

Documentation of Steps – Weather Dataset

This document serves to record the procedures used when working with the dataset *WeatherHistory.csv* in Excel, SQL, and Power BI. The dataset was obtained from Kaggle.com. Each step is described, and some include screenshots. This work serves as a demonstration of my current data-handling skills and as a portfolio example for a junior data analyst position.

This document is intended to formally document the procedures employed during work processes.

Step 1: Data Loading

I loaded the dataset *weatherHistory.csv* into Power Query in Excel. The dataset contains 12 columns and 96,453 rows.

Nalezeno 12 řádků, 999x • Počítání řádků na horní 1000 řádek

Fig. 1: Loaded WeatherHistory dataset in Power Query (Excel)

The column names are as follows: *Formatted Date*, *Summary*, *Precip Type*, *Temperature (°C)*, *Apparent Temperature (°C)*, *Humidity*, *Wind Speed (km/h)*, *Wind Bearing (degrees)*, *Visibility (km)*, *Loud Cover*, *Pressure (millibars)*, *Daily Summary*.

Step 2: Setting Data Types

After checking the data types in individual columns, I found that most of them were set incorrectly. Therefore, I adjusted the data types — I set the date column to *Date/Time*, numeric columns to *Decimal Number* or *Int64*, and descriptive text columns to *Text*.

While converting numeric values, I encountered an error caused by different decimal separators. To ensure proper conversion, I used the *Using Locale* function and selected *English (United States)*. This allowed the data to load correctly and without errors.

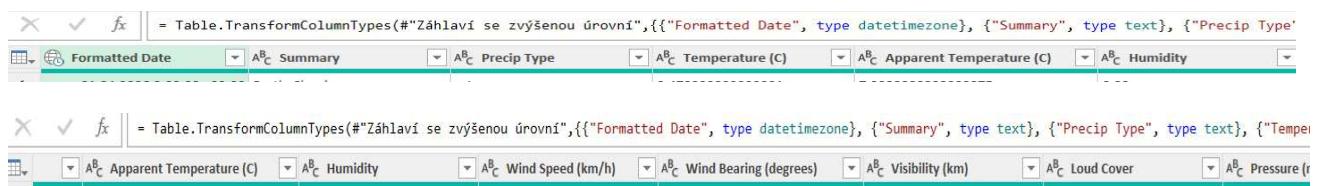


Fig. 2: Example of selected data types after loading the file



Fig. 3: Changing the locale for correct data type settings

A ^B _C Precip Type	▼	1.2 Temperature (C)	▼	1.2 Apparent Temperature (C)	▼	1.2 Humidity	▼
A ^B _C Precip Type	▼	1.2 Temperature (C)	▼	1.2 Apparent Temperature (C)	▼	1.2 Wind Speed (km/h)	▼

Fig. 4: Example of selected data types after adjustment

Step 3: Data Cleaning

3.1 Removing Duplicate Values

The dataset contained 24 duplicate records, corresponding to 48 rows in total (the original record plus its duplicate). I identified the duplicates using the *Keep Duplicates* function and then removed them. The final dataset contains 96,429 rows.

	Formatted Date	A ^B _C Summary	A ^B _C Precip Type
1	02.08.2010 16:00:00	Partly Cloudy	rain
2	02.08.2010 17:00:00	Partly Cloudy	rain
3	02.08.2010 15:00:00	Partly Cloudy	rain
4	02.08.2010 18:00:00	Partly Cloudy	rain
5	02.08.2010 14:00:00	Partly Cloudy	rain
6	02.08.2010 13:00:00	Partly Cloudy	rain
7	02.08.2010 12:00:00	Clear	rain
8	02.08.2010 19:00:00	Clear	rain
9	02.08.2010 11:00:00	Clear	rain
10	02.08.2010 10:00:00	Clear	rain
11	02.08.2010 9:00:00	Clear	rain
12	02.08.2010 20:00:00	Clear	rain
13	02.08.2010 8:00:00	Clear	rain
14	02.08.2010 21:00:00	Clear	rain
15	02.08.2010 22:00:00	Partly Cloudy	rain
16	02.08.2010 7:00:00	Clear	rain
17	02.08.2010 23:00:00	Clear	rain
18	02.08.2010 0:00:00	Clear	rain
19	02.08.2010 1:00:00	Clear	rain
20	02.08.2010 2:00:00	Clear	rain
21	02.08.2010 6:00:00	Clear	rain
22	02.08.2010 3:00:00	Clear	rain
23	02.08.2010 4:00:00	Clear	rain
24	02.08.2010 5:00:00	Clear	rain

