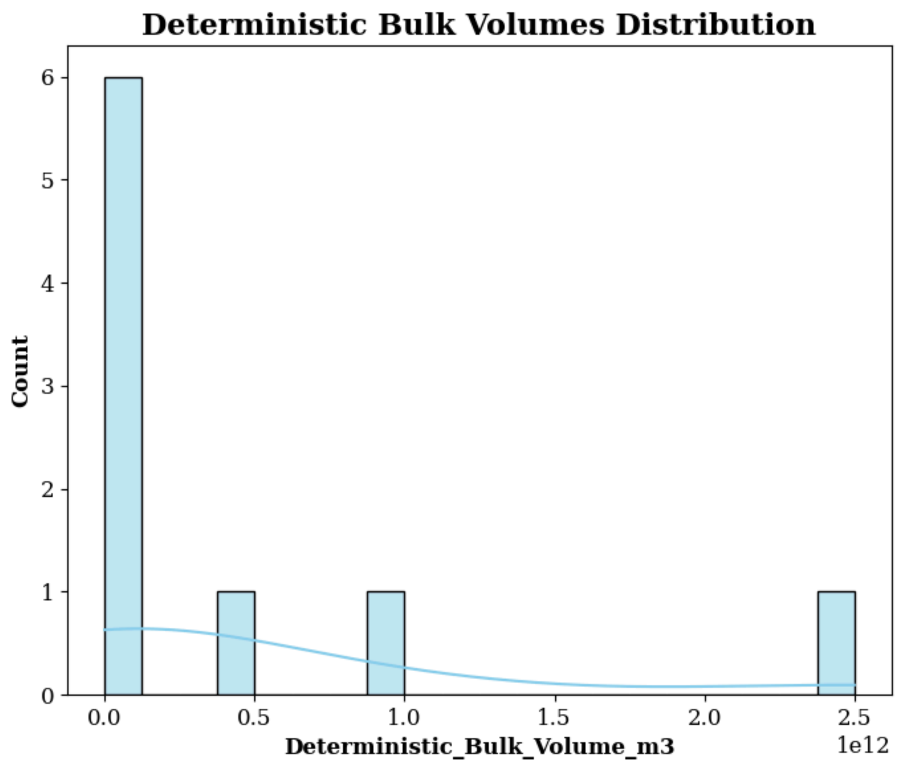
Outcome:

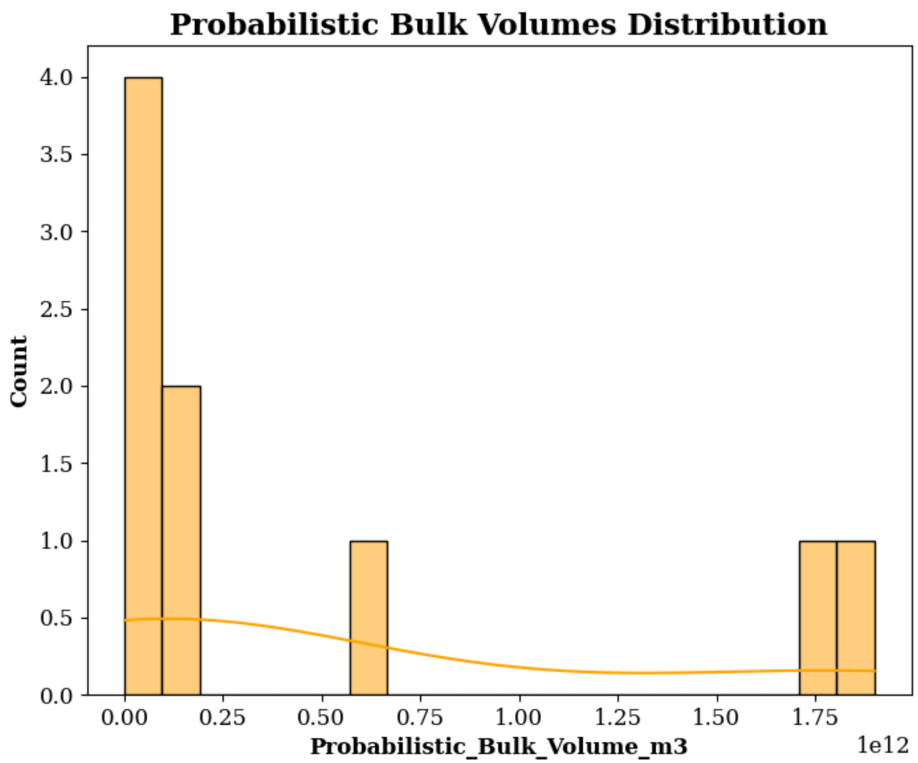
The `vei_toMass` object enables generating probabilistic TEM values for subsequent calculations.

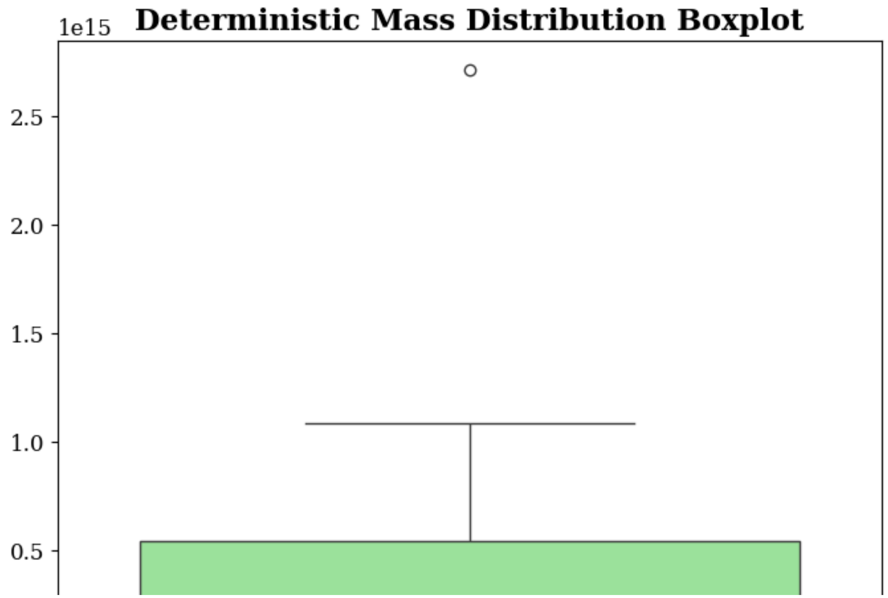
In [44]:

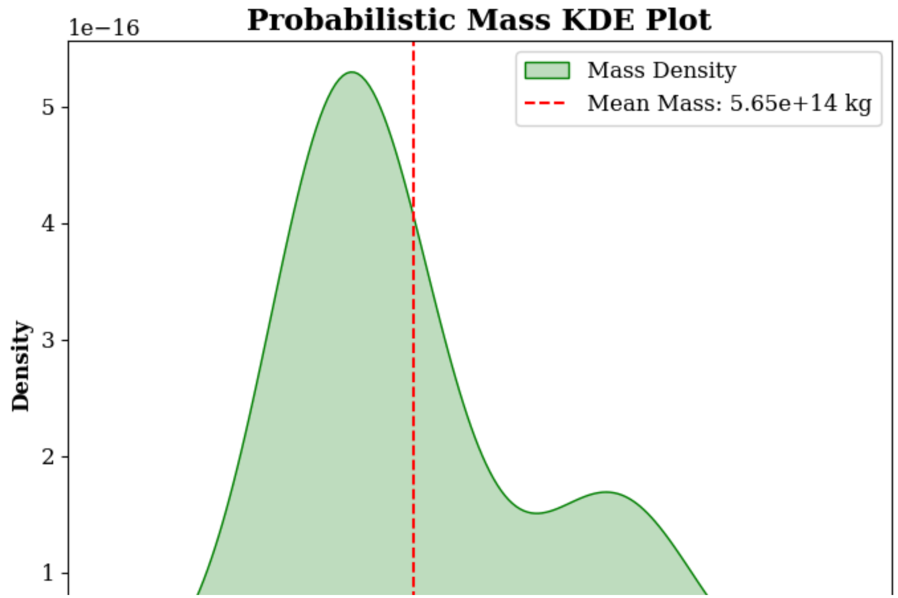
```
from vei import VEI_BulkVolume_Mass

# Initialize the class
vei_toMass = VEI_BulkVolume_Mass(use_default_densities=True, density_min=800, density_max=1200, num_samples=10000000)


# Generate probabilistic volumes
vei_toMass.generate_probabilistic_volumes()

# Calculate masses using probabilistic volumes
vei_toMass.calculate_mass(calculate_deterministic=True, calculate_probabilistic=True)

vei_toMass.calculate_percentile_bands()



# # Generate summary statistics
vei_toMass.generate_summary_statistics()

# # Visualize the results
```

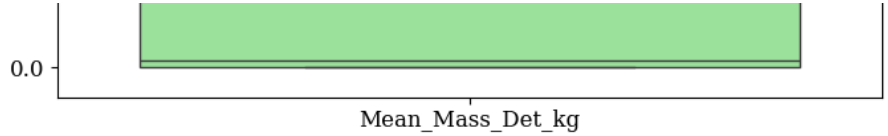
```
vei_toMass.visualize_statistics()

# # Calculate and plot percentile bands

vei_toMass.plot_percentile_bands()

# # Export results
vei_toMass.export_statistics(filename="summary_statistics.csv")
vei_toMass.export_volumes_and_masses()

vei_toMass.export_data()

vei_toMass.save_outputs_to_pdf()
```

