

# COMPUTATIONAL INTELLIGENCE IN THE ANALYSIS OF LOCAL CLIMATE AND ITS PREDICTIONS

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**Abstract.** *The purpose of this work is to present computational intelligence tools implemented by Wolfram Language and included in Wolfram|Alpha and Wolfram Mathematica designed to weather and climate data analysis. In this work, I showed that climate problems in structural mechanics, urban planning, and building physics can be analyzed within the Wolfram Language. Ostrava was taken as a sample place of interest. It is also possible to estimate changes in climatic parameters in the future. The results presented could hopefully be an inspiration for other researchers dealing with stochastic and statistical problems in modeling mechanical problems.*

## Keywords

*Local Climate, Computational Intelligence, Wolfram Language, Mathematica, Wolfram|Alpha.*

## 1. Introduction

The idea of this contribution is based on an article by colleagues from the VŠB Technical University of Ostrava and I [8]. Its origin was in a lecture for civil engineering students in 2019. This lecture was given during my visit to Erasmus+ International Week at VŠB-TUO. In this lecture, among other problems, I showed that climate problems can be analyzed within Wolfram Mathematica. Professor Petr Konečný asked me to collect some climatic data for a certain period in the Ostrava region, and they were used for some structural analyzes. Here, we paid attention to the climate, but there were a few different aspects that were analyzed in [8] where a deeper evaluation of the

data was carried out, such as statistical classification and further evaluation.

Mathematica and other computer algebra systems are used to help in structural analysis. Examples are [1] or [4].

The purpose of this work is to present computational intelligence tools provided by Wolfram Research Inc [7] in Wolfram Mathematica [5] and Wolfram|Alpha [6]. The most useful thing is to help predict what may happen in the future, since buildings must survive for many years. Estimating the climatic load in structural mechanics requires statistical tools.

The use of data collected in Wolfram|Alpha and Wolfram|Alpha and Wolfram Data Repository [27] becomes increasingly popular. Other examples for many scientific and engineering purposes may be found there.

## 2. Global warming versus local climate

We will start with the problem that becomes one of the most important for mass media and international politics. Therefore, the knowledge about global warming is vast. Wolfram|Alpha asked about it returns information shown in Fig. 1.

For the researcher or engineer who analyzes an existing or designed structure, it is important to have knowledge of the local climate. Changes in it are also important for future updates in design standards (Eurocodes). Additionally, for buildings and urban design, information on the direction in which the wind blows in a certain place is the most important is also important.

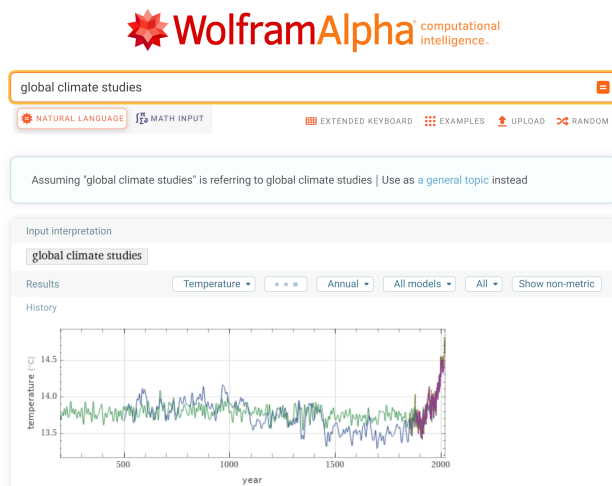


Fig. 1: Global climate changes according to Wolfram|Alpha.

### 3. What Wolfram|Alpha knows about Ostrava climate?

If we open a page [www.wolframalpha.com](http://www.wolframalpha.com) in any web browser and make an inquiry Ostrava climate, we will get the following answer, Fig. 2.

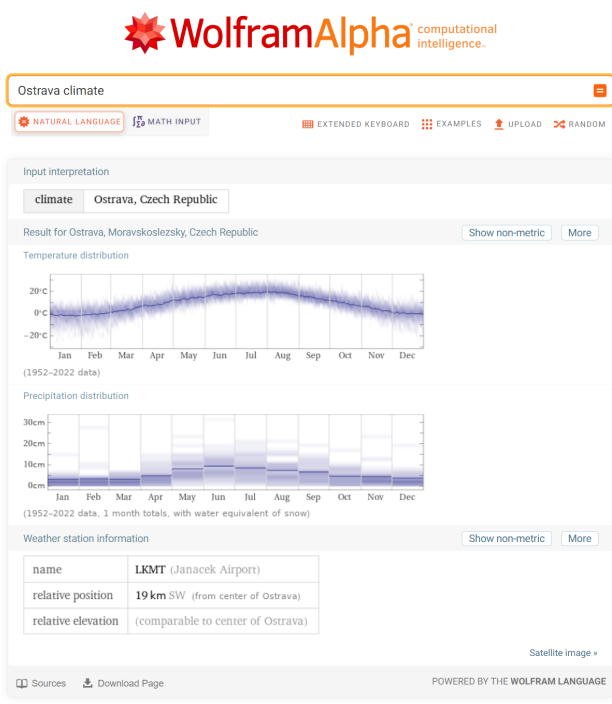


Fig. 2: Ostrava climate according to Wolfram|Alpha.

As we can see, a general date for temperature and precipitation is given within a year. We can ask about certain data in different periods. Sometimes, in case of expertise of existing structures, we are interested in what temperature was on the building site during

construction of analyzed elements, say, cast on site. Wolfram|Alpha will give us the answer that at the end of January 1999 a temperature below  $-10^{\circ}\text{C}$  was observed and we have an explanation for the damage, Fig. 3.