Table 1: List of 24 Duplicate Rows

3.2 Checking Value Ranges

I checked the value ranges and missing values in each column. The data in the columns generally make sense — they fall within the expected ranges and do not contain negative values where they shouldn't.

However, in the Pressure column, I found unrealistic values where pressure was recorded as 0 in 1,288 rows. I decided to replace these values with null to prevent their inclusion in calculations.

In the Loud Cover column, all values are 0.

Out of the 12 columns, 8 contain numeric values — their minimum and maximum values are summarized in the tables below.

	ABC 123	Column	ABC 123	Minimum	ABC 123	Maximum	ABC 123
1		Temperature (C)		-21,82222222		39,90555556	
2		Apparent Temperature (C)		-27,71666667		39,34444444	
3		Humidity		0		1	
4		Wind Speed (km/h)		0		63,8526	
5		Wind Bearing (degrees)		0		359	
6		Visibility (km)		0		16,1	
7		Loud Cover		0		0	
8		Pressure (millibars)		0		1046,38	

Table 2: Value ranges in numeric columns before correcting unrealistic values in the Pressure column.

	ABC 123	Column	ABC 123	Minimum	ABC 123	Maximum	ABC 123
1		Temperature (C)		-21,82222222		39,90555556	
2		Apparent Temperature (C)		-27,71666667		39,34444444	
3		Humidity		0		1	
4		Wind Speed (km/h)		0		63,8526	
5		Wind Bearing (degrees)		0		359	
6		Visibility (km)		0		16,1	
7		Loud Cover		0		0	
8		Pressure (millibars)		973,78		1046,38	

Table 3: Final table of value ranges in numeric columns.

The dataset also contains three text columns (*Summary*, *Daily Summary*, and *Precip Type*). The number of unique categories in each column is summarized in the table below. In the *Precip Type* column, there are three possible values — *snow*, *rain*, and *null*. The handling of *null* values in this column is discussed in the next section.

ABC 123	Column	ABC 123	DistinctCount
1	Summary		27
2	Daily Summary		214
3	Precip Type		3

Table 4: Summary of the number of categories in the text columns

The last column, *Formatted Date*, contains date values — the date ranges are summarized in the table below. From the data, it is evident that data collection took place over a period of 10 years.

ABC 123	Column	ABC 123	Minimum	ABC 123	Maximum
1	Formatted Date		01.01.2006 0:00:00		31.12.2016 23:00:00

Table 5: Summary of date ranges in the Formatted Date column

3.3 Checking Missing Values

I found that the dataset is fairly complete. *Null* values appeared only in the *Precip Type* column, where 517 *null* entries were identified. Since this column records the type of precipitation, I assumed that these *null* values indicate that no precipitation occurred on that day.