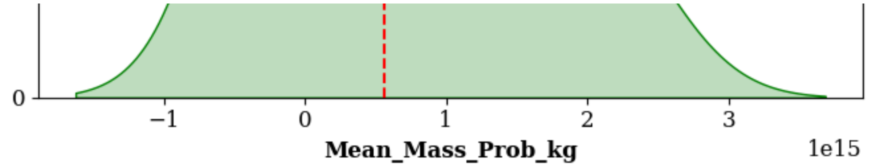

Deterministic Bulk Volumes Distribution
Count
Deterministic_Bulk_Volume_m3
1e12


Probabilistic Bulk Volumes Distribution
Count
Probabilistic_Bulk_Volume_m3
1e12

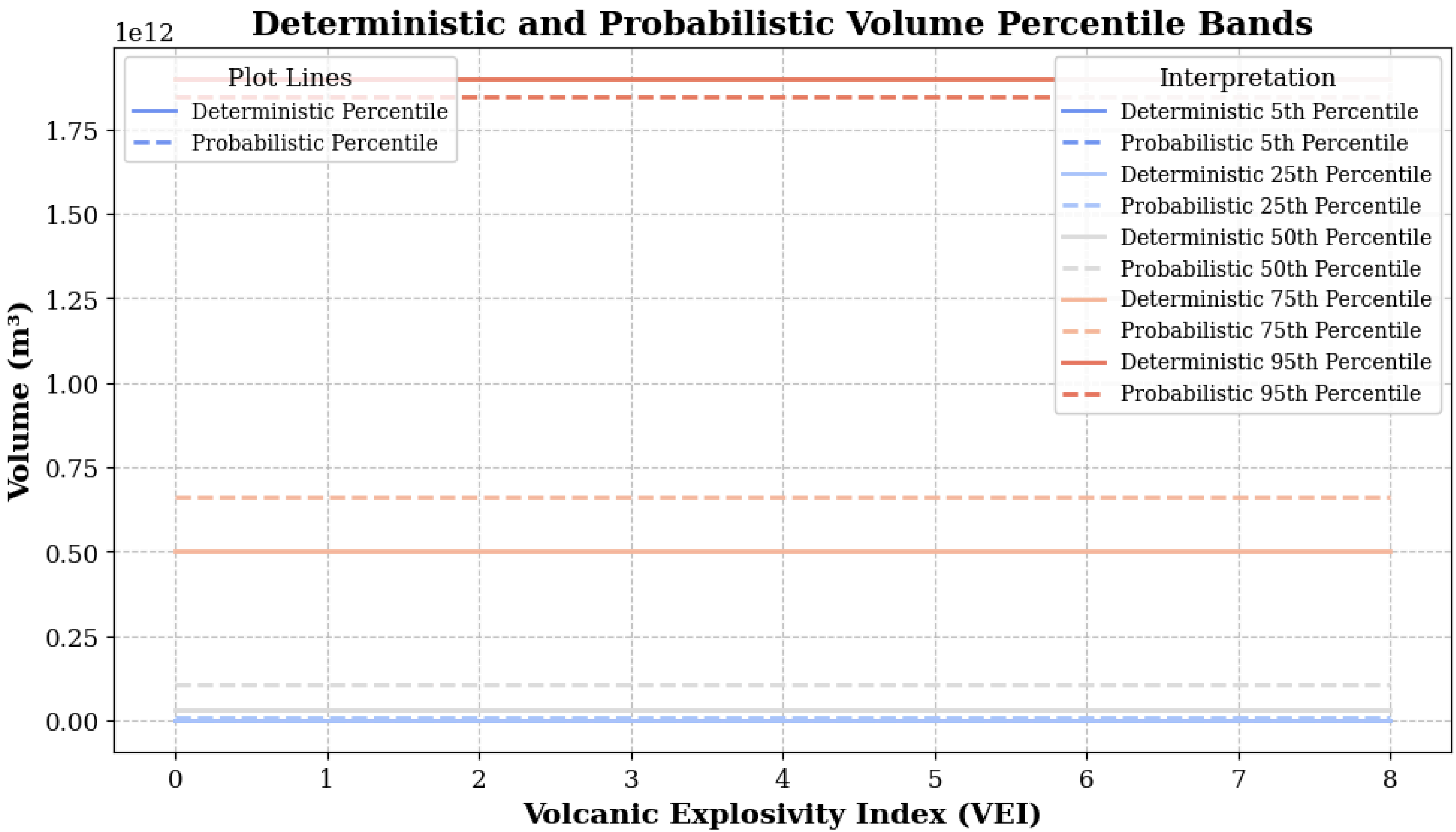

Deterministic Mass Distribution Boxplot
1e15

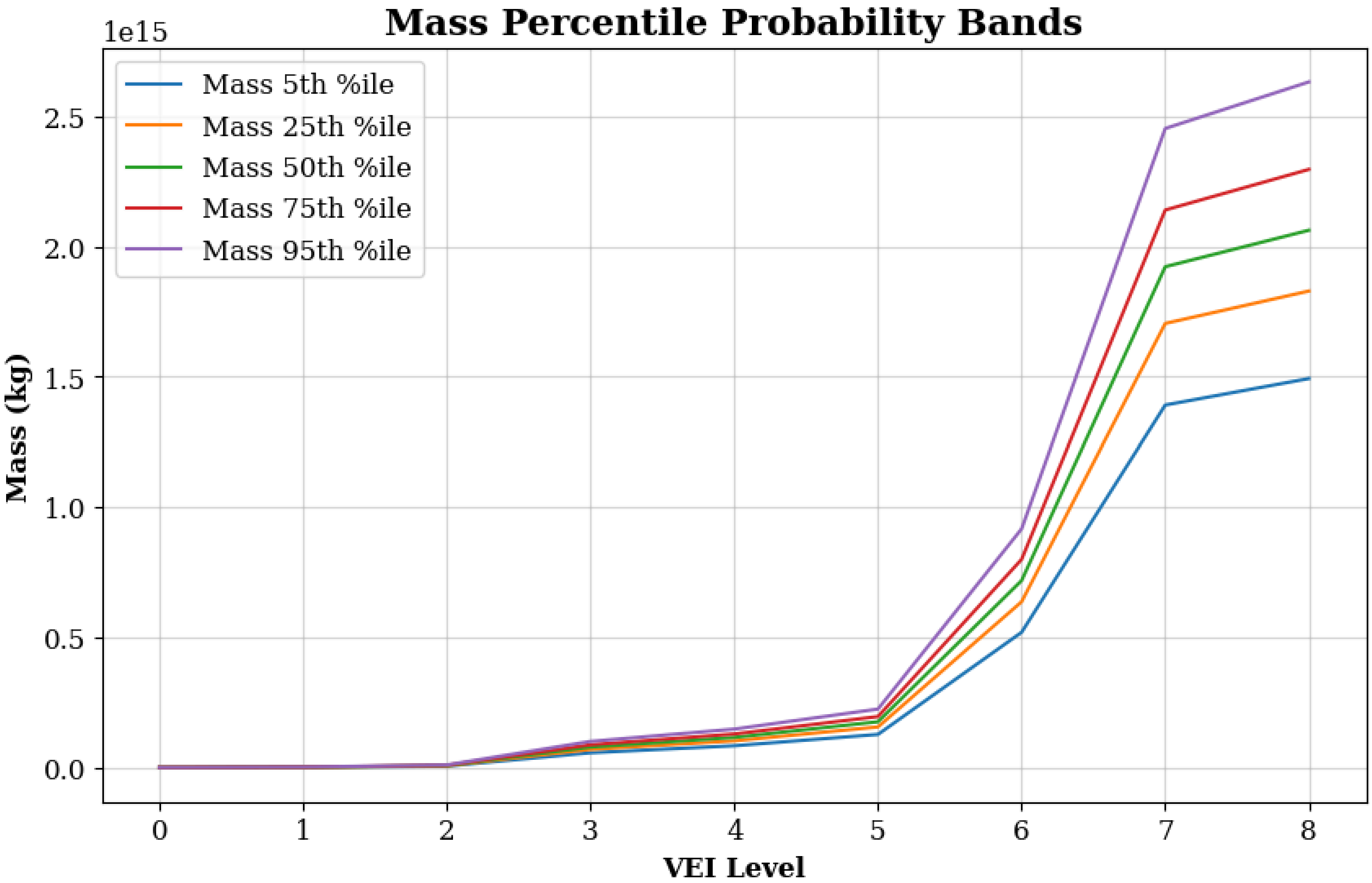

Probabilistic Mass KDE Plot
1e−16
Mass Density
Mean Mass: 5.65e+14 kg
Density

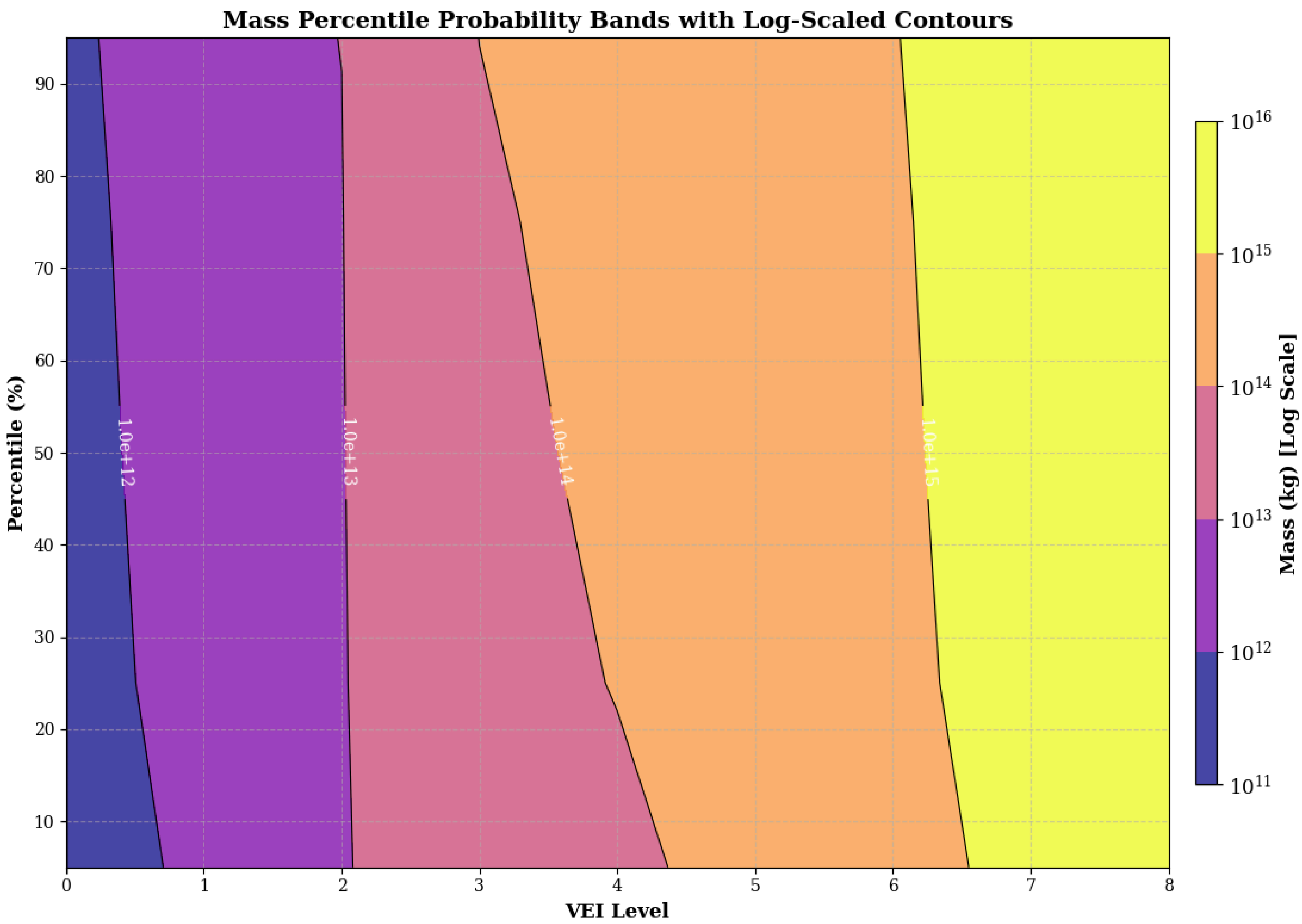





```
c:\Users\mahmud\OneDrive\Singapore_project\data\Modules\phase_1\vei.py:778: UserWarning: Mismatched number of handles and label
s: len(handles) = 0 len(labels) = 4
  interpretation_legend = plt.legend(handles=[], labels=interpretation_text,
```




Mass Percentile Probability Bands
1e15
Mass 5th %ile
Mass 25th %ile
Mass 50th %ile
Mass 75th %ile
Mass 95th %ile
2.5
2.0
1.5
1.0
0.5
0.0
Mass (kg)
0
1
2
3
4
5
6
7
8
VEI Level



Mass Percentile Probability Bands with Log-Scaled Contours
Percentile (%)
90
80
70
60
50
40
30
20
10
VEI Level
0
1
2
3
4
5
6
7
8
1.0e+12
1.0e+13
1.0e+14
1.0e+15
Mass (kg) [Log Scale]
10^{16}
10^{15}
10^{14}
10^{13}
10^{12}
10^{11}

```
c:\Users\mahmud\OneDrive\Singapore_project\data\Modules\phase_1\vei.py:778: UserWarning: Mismatched number of handles and label
s: len(handles) = 0 len(labels) = 4
  interpretation_legend = plt.legend(handles=[], labels=interpretation_text,
```

Step 2: Load Volcanic Data for Model Inputs and Validation

This cell loads datasets containing eruption source parameters and metadata.

Data Sources:

1. `Mastin` : Dataset of VEI-related eruption parameters.
2. `Aubrey` : Dataset with parameters for eruption dynamics.
3. `IVESPA` : Integrated Volcanic Eruption Source Parameters Archive for further modeling.

Purpose:

- These datasets provide observational constraints and inputs for modeling eruption parameters.
- Support statistical analysis and correlation studies to validate models.

In [45]:

```
import vei
from vei import  analyze_correlations

data_loader=vei.LOADDATA()


Mastin = data_loader.load_Mastin(as_geodataframe=False)
Aubrey=data_loader.load_Aubry(as_geodataframe=False)
IVESPA=data_loader.load_IVESPA(as_geodataframe=False)
Sparks=data_loader.load_Sparks(as_geodataframe=False)
mastin_a=data_loader.load_Mastin_a(as_geodataframe=True)

# analyze_correlations(Mastin, 'Mastin', threshold=0.7)

# analyze_correlations(Aubrey, 'Aubrey', threshold=0.7)
```

```
# analyze_correlations(Sparks, 'Sparks', threshold=0.7)

# analyze_correlations(IVESPA, 'IVESPA', threshold=0.7)

#analyze_correlations(mastin_a, 'IVESPA', threshold=0.9)

import pandas as pd

df= pd.concat([ Aubrey, IVESPA], axis=0, join='inner')
```

Step 3: Estimate Mass Eruption Rate (MER)

This cell prepares TEM data for use with the `MERPredictor` class.

Inputs:

- `tem_values` : Extracted mean probabilistic TEM values (`Mean_Mass_Prob_kg`) generated by the VEI model.

Purpose:

- `tem_values` serve as input to estimate MER, an essential eruption source parameter.
- MER will be used in subsequent steps to calculate eruption duration and plume rise.

In [46]:
```
from mer_predict import MERPredictor
import pandas as pd

data=vei_toMass.data

# Drop first row (VEI zero) because VEI zero is None Explosive

#data = data.drop(index=data.index[0]).reset_index(drop=True)
```

```python
# Ensuring the VEI column is numeric
data['VEI'] = pd.to_numeric(data['VEI'], errors='coerce')

# Filtering the dataframe based on VEI column and list
data = data[data['VEI'].isin(vei_range)].reset_index(drop=True)

data
```

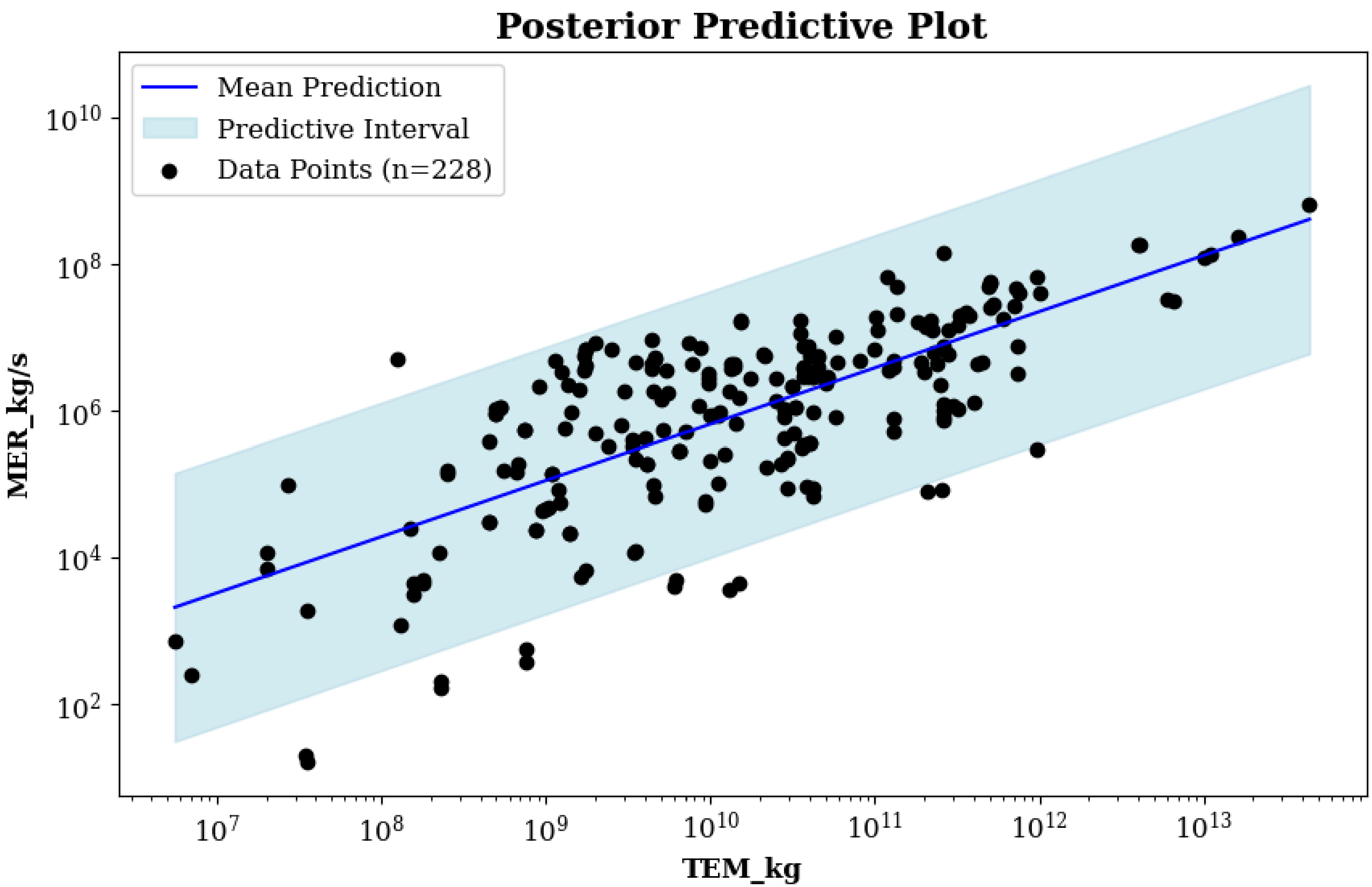
Out[46]:

	VEI	Bulk_Volume_km3	Deterministic_Bulk_Volume_m3	Probabilistic_Bulk_Volume_m3	Mean_Mass_Det_kg	Std_Mass_Det_kg	Mean_Mass_
0	2	0.1	1.000000e+08	7.388868e+09	1.084903e+11	3.027580e+09	8.021
1	3	3.0	3.000000e+09	7.258250e+10	3.254692e+12	9.081072e+10	7.879

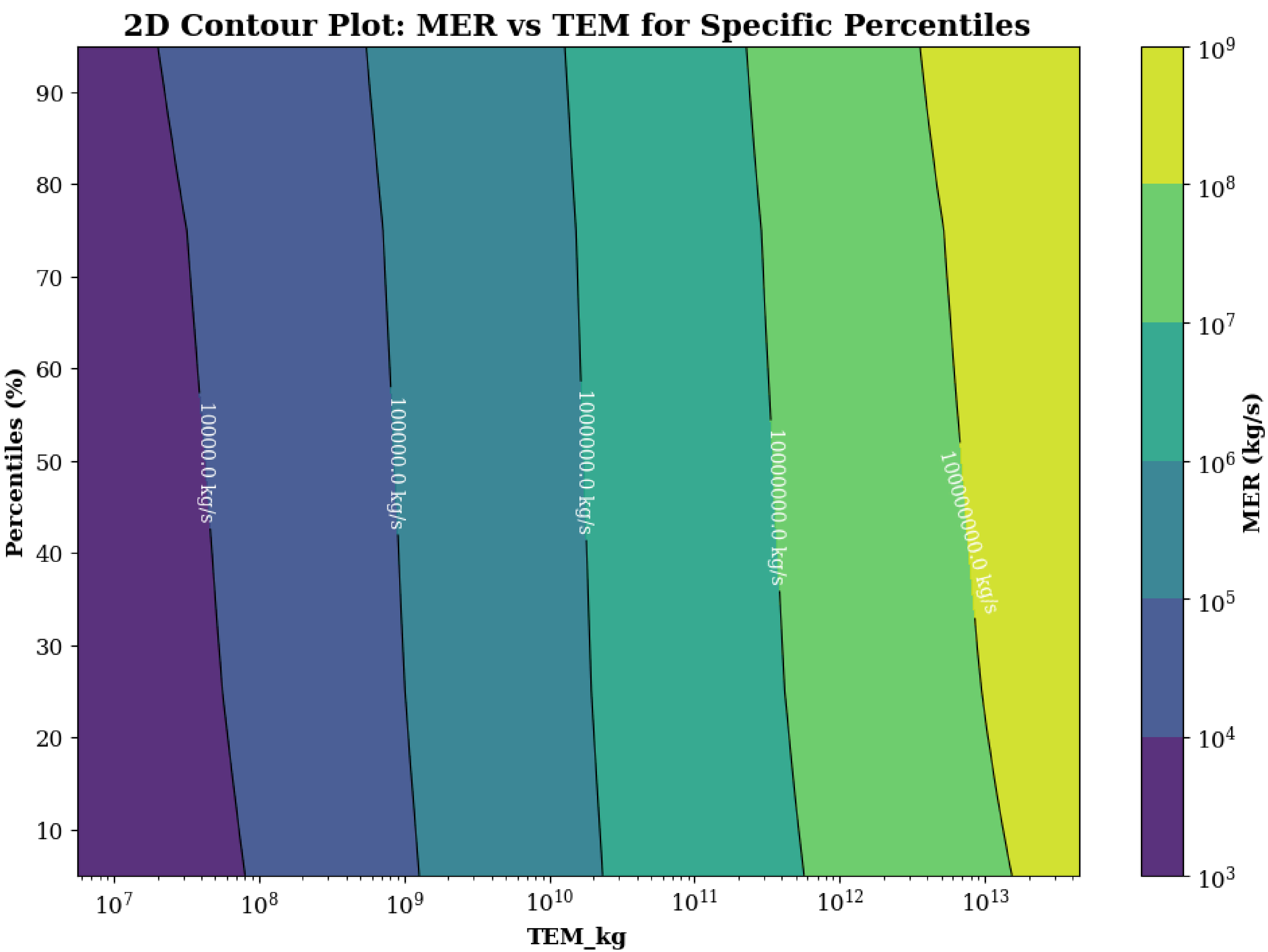
2 rows × 40 columns

In [47]:

```python
#tem_values=data.Mean_Mass_Prob_kg.to_list()
tem_values=data.Mean_Mass_Det_kg.to_list()




#tem_values=[1.998468e+11 , 3.585472e+14 ]



model = MERPredictor(df)
model.plot_posterior_predictive()
mer_results=model.predict_mer(tem_values)
model.plot_percentiles_vs_tem()
durations = model.convert_percentiles_to_duration(tem_values)
print(durations)
```



Posterior Predictive Plot
Mean Prediction
Predictive Interval
Data Points (n=228)
MER_kg/s
TEM_kg
10^{2}
10^{4}
10^{6}
10^{8}
10^{10}
10^{7}
10^{8}
10^{9}
10^{10}
10^{11}
10^{12}
10^{13}



2D Contour Plot: MER vs TEM for Specific Percentiles
Percentiles (%)
TEM_kg
MER (kg/s)
10000.0 kg/s
100000.0 kg/s
1000000.0 kg/s
10000000.0 kg/s
100000000.0 kg/s
90
80
70
60
50
40
30
20
10
10^7
10^8
10^9
10^{10}
10^{11}
10^{12}
10^{13}
10^3
10^4
10^5
10^6
10^7
10^8
10^9

Step 4: Correlate VEI with MER Results

This cell adds the VEI values from the processed data into the `mer_results` DataFrame.

Purpose:

- Ensures that MER results are directly associated with their corresponding VEI values.
- Facilitates traceability and cross-comparison during analysis.

In [48]:
```
mer_results["VEI"]=data['VEI']
```

Step 5: Review Mass Eruption Rate (MER) Results

This cell displays the `mer_results` DataFrame, which includes the calculated MER values and associated VEI data.

Purpose:

- Provides an overview of the MER estimates to verify accuracy and consistency.