Therefore, I replaced the *null* values with *no precipitation*. After this adjustment, the column contains three possible values — *snow*, *rain*, and *no precipitation*.

```
.e.SelectRows(#"Změněný typ", each true)
```

The screenshot displays two side-by-side context menus from a Power BI application. Both menus are for the 'Precip Type' column, as indicated by the header at the top of each window. The left menu is in Czech, and the right menu is in English. Both menus include standard options like 'Seřadit vzestupně' (Sort Ascending), 'Seřadit sestupně' (Sort Descending), 'Zrušit řazení' (Unsort), 'Vymazat filtr' (Clear Filter), 'Odebrat prázdné' (Remove Blanks), and 'Filtry textu' (Text Filters). Below these are 'Hledat' (Search) and 'Filtrovat' (Filter) sections. In the 'Hledat' section, there is a list of checked items: '(Vybrat vše)' (Select All), 'null', 'rain', and 'snow'. At the bottom of each menu are 'OK' and 'Zrušit' (Cancel) buttons.

Table 6: Replaced null values in the Precip Type column

The dataset is now cleaned and verified in terms of data types, duplicates, missing and unrealistic values, as well as categorical variables. It is ready to be saved and further processed in SQL or Power BI. The file was saved in CSV format.

Step 4: SQL Analysis (MotherDuck)

After cleaning and exporting the dataset from Excel, I imported it into the MotherDuck SQL environment. The purpose of this step was to explore the data using SQL queries and prepare analytical summaries that were later visualized in Power BI.

4.1 Loading the Dataset

The cleaned dataset was uploaded to MotherDuck in .csv format.

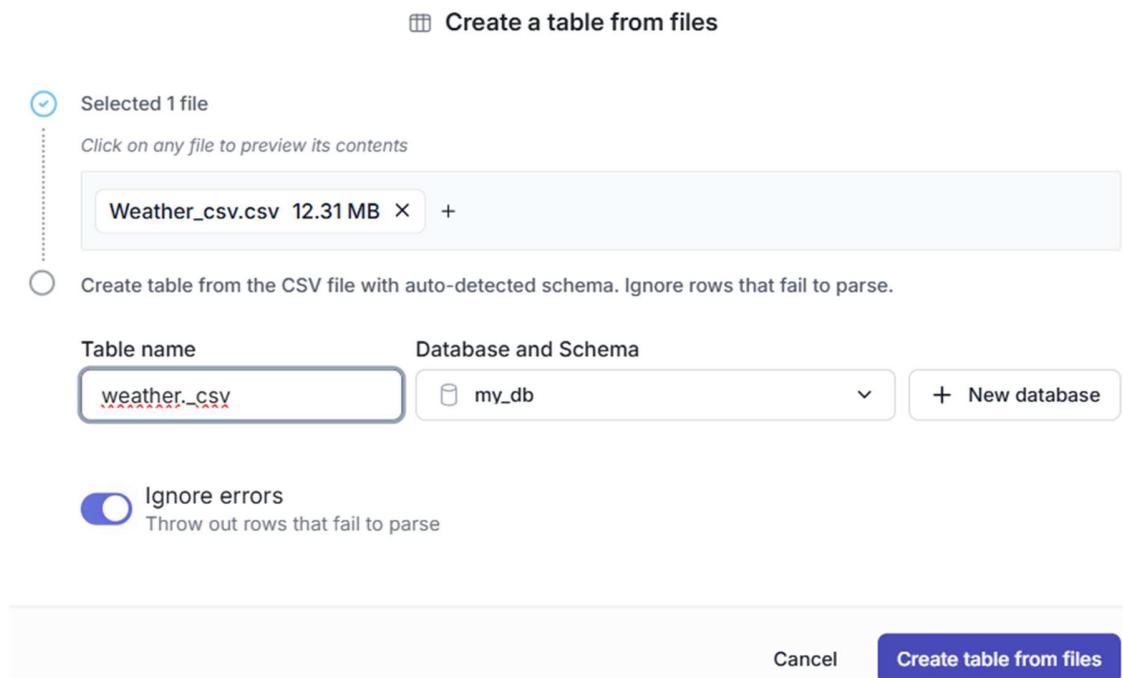


Fig. 5: Uploading the weather_csv file to MotherDuck.