In [49]:
```
mer_results
```

Out[49]:

	TEM_kg	MERPercentile_5	Uncertainty_Lower_5	Uncertainty_Upper_5	MERPercentile_25	Uncertainty_Lower_25	Uncertainty_Upper_
0	1.084903e+11	3.096971e+06	2.118679e+06	3.302910e+06	3.648775e+06	3.545267e+06	3.744617e+
1	3.254692e+12	3.395452e+07	1.838617e+07	3.760288e+07	4.547414e+07	4.310616e+07	4.774144e+

2 rows × 26 columns

Step 6: Select Central MER Values for Plume Height Prediction

This cell extracts the 50th percentile (median) MER values from the `mer_results` DataFrame.

Purpose:

- Focuses on the central tendency of the MER distribution, minimizing the influence of outliers.
- The Best MER values (`mer_list`) are determined using the range between the (`95th and 5th percentiles`) and are used as input for plume height predictions..

In [50]:
```
mer_list=mer_results['Best_MER_Estimate_kg/s'].to_list()
```

Step 7: Estimate Plume Rise Based on MER

This cell initializes the `PlumeHeightPredictor` class and calculates plume heights using the median MER values.

Methodology:

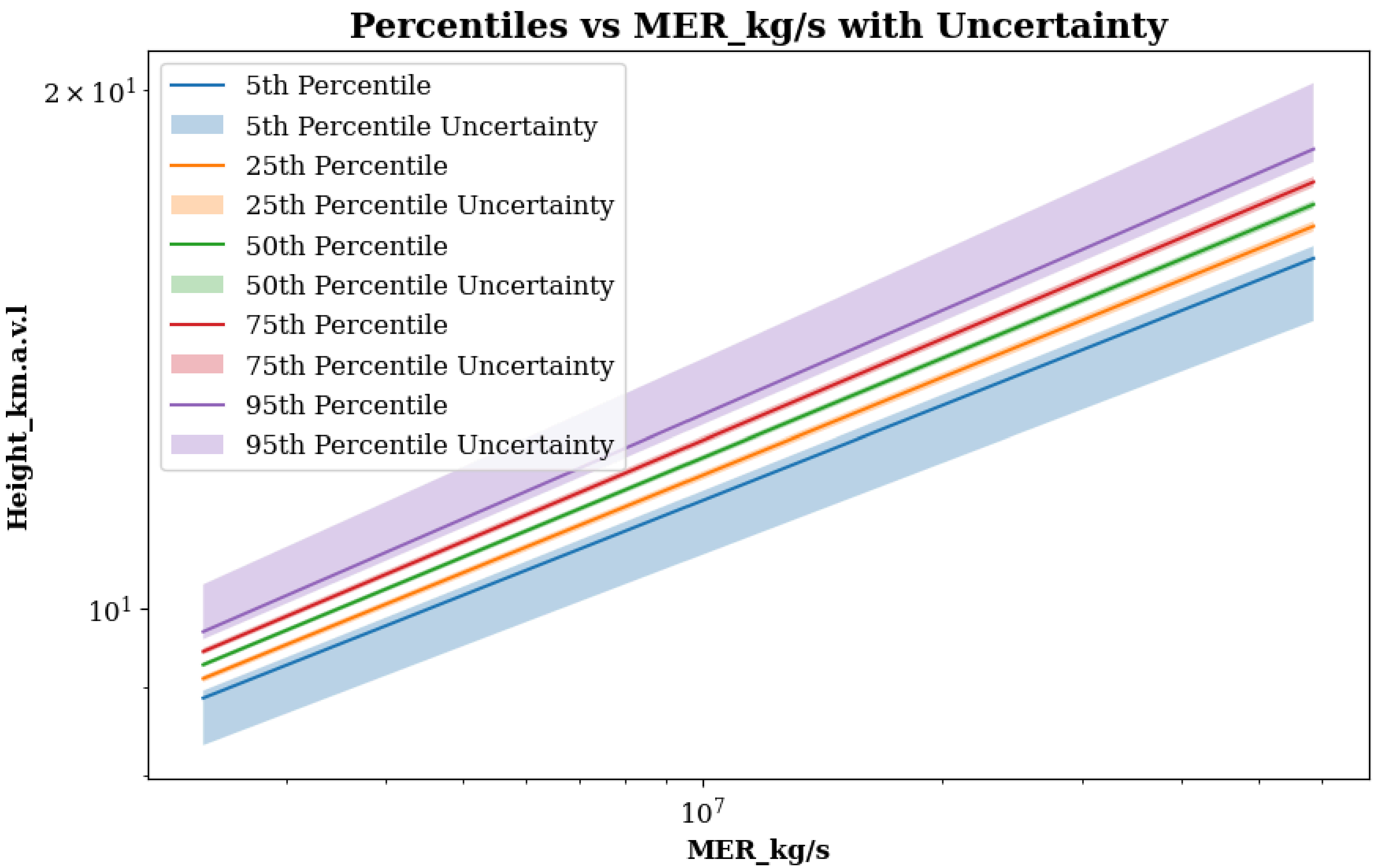
- Utilizes the `IVESPA` dataset for plume height predictions with uncertainty quantification.
- Outputs plume height estimates based on the MER values (`mer_list`).

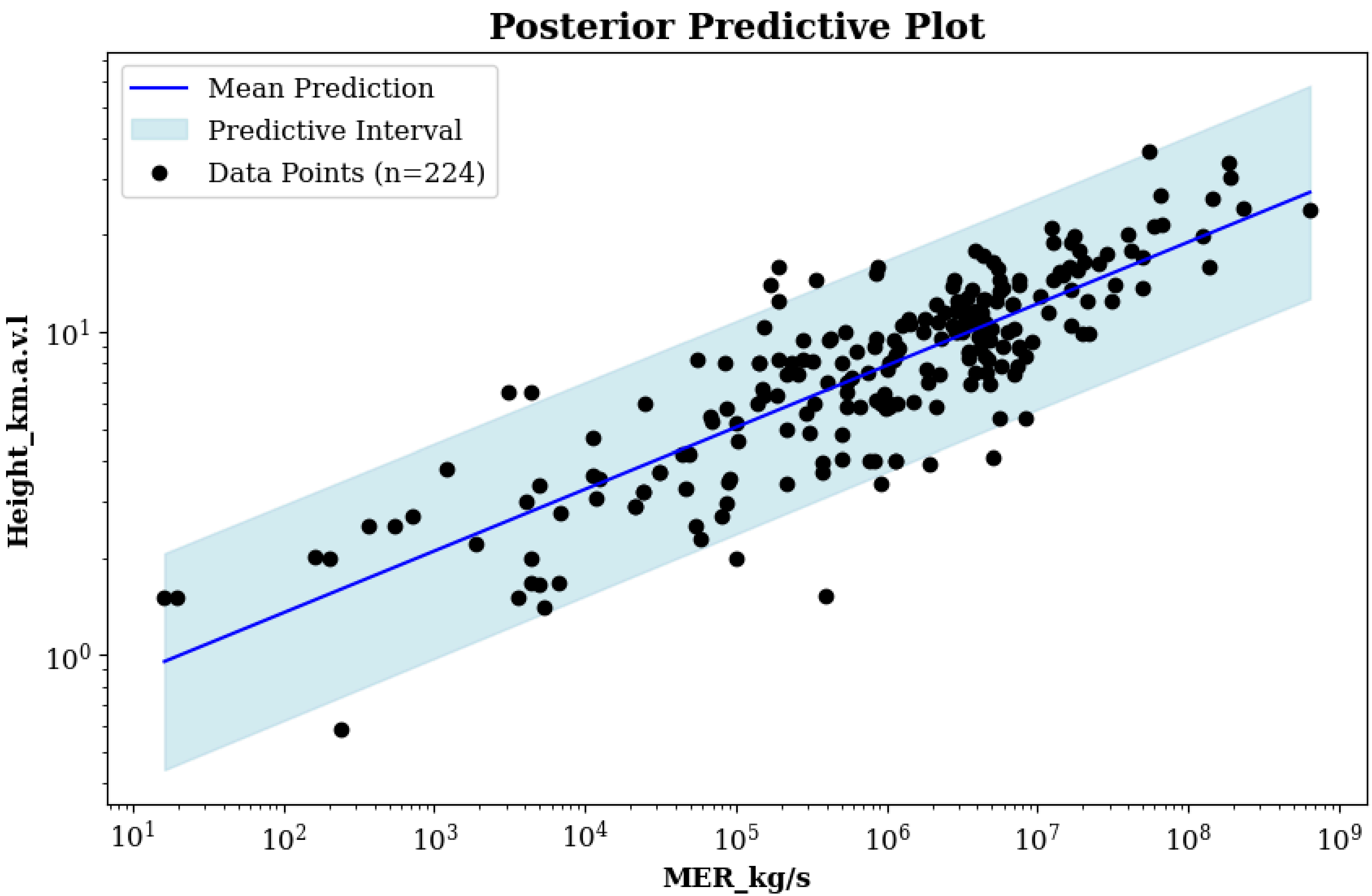
Purpose:

- Plume rise estimation is critical for assessing the environmental and aviation impacts of volcanic eruptions.

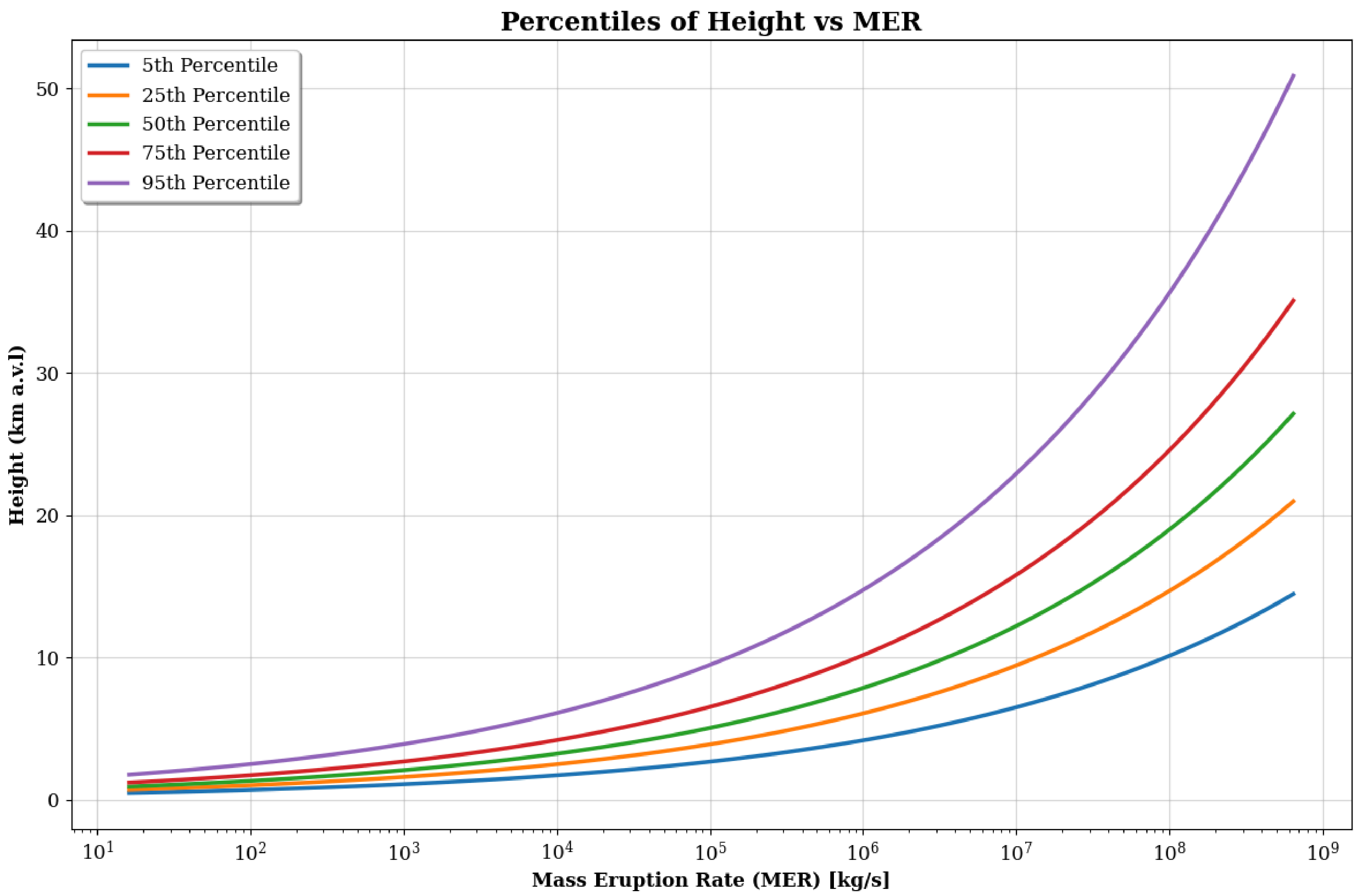
In [51]:
```
from plume_rise_predict import PlumeHeightPredictor

# Initialize the PlumeHeightPredictor
predictor = PlumeHeightPredictor(df)
```

```python
heights=predictor.predict_height_with_uncertainty(mer_list, output_file='predicted_height_with_uncertainty.csv')

# Calculate Percentiles with Uncertainty

percentiles_results = predictor.calculate_percentiles_with_uncertainty(mer_list)
print(percentiles_results)

# Plot Percentiles with Uncertainty
predictor.plot_percentiles_with_uncertainty(mer_list)

# Plot Posterior Predictive Distribution
predictor.plot_posterior_predictive()

# Plot Percentiles Without Uncertainty
predictor.plot_percentiles_vs_mer()
```

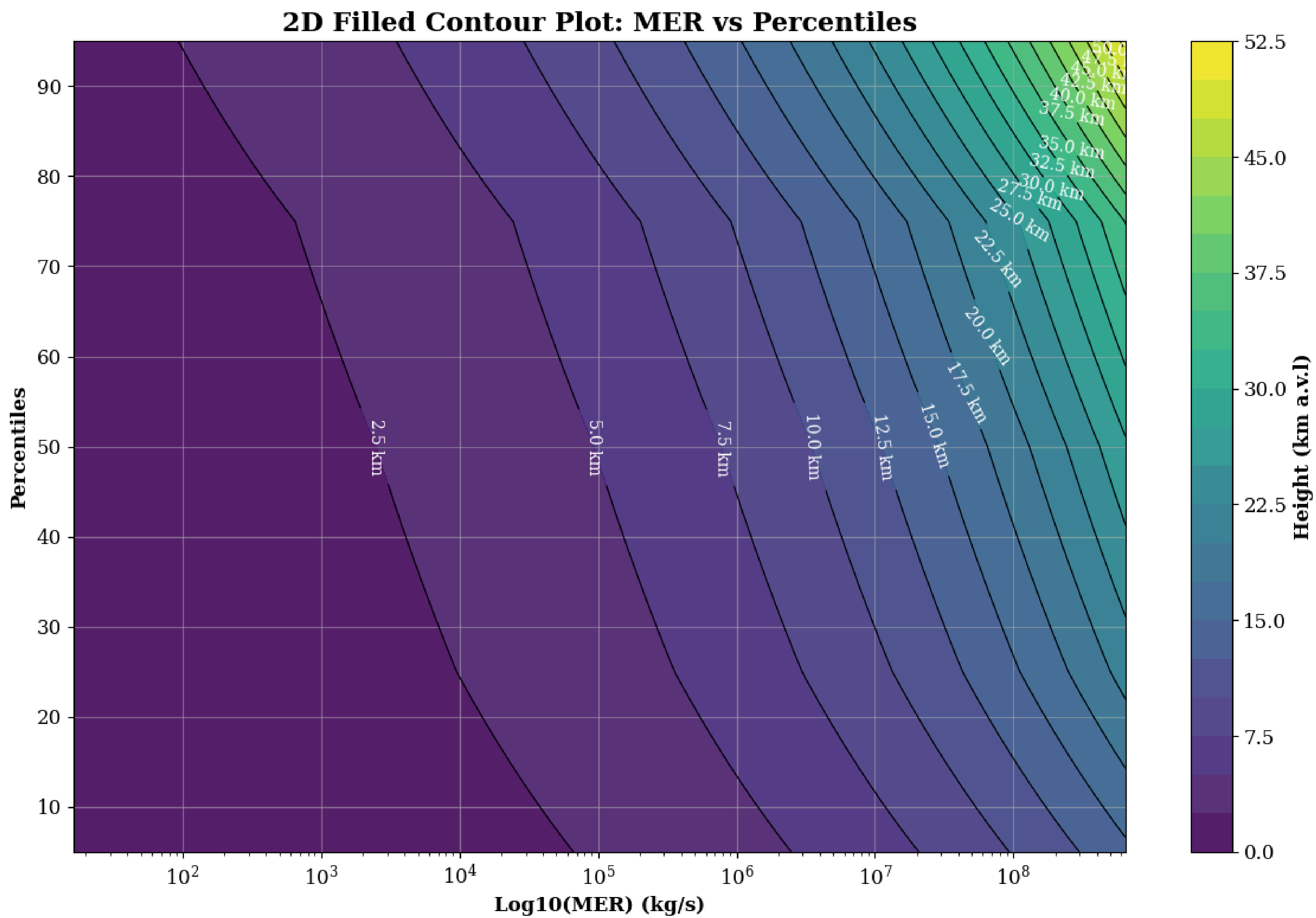

Percentiles vs MER_kg/s with Uncertainty
5th Percentile
5th Percentile Uncertainty
25th Percentile
25th Percentile Uncertainty
50th Percentile
50th Percentile Uncertainty
75th Percentile
75th Percentile Uncertainty
95th Percentile
95th Percentile Uncertainty
2×10^1
10^1
10^7
Height_km.a.v.l
MER_kg/s



Posterior Predictive Plot
Mean Prediction
Predictive Interval
Data Points (n=224)
Height_km.a.v.l
10^1
10^0
10^1
10^2
10^3
10^4
10^5
10^6
10^7
10^8
10^9
MER_kg/s



Percentiles of Height vs MER
5th Percentile
25th Percentile
50th Percentile
75th Percentile
95th Percentile
Height (km a.v.l)
Mass Eruption Rate (MER) [kg/s]


2D Filled Contour Plot: MER vs Percentiles
Percentiles
Log10(MER) (kg/s)
Height (km a.v.l)
2.5 km
5.0 km
7.5 km
10.0 km
12.5 km
15.0 km
17.5 km
20.0 km
22.5 km
25.0 km
27.5 km
30.0 km
32.5 km
35.0 km
37.5 km
40.0 km
42.5 km
10
20
30
40
50
60
70
80
90
10^2
10^3
10^4
10^5
10^6
10^7
10^8
0.0
7.5
15.0
22.5
30.0
37.5
45.0
52.5

Step 8: Review Plume Height Estimates

This cell displays the predicted plume heights.

Purpose:

- Offers an immediate review of the plume height results for quality control and interpretation.

In [52]:

```
heights['VEI']=mer_results['VEI']
# List of columns to be assigned
columns_to_assign = ['Duration_hr_P5', 'Duration_hr_P25', 'Duration_hr_P50', 'Duration_hr_P75', 'Duration_hr_P95', 'Duration_h

# Assign values from mer_results to heights for these columns
heights[columns_to_assign] = mer_results[columns_to_assign]



heights.to_csv('Final_prediction_results.csv')



#heights.head(10)
heights
```

Out[52]:

	MER_kg/s	HeightPercentile_5	Uncertainty_Lower_5	Uncertainty_Upper_5	HeightPercentile_25	Uncertainty_Lower_25	Uncertainty_Up
0	2.356004e+06	8.879990	8.329733	8.962584	9.111412	9.069960	9.
1	5.856907e+07	15.946091	14.410793	16.217911	16.660109	16.533267	16.

2 rows × 26 columns

In [53]:

```
from rich.console import Console
from rich.table import Table
```

```python
# Ensure VEI is first
if "VEI" not in heights.columns:
    raise KeyError("The 'VEI' column is missing from the DataFrame.")

cols = ["VEI"] + [col for col in heights.columns if col != "VEI"]
heights = heights[cols]

# Rich Console for better formatting
console = Console()

# Function to print DataFrame in chunks of six columns, keeping VEI first
def print_six_columns_with_vei_first(df):
    num_cols = len(df.columns)
    for i in range(1, num_cols, 3):  # 5 because VEI is fixed
        # Slice five columns at a time, after the first column
        cols = ["VEI"] + list(df.columns[i:i+3])

        # Create a table for this chunk
        table = Table(title="VEI and Related Data")
        for col in cols:
            table.add_column(col, justify="center")

        # Add rows to the table
        for _, row in df[cols].iterrows():
            table.add_row(*[str(cell) for cell in row])

        # Print the table
        console.print(table)

# Display the DataFrame
print_six_columns_with_vei_first(heights)
```

VEI and Related Data

VEI	MER_kg/s	HeightPercentile_5	Uncertainty_Lower_5
2.0	2356004.493507403	8.879989575805126	8.329732619298941
3.0	58569065.61349128	15.946091231530955	14.41079254583193

VEI and Related Data

VEI	Uncertainty_Upper_5	HeightPercentile_25	Uncertainty_Lower_25
2.0	8.962584275883845	9.111411665138741	9.069959841114452
3.0	16.217910902984674	16.660108929660076	16.533266897867836

VEI and Related Data

VEI	Uncertainty_Upper_25	HeightPercentile_50	Uncertainty_Lower_50
2.0	9.147674297363453	9.281694861835053	9.249512566088953
3.0	16.775158190485048	17.161960406554524	17.069272864228402

VEI and Related Data

VEI	Uncertainty_Upper_50	HeightPercentile_75	Uncertainty_Lower_75
2.0	9.316691619223205	9.4565608466045	9.417700109343388
3.0	17.258340386815195	17.683022340489803	17.563276298188235

VEI and Related Data

VEI	Uncertainty_Upper_75	HeightPercentile_95	Uncertainty_Lower_95
2.0	9.497008495813102	9.701671948493086	9.606614281854208
3.0	17.815733497350113	18.46292753959523	18.17518155950278

VEI and Related Data

VEI	Uncertainty_Upper_95	Best_Height_Estimate_km	Best_Height_Estimate_km_Uncertainty
2.0	10.354204831003699	0.8216823726879596	1.3916205551198537
3.0	20.146137355669925	2.516836308064276	3.9282264526852515

VEI and Related Data

VEI	Duration_hr_P5	Duration_hr_P25	Duration_hr_P50
2.0	9.697413664498807	8.238385887066197	7.3381082145273195
3.0	26.406887606263332	19.794934343101506	16.192162872673403

VEI and Related Data

VEI	Duration_hr_P75	Duration_hr_P95	Duration_hr_best_estimate
2.0	6.548808846345508	5.527220272531921	12.85305892546757
3.0	13.222836376123913	9.822467187015429	15.640027234396946