4.2 Checking Table Structure

To confirm column names and data types, I used:

```
PRAGMA table_info('weather_csv');
```

The table contained **12 columns**, consistent with the original dataset.

The screenshot shows a database interface with a command-line input field containing the SQL command `PRAGMA table_info('weather_csv');`. Below the command, it says "12 rows returned in 40ms, queued for 37ms". The main area displays a table with 12 rows of information about the columns of the `weather_csv` table. The table has columns: `cid`, `name`, `type`, `notnull`, `dflt_value`, and `pk`. The data is as follows:

	cid	T name	T type	T _F notnull	T dflt_value	T _F pk
1	0	Formatted Date	VARCHAR	false	NULL	false
2	1	Summary	VARCHAR	false	NULL	false
3	2	Precip Type	VARCHAR	false	NULL	false
4	3	Temperature (C)	VARCHAR	false	NULL	false
5	4	Apparent Temperature (C)	VARCHAR	false	NULL	false
6	5	Humidity	VARCHAR	false	NULL	false
7	6	Wind Speed (km/h)	VARCHAR	false	NULL	false
8	7	Wind Bearing (degrees)	BIGINT	false	NULL	false
9	8	Visibility (km)	VARCHAR	false	NULL	false
10	9	Loud Cover	BIGINT	false	NULL	false
11	10	Pressure (millibars)	VARCHAR	false	NULL	false
12	11	Daily Summary	VARCHAR	false	NULL	false

Fig. 6: Information about the `weather_csv` table after it was uploaded

Using the **PRAGMA** command, I identified that most columns were imported with incorrect data types. Additionally, decimal commas were used instead of decimal points. I resolved these issues by applying the **CAST** command to set the correct data types and using the **REPLACE()** function to substitute commas with dots.

To convert date and time information stored as text into a proper timestamp format, I used the **STRPTIME()** function. This function parses a string according to a specified date-time format (in this case '`%d.%m.%Y %H:%M`') and returns a SQL-compatible **TIMESTAMP** value.

```

1 CREATE OR REPLACE TABLE weather_clean AS
2 SELECT
3     STRPTIME("Formatted Date", '%d.%m.%Y %H:%M') AS datetime,
4     "Summary",
5     "Precip Type",
6     "Wind Bearing (degrees)",
7     CAST(REPLACE("Temperature (C)", ',', '.') AS DOUBLE) AS temperature_c,
8     CAST(REPLACE("Apparent Temperature (C)", ',', '.') AS DOUBLE) AS apparent_temp_c,
9     CAST(REPLACE("Humidity", ',', '.') AS DOUBLE) AS humidity,
10    CAST(REPLACE("Wind Speed (km/h)", ',', '.') AS DOUBLE) AS wind_speed_kmh,
11    CAST(REPLACE("Visibility (km)", ',', '.') AS DOUBLE) AS visibility_km,
12    CAST(REPLACE("Pressure (millibars)", ',', '.') AS DOUBLE) AS pressure_mb,
13    "Loud Cover",
14    "Daily Summary"
15 FROM weather_csv;

```

Fig. 7: Query for adjusting data types in the **weather_csv** dataset.

After verifying the updated data types with the **PRAGMA** command, I confirmed that all conversions were correct.

```

1 PRAGMA table_info('weather_clean');

```

12 rows returned in 44ms, queued for 62ms

	123	cid	T name	T type	T _F notnull	T dflt_value	T _F pk
1		0	datetime	TIMESTAMP	false	NULL	false
2		1	Summary	VARCHAR	false	NULL	false
3		2	Precip Type	VARCHAR	false	NULL	false
4		3	Wind Bearing (degrees)	BIGINT	false	NULL	false
5		4	temperature_c	DOUBLE	false	NULL	false
6		5	apparent_temp_c	DOUBLE	false	NULL	false
7		6	humidity	DOUBLE	false	NULL	false
8		7	wind_speed_kmh	DOUBLE	false	NULL	false
9		8	visibility_km	DOUBLE	false	NULL	false
10		9	pressure_mb	DOUBLE	false	NULL	false
11		10	Loud Cover	BIGINT	false	NULL	false
12		11	Daily Summary	VARCHAR	false	NULL	false