VEI and Related Data

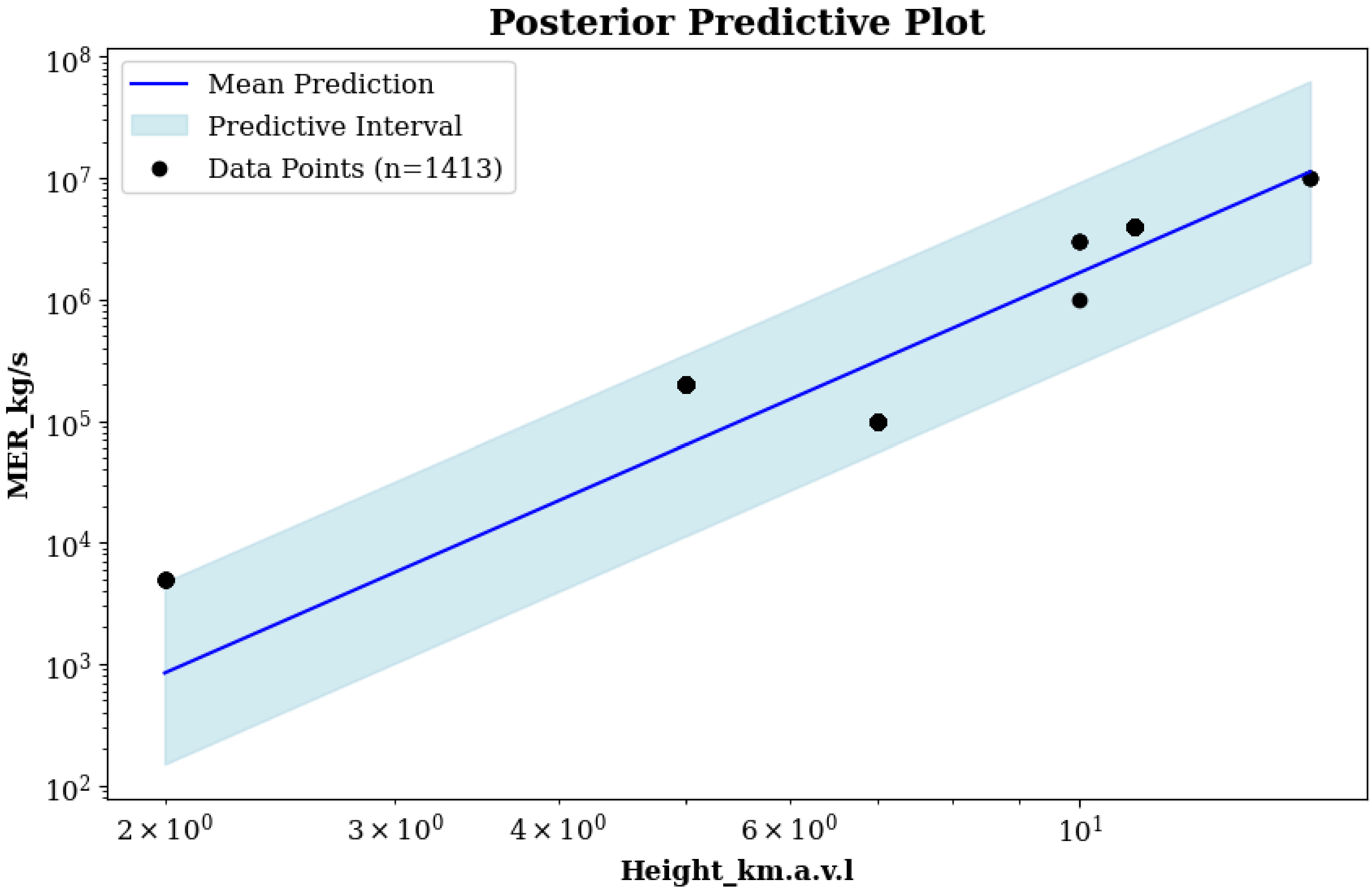
VEI	Duration_hr_best_estimate_Uncertainty
2.0	6.596794317718479
3.0	5.875602313234533

Refining Mass Eruption Rate (MER) Estimates Using Observed Plume Height

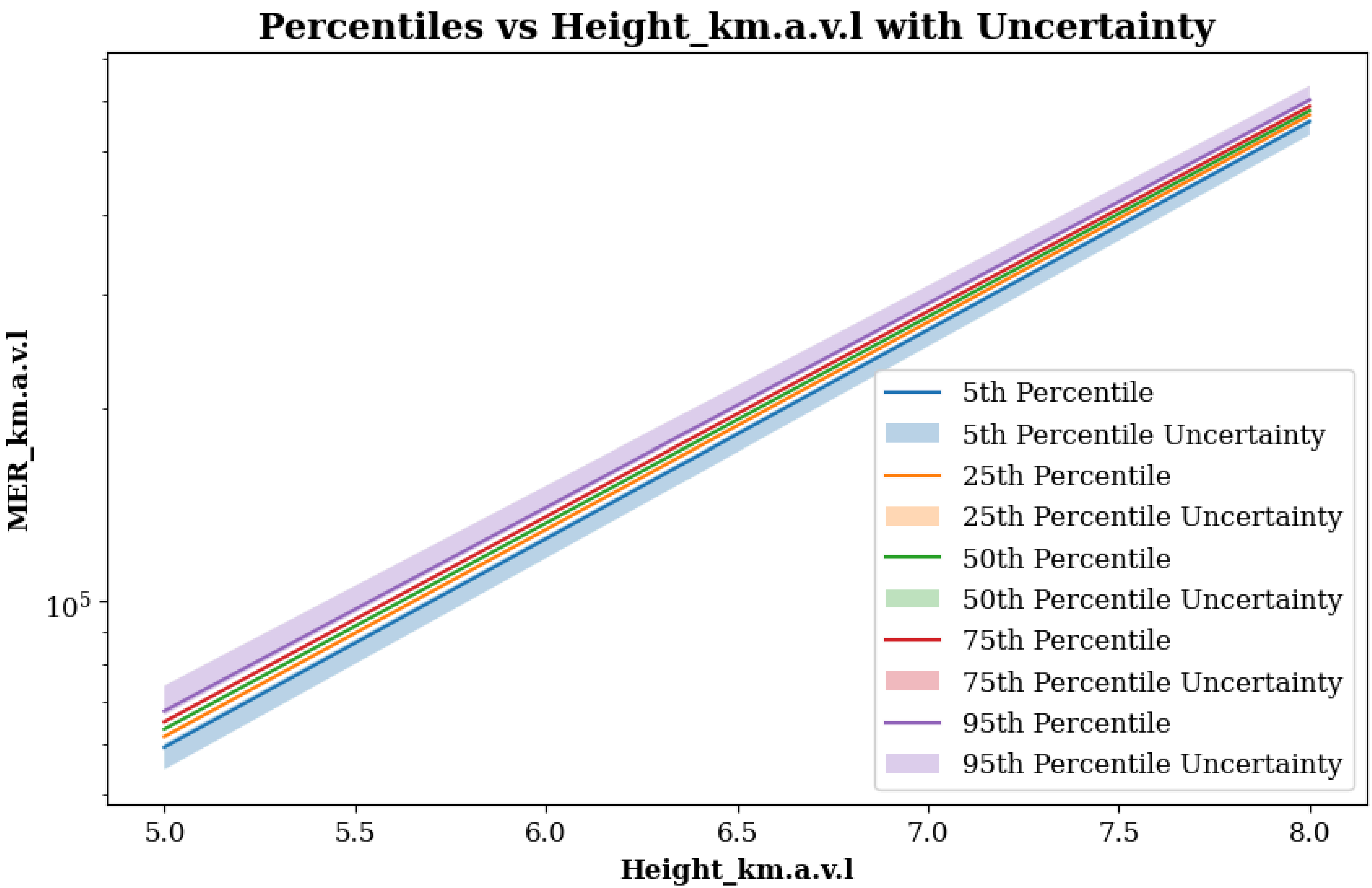
When plume height is observed through satellite imagery or infrasound data, it provides an opportunity to enhance previously predicted MER values. By leveraging this direct observation of plume height, we can derive a more accurate estimate of the MER, aligning it closely with the actual eruption dynamics.

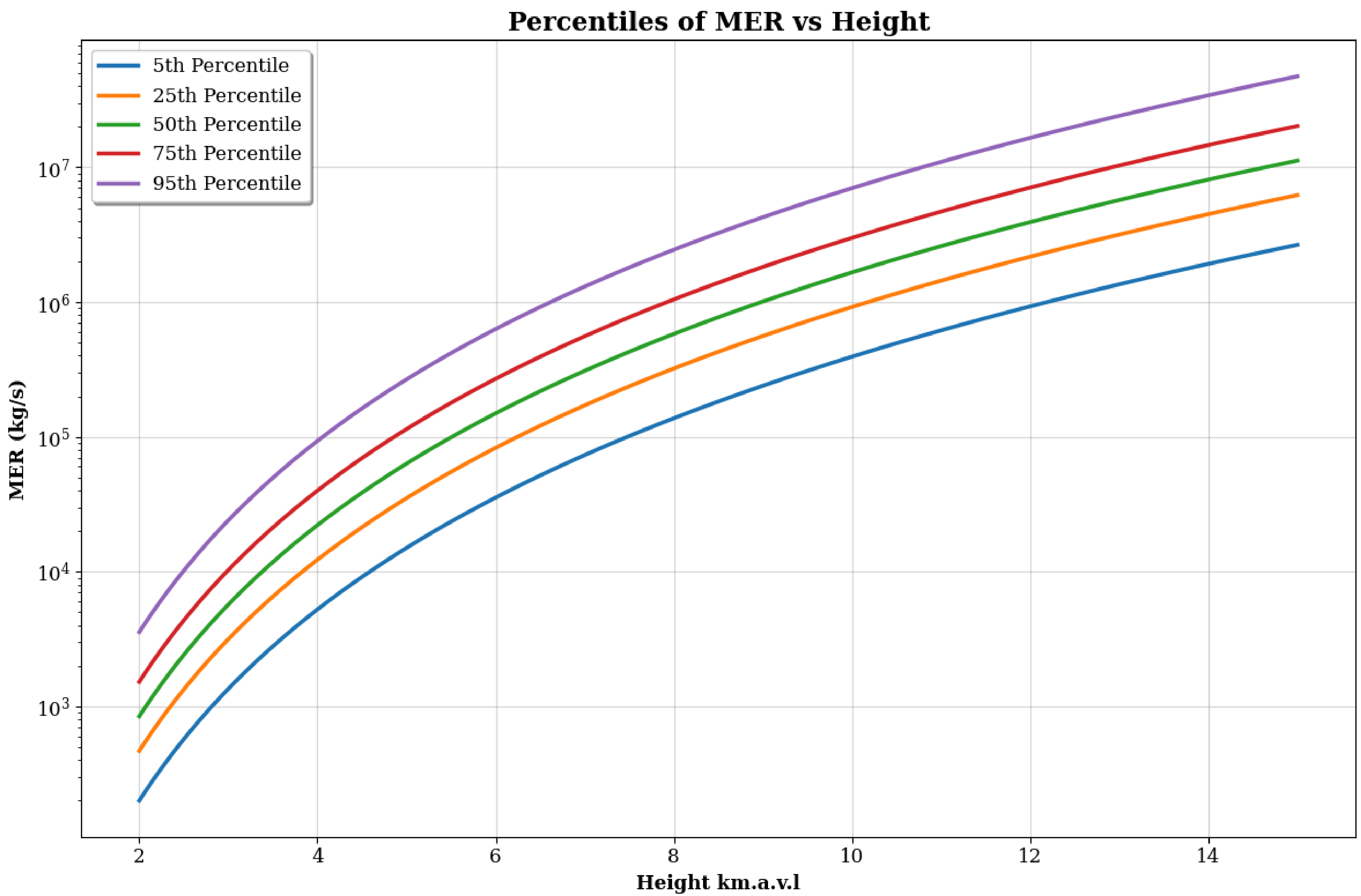
In [54]:
```
from mer_from_height import MERPredictorFromHeight

predictor = MERPredictorFromHeight(mastin_a)
# Predict MER for specific heights
# Save predictions to a CSV
Observed_plume_height=[5,8]
predictions=predictor.predict_MER_with_uncertainty(Observed_plume_height, output_file='predicted_mer_fromheight.csv')
```