Fig. 8: Table information for **weather_clean** after data type adjustments

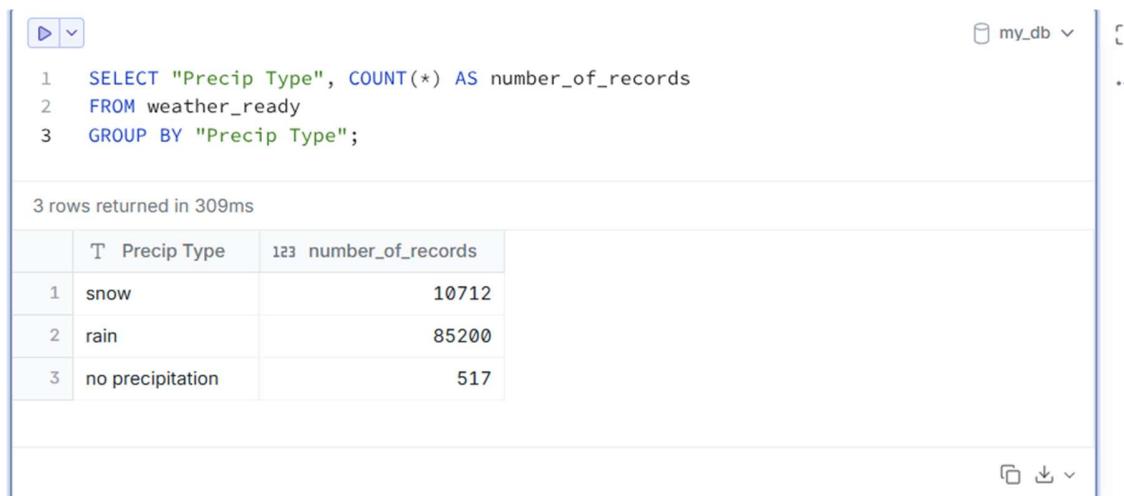
4.3 Exploratory Queries

I created a series of 10 analytical SQL queries, each focusing on a specific question related to weather behavior.

These queries were used to prepare data summaries for visualization in Power BI.

Query 1 — Number of Records by Precipitation Type

Counts the number of weather records for each type of precipitation.



The screenshot shows a SQL query interface with the following details:

- Query ID: 1
- Database: my_db
- Query Text:

```
1  SELECT "Precip Type", COUNT(*) AS number_of_records
2  FROM weather_ready
3  GROUP BY "Precip Type";
```
- Execution Time: 309ms
- Result Set:

T	Precip Type	number_of_records
1	snow	10712
2	rain	85200
3	no precipitation	517

Fig. 9: Query 1

Query 2 — Average Temperature by Weather Condition

Calculates the average temperature for each weather condition (summary).

The screenshot shows a database query interface with the following details:

- Query Text:

```
1 SELECT "Summary", round(AVG(temperature_c)) AS average_temperature_C
2 FROM weather_clean
3 GROUP BY "Summary"
4 ORDER BY average_temperature_C DESC;
```
- Execution Result:

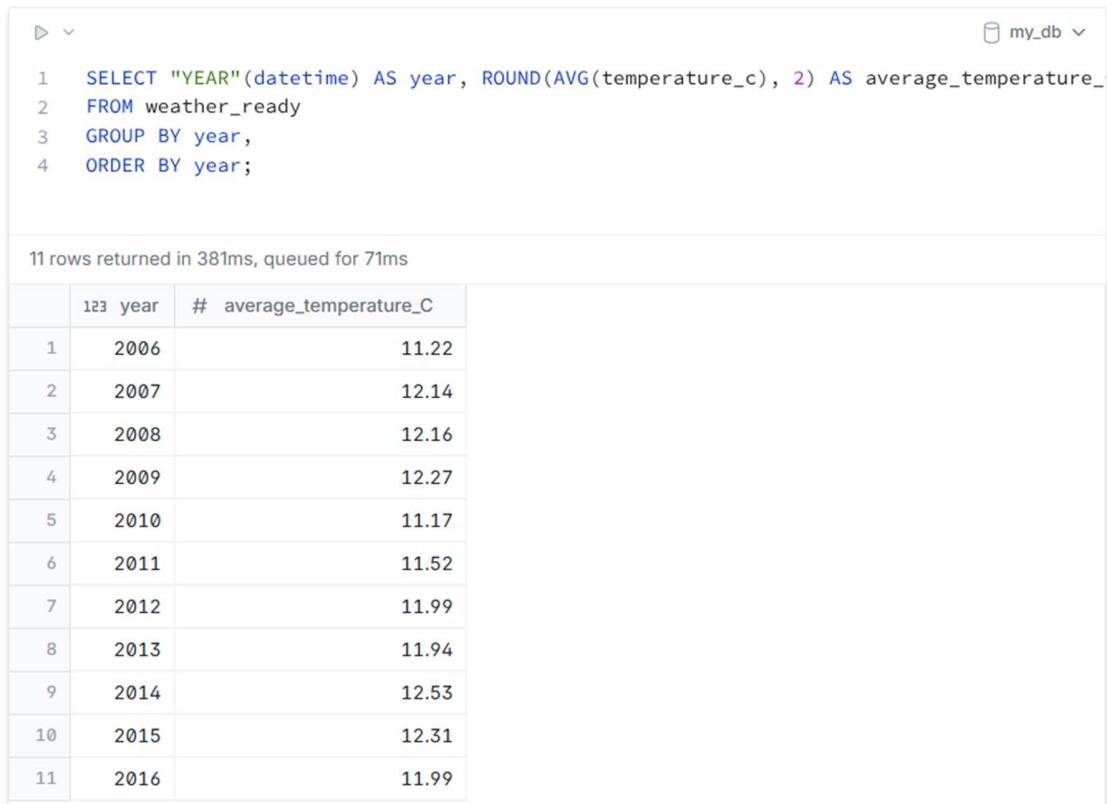
27 rows returned in 334ms, queued for 96ms

T	Summary	# average_temperature_C
1	Dry	29
2	Windy and Dry	27
3	Dry and Mostly Cloudy	27
4	Dry and Partly Cloudy	27
5	Humid and Overcast	22
6	Humid and Partly Cloudy	22
7	Humid and Mostly Cloudy	21
8	Breezy and Dry	21
9	Partly Cloudy	16
10	Mostly Cloudy	13
11	Breezy and Partly Cloudy	12
12	Clear	12
13	Windy and Foggy	12
14	Windy and Mostly Cloudy	12

Fig. 10: Query 2

Query 3 — Average Yearly Temperature (2006-2016)

Calculates the average temperature for each year in the dataset (2006–2016).



The screenshot shows a database query interface. At the top, there is a dropdown menu with a triangle icon and the text "my_db". Below the query window, a message says "11 rows returned in 381ms, queued for 71ms". The query itself is:

```
1 SELECT "YEAR"(datetime) AS year, ROUND(AVG(temperature_c), 2) AS average_temperature_
2 FROM weather_ready
3 GROUP BY year,
4 ORDER BY year;
```

The result table has two columns: "year" and "average_temperature_C". The data is as follows:

	year	# average_temperature_C
1	2006	11.22
2	2007	12.14
3	2008	12.16
4	2009	12.27
5	2010	11.17
6	2011	11.52
7	2012	11.99
8	2013	11.94
9	2014	12.53
10	2015	12.31
11	2016	11.99

Fig. 11: Query 3

Query 4 — Average Temperature by Year and Month

Calculates the average temperature grouped by year and month.