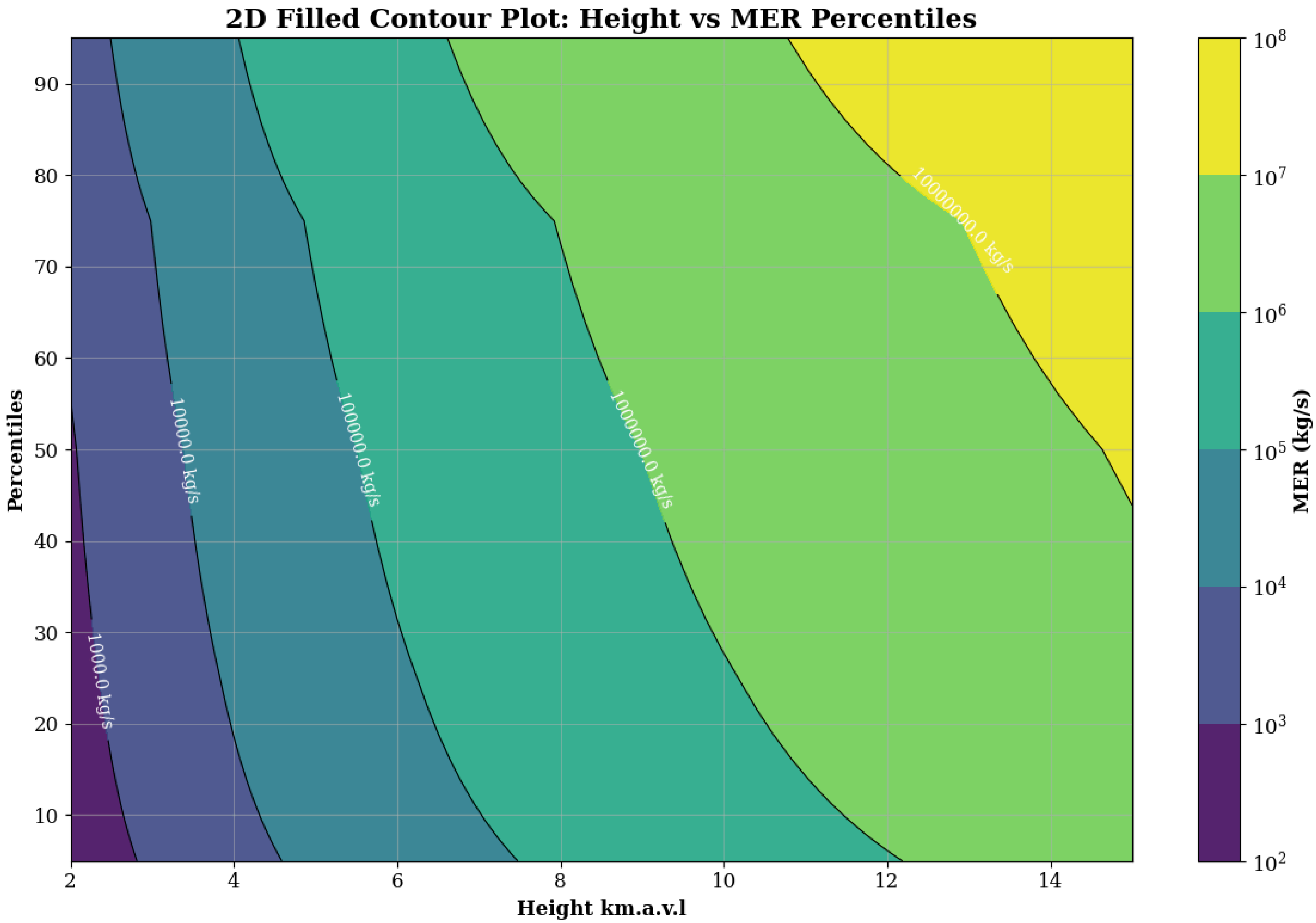
```python
# Visualize the posterior predictive distribution
predictor.plot_posterior_predictive()

# Visualize percentiles with uncertainty
predictor.plot_percentiles_with_uncertainty(Observed_plume_height)

predictor.plot_percentiles_vs_mer()

predictions
```



Posterior Predictive Plot
Mean Prediction
Predictive Interval
Data Points (n=1413)
MER_kg/s
Height_km.a.v.l
10^2
10^3
10^4
10^5
10^6
10^7
10^8
2×10^0
3×10^0
4×10^0
6×10^0
10^1


Percentiles vs Height_km.a.v.l with Uncertainty
MER_km.a.v.l
10^5
5.0
5.5
6.0
6.5
7.0
7.5
8.0
Height_km.a.v.l
5th Percentile
5th Percentile Uncertainty
25th Percentile
25th Percentile Uncertainty
50th Percentile
50th Percentile Uncertainty
75th Percentile
75th Percentile Uncertainty
95th Percentile
95th Percentile Uncertainty


Percentiles of MER vs Height
5th Percentile
25th Percentile
50th Percentile
75th Percentile
95th Percentile
MER (kg/s)
10^3
10^4
10^5
10^6
10^7
2
4
6
8
10
12
14
Height km.a.v.l

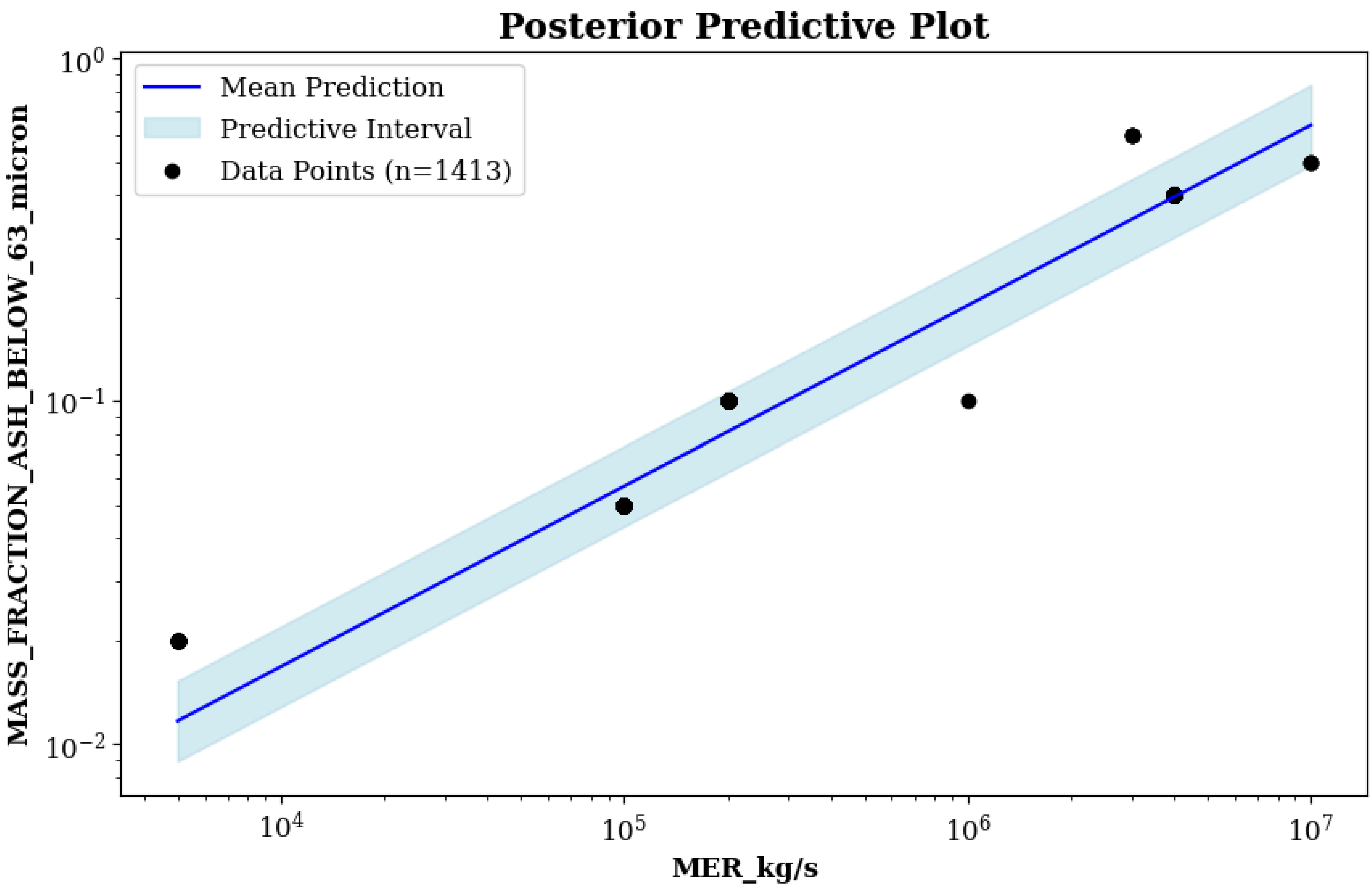

2D Filled Contour Plot: Height vs MER Percentiles
Percentiles
Height km.a.v.l
MER (kg/s)
1000.0 kg/s
10000.0 kg/s
100000.0 kg/s
1000000.0 kg/s
10000000.0 kg/s
10
20
30
40
50
60
70
80
90
2
4
6
8
10
12
14
10^2
10^3
10^4
10^5
10^6
10^7
10^8

Out[54]:

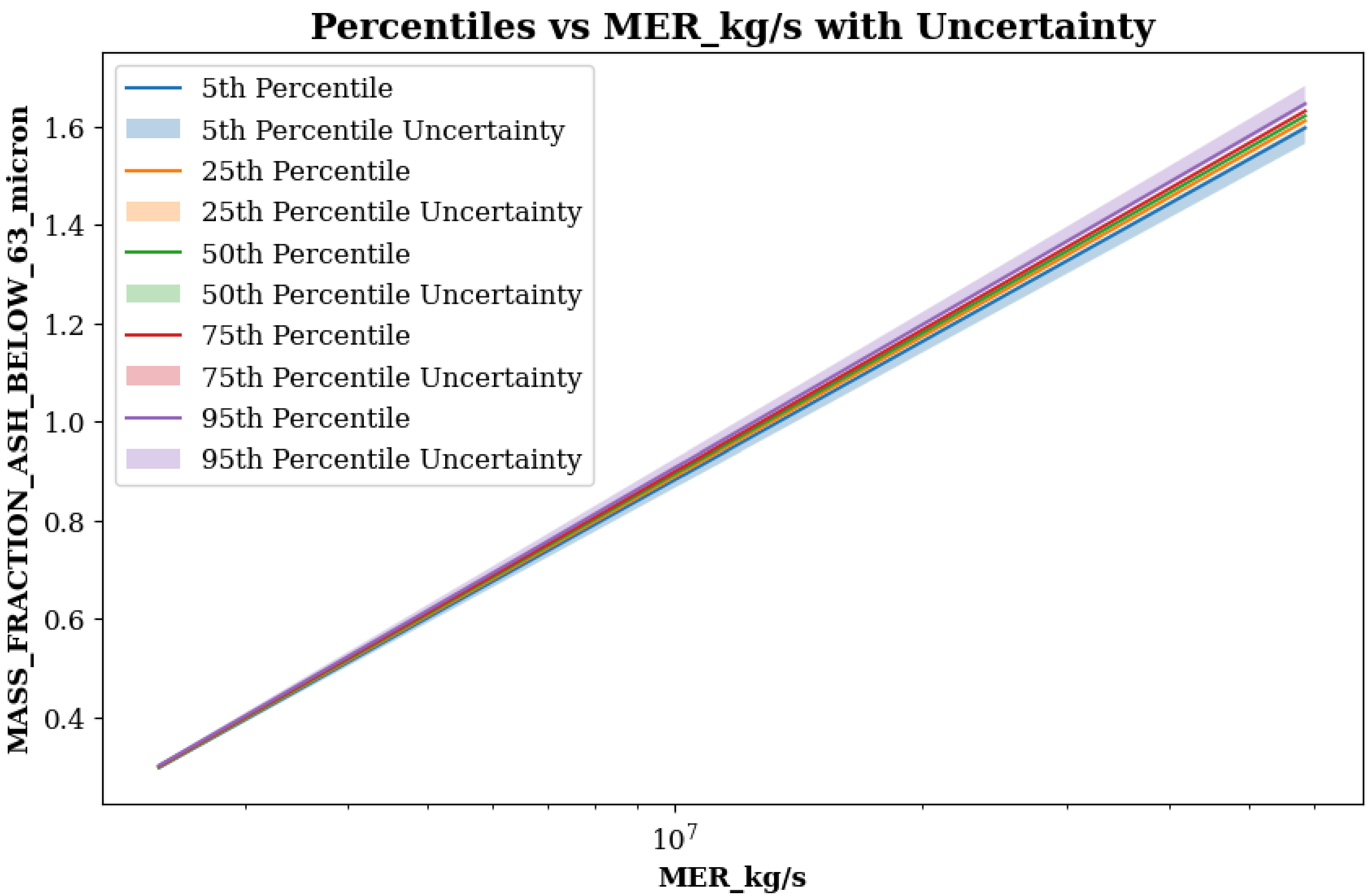
	Height_km.a.v.l	MERPercentile_5	Uncertainty_Lower_5	Uncertainty_Upper_5	MERPercentile_25	Uncertainty_Lower_25	Uncertainty_Uppe
0	5	59298.970586	54834.818641	60095.380949	61591.084214	61188.465025	61971.53
1	8	558116.631819	535593.067374	562847.030880	571064.654538	568801.956990	573189.57