The screenshot shows a database query interface with the following details:

- Query Text:

```
1  SELECT "YEAR"(datetime) AS year, "MONTH"(datetime) AS month, ROUND(AVG(temperature_c))
2  FROM weather_ready
3  GROUP BY year, month
4  ORDER BY year, month;
```
- Execution Result:

132 rows returned in 424ms, queued for 43ms

#	year	month	average_temperature_C
1	2006	1	-1.67
2	2006	2	-0.06
3	2006	3	4.53
4	2006	4	12.63
5	2006	5	15.67
6	2006	6	19.33
7	2006	7	23.58
8	2006	8	19.49

Fig. 12: Query 4

Query 5 — Average Humidity by Weather Condition

Calculates the average humidity for each weather condition.



The screenshot shows a database query interface. At the top, there are navigation buttons (refresh, back, forward) and a dropdown menu labeled "my_db". Below the interface, the query code is displayed:

```
1 SELECT "Summary", ROUND(AVG(humidity * 100), 1) AS average_humidity_percent
2 FROM weather_ready
3 GROUP BY "Summary"
4 ORDER BY average_humidity_percent DESC;
```

Below the code, a message indicates "27 rows returned in 439ms, queued for 121ms". A table is shown with the following data:

#	Summary	average_humidity_percent
1	Foggy	95.1
2	Rain	94.7
3	Breezy and Foggy	93.9
4	Windy and Foggy	90
5	Light Rain	88.8
6	Humid and Overcast	88.1
7	Humid and Mostly Cloudy	87.4
8	Drizzle	86.8

Fig. 13: Query 5

Query 6 — Average Temperature and Average Humidity by Weather Condition

Calculates the average temperature and average humidity for each weather condition.



The screenshot shows a database query interface with the following details:

- Query Text:

```
1 SELECT "Summary" AS weather_condition,
2 ROUND(AVG(temperature_c), 1) AS average_temperature_C,
3 ROUND(AVG(humidity * 100), 1) AS average_humidity_percent
4 FROM weather_ready
5 GROUP BY weather_condition
6 ORDER BY average_temperature_C DESC;
```
- Execution Results:

27 rows returned in 411ms, queued for 114ms

#	weather_condition	# average_temperature_C	# average_humidity_percent
1	Dry	29.1	23.1
2	Windy and Dry	27.2	24.1
3	Dry and Mostly Cloudy	26.8	24.1
4	Dry and Partly Cloudy	26.6	24.1
5	Humid and Partly Cloudy	21.6	84.1
6	Humid and Overcast	21.5	88.1
7	Breezy and Dry	21.1	24.1

Fig. 14: Query 6

Query 7 — Min and Max Yearly Temperatures (2006–2016)

Shows the minimum and maximum temperatures recorded for each year from 2006 to 2016.



The screenshot shows a database query interface with the following details:

- Query ID: 1
- Database: my_db
- SQL Query:

```
1 SELECT "YEAR"(datetime) AS year, ROUND(MIN(temperature_c), 1) AS min_temperature_C,
2 |ROUND (MAX(temperature_c),1) AS max_temperature_C
3 FROM weather_ready
4 GROUP BY year,
5 ORDER BY year DESC;
```
- Execution Result:

11 rows returned in 449ms, queued for 90ms

#	year	# min_temperature_C	# max_temperature_C
1	2016	-10.1	34.8
2	2015	-13.1	37.2
3	2014	-13.3	33.9
4	2013	-9	37.9
5	2012	-21.8	38.9
6	2011	-11.7	37.8
7	2010	-15.5	34.9
8	2009	-16.7	36.1
9	2008	-11.1	37.8
10	2007	-10.2	39.9
11	2006	-14.1	34

Fig. 15: Query 7

Query 8 — Average Visibility by Weather Condition

Calculates the average visibility for each weather condition.

The screenshot shows a database query interface with the following details:

- Query Text:

```
1 SELECT "Summary" AS weather_condition, ROUND(AVG(visibility_km), 1) AS average_visibility_km
2 FROM weather_ready
3 GROUP BY weather_condition
4 ORDER BY average_visibility_km DESC;
```
- Execution Results:

27 rows returned in 392ms, queued for 129ms

T	weather_condition	# average_visibility_km
1	Partly Cloudy	11.8
2	Breezy and Mostly Cloudy	11.5
3	Windy and Partly Cloudy	11.5
4	Dangerously Windy and Partly Cloudy	11.4

Fig. 16: Query 8

Query 9 — Average Comfort Gap by Month

Calculates the average difference between actual and apparent temperature (comfort gap) for each month.

The screenshot shows a database query interface with the following details:

- Query Text:

```
1 SELECT "MONTH"(datetime) AS month,
2 ROUND(AVG(ABS(temperature_c - apparent_temp_c)),2) AS average_comfort_gap_C
3 FROM weather_ready
4 GROUP BY month
5 ORDER BY month;
```
- Execution Results:

12 rows returned in 493ms, queued for 126ms

123	month	# average_comfort_gap_C
1	1	2.75
2	2	2.73
3	3	1.83

Fig. 17: Query 9

Query 10 — Average Temperature by Hour of Day

Shows how the average temperature changes throughout the day, grouped by hour.



The screenshot shows a database interface with a query editor and a results grid. The query editor contains the following SQL code:

```
1 SELECT "HOUR"(datetime) AS hour,ROUND(AVG(temperature_c), 2) AS average_temperature_C
2 FROM weather_ready
3 GROUP BY hour
4 ORDER BY hour;
```

Below the code, a message indicates: "24 rows returned in 440ms, queued for 139ms". The results grid displays four rows of data:

	hour	average_temperature_C
1	0	9.47
2	1	9.05
3	2	8.74
4	3	8.32

Fig. 18: Query 10

The prepared **SELECT** queries were exported as **CSV** files, then uploaded to **Power BI** for visualization.

Název	Stav	Datum změny	Typ	Velikost
Query 1 - Number of Records by Precipitation Type	✓	12.10.2025 10:22	Textový soubor s oddělovačí Microsoft Excelu	1 kB
Query 2 - Average temperature by weather condition	✓	12.10.2025 10:38	Textový soubor s oddělovačí Microsoft Excelu	1 kB
Query 3 - Average yearly temperature	✓	12.10.2025 14:55	Textový soubor s oddělovačí Microsoft Excelu	1 kB
Query 4 - Average temperature by year and month	✓	12.10.2025 15:21	Textový soubor s oddělovačí Microsoft Excelu	2 kB
Query 5 - Average humidity by weather condition	✓	12.10.2025 16:35	Textový soubor s oddělovačí Microsoft Excelu	1 kB
Query 6 - Temperature vs humidity by weather condition	✓	12.10.2025 17:06	Textový soubor s oddělovačí Microsoft Excelu	1 kB
Query 7 - Min and max temperature by year	✓	21.10.2025 17:27	Textový soubor s oddělovačí Microsoft Excelu	1 kB
Query 8 - Average visibility by weather condition	✓	21.10.2025 18:19	Textový soubor s oddělovačí Microsoft Excelu	1 kB
Query 9 - Comfort gap (difference between real and perceived temperature)	✓	21.10.2025 18:33	Textový soubor s oddělovačí Microsoft Excelu	1 kB
Query 10 - Average temperature by hour of day	✓	21.10.2025 19:14	Textový soubor s oddělovačí Microsoft Excelu	1 kB

Fig. 19: Queries 1–10 in CSV format, prepared for export to Power BI

Step 5 – Power BI visualization

The visualizations are available in a separate Power BI file.