In [55]:

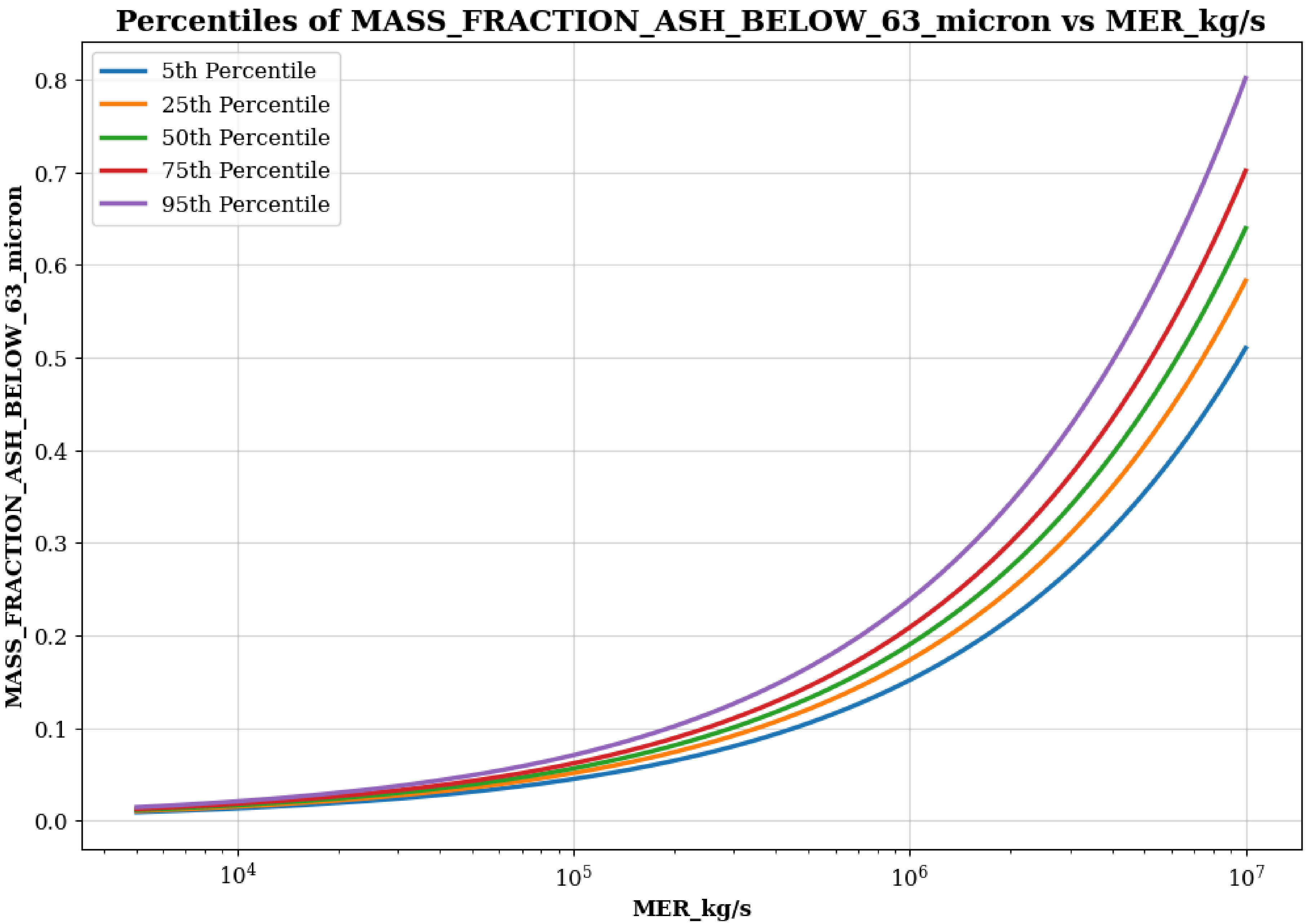
```
from ParticleSize_MER import Predict_ASH_BELOW_63_Micron

from vei import data_loader

#mastin_a=data_loader.load_Mastin_a(as_geodataframe=True)

psize_model=Predict_ASH_BELOW_63_Micron(mastin_a)

psize_model.set_xvar('MER_kg/s')
psize_model.set_yvar('MASS_FRACTION_ASH_BELOW_63_micron')


psize_model.calculate_percentiles_with_uncertainty(mer_list)
psize_model.predict_with_uncertainty(mer_list)

psize_model.plot_posterior_predictive()


# Visualize percentiles with uncertainty
psize_model.plot_percentiles_with_uncertainty(mer_list)

psize_model.plot_percentiles()

psize_predictions=psize_model.predict_with_uncertainty(mer_list)
```



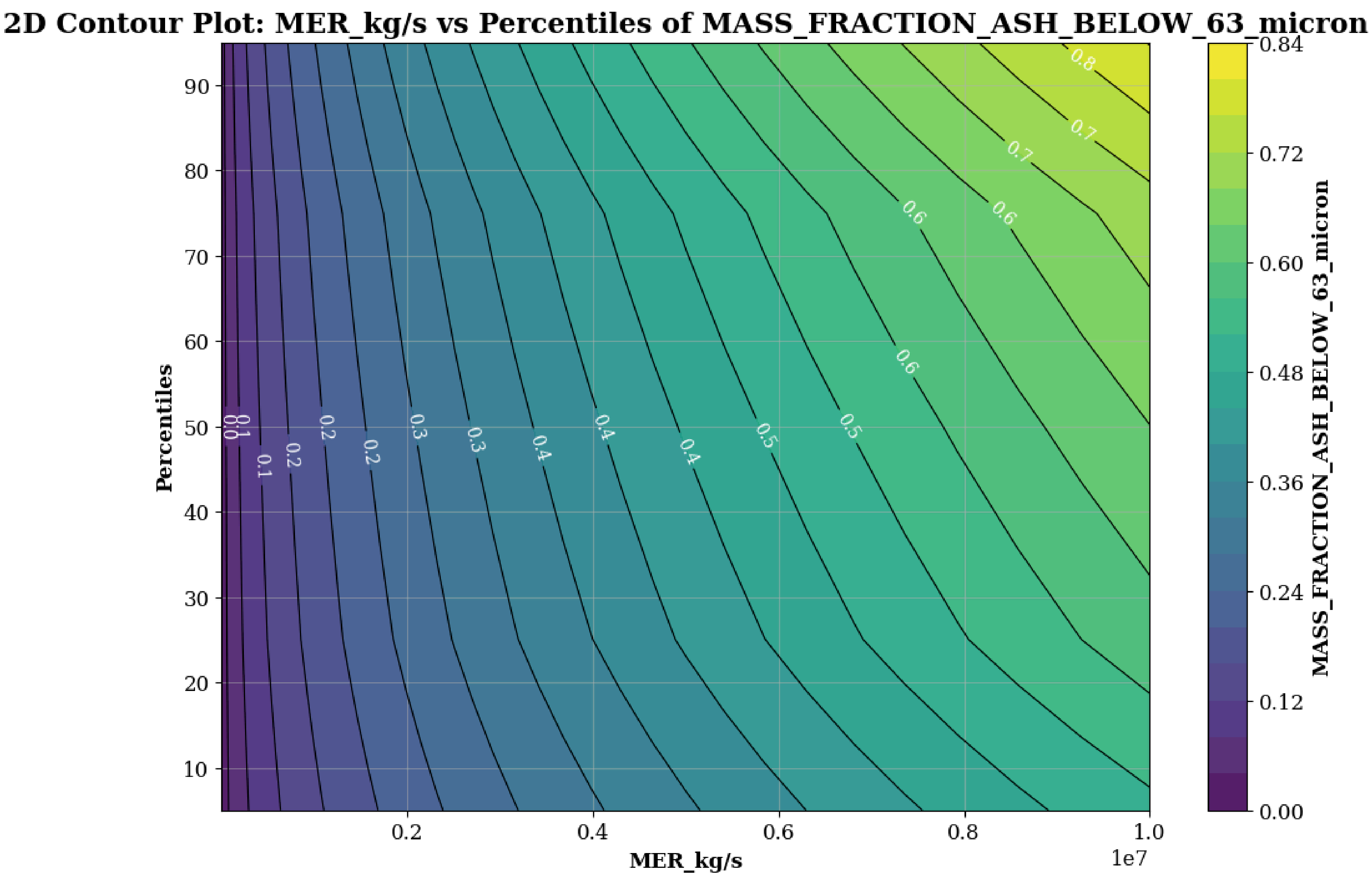
Posterior Predictive Plot
Mean Prediction
Predictive Interval
Data Points (n=1413)
MASS_FRACTION_ASH_BELOW_63_micron
10^0
10^{-1}
10^{-2}
10^4
10^5
10^6
10^7
MER_kg/s



Percentiles vs MER_kg/s with Uncertainty
5th Percentile
5th Percentile Uncertainty
25th Percentile
25th Percentile Uncertainty
50th Percentile
50th Percentile Uncertainty
75th Percentile
75th Percentile Uncertainty
95th Percentile
95th Percentile Uncertainty
MASS_FRACTION_ASH_BELOW_63_micron
1.6
1.4
1.2
1.0
0.8
0.6
0.4
10^7
MER_kg/s



Percentiles of MASS_FRACTION_ASH_BELOW_63_micron vs MER_kg/s
5th Percentile
25th Percentile
50th Percentile
75th Percentile
95th Percentile
MASS_FRACTION_ASH_BELOW_63_micron
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
MER_kg/s
10^4
10^5
10^6
10^7




```
In [56]: psize_predictions
```

Out[56]:

	MER_kg/s	MASS_FRACTION_ASH_BELOW_63_micron_Percentile_5	Uncertainty_Lower_5	Uncertainty_Upper_5	MASS_FRACTION_ASH_BE
0	2.356004e+06	0.296646	0.293821	0.297122	
1	5.856907e+07	1.596457	1.565323	1.602008	

In [57]:

```
columns_to_assign=list(psize_predictions.columns)
columns_to_assign=columns_to_assign[1:]

# Assuming `columns_to_assign` contains column names and `heights` and `psize_predictions` are DataFrames

heights.loc[:, columns_to_assign] = psize_predictions[columns_to_assign]


heights.to_csv('Final_prediction_results.csv')
```

In [58]:

```
psize_predictions
```

Out[58]:

	MER_kg/s	MASS_FRACTION_ASH_BELOW_63_micron_Percentile_5	Uncertainty_Lower_5	Uncertainty_Upper_5	MASS_FRACTION_ASH_BE
0	2.356004e+06	0.296646	0.293821	0.297122	
1	5.856907e+07	1.596457	1.565323	1.602008	