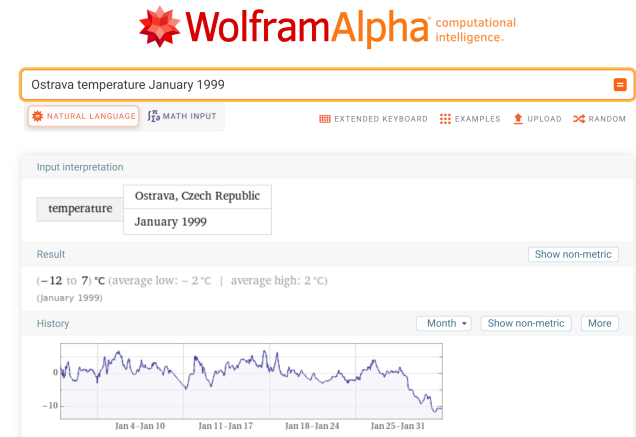


Fig. 3: Temperature in Ostrava in January 1999

If we ask, for example, air pressure in Ostrava 1951 to 2022 and the answer also gives information about some other characteristics of the climate, see Fig. 4. The diagrams provided show that on Wolfram servers they stored data from 1951. There are some gaps, but some trends in climate change can be observed.

The advantage of Wolfram|Alpha is that we can use natural language for inquiries.

Wolfram|Alpha can be called within Wolfram Mathematica. Mathematica itself has more advanced tools for data analysis.

### 4. Wind speed

Wolfram|Alpha asked about the wind speed in Ostrava gives the following answer, see Fig. 5.

If we want to do a more advanced analysis, we should use Wolfram Mathematica. The function **WindSpeedData** [13] can be used to analyze these data in Wolfram language. The following code takes these data from Wolfram servers and converts units from standard  $\text{km/h}$  to  $\text{m/s}$ . Data are stored as **TimeSeries** [14].

```
data = UnitConvert[WindSpeedData[Ostrava CITY,
  {Mon 1 Jan 1900, Tue 3 May 2022}], All],
  "Meters" / "Seconds"]
```

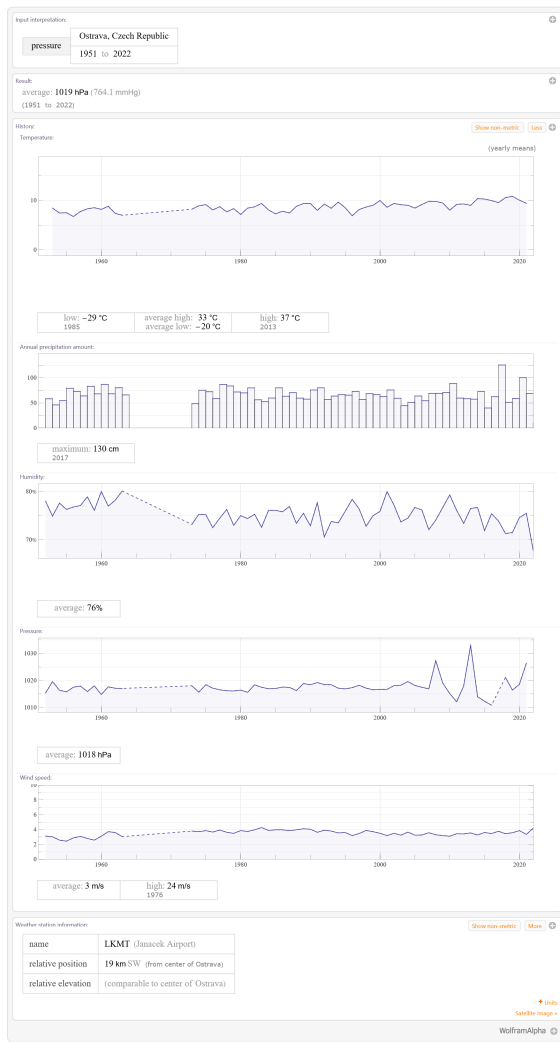


Fig. 4: What more Wolfram|Alpha knows about climate in Ostrava?

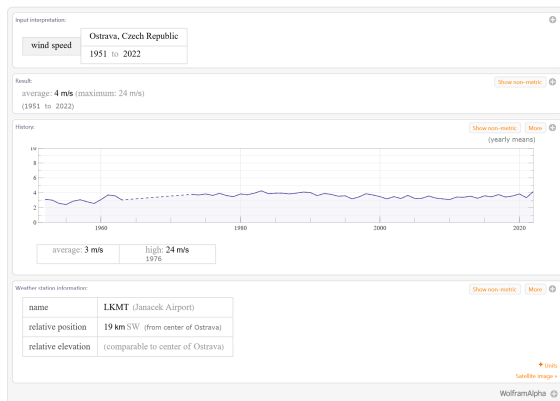


Fig. 5: Wind speed in Ostrava 1951–2022 according to Wolfram|Alpha.

Mathematica has many tools for time series analysis. For example, having these data stored, we can see how many wind speed data were collected in years; see Fig. 6. It can be done with the following function **DateHistogram** [23].

```
DateHistogram[data, 71,
GridLines -> {Automatic, Table[2500 i, {i, 1, 7}]},
AxesLabel -> {"year", "measurements"}]
```

Figure 6 shows that the climatic observatory at Janáček Airport began intensive measurement at the end of the 20<sup>th</sup> century. It also refers to other measurements, for example, the air pressure shown in Fig. 10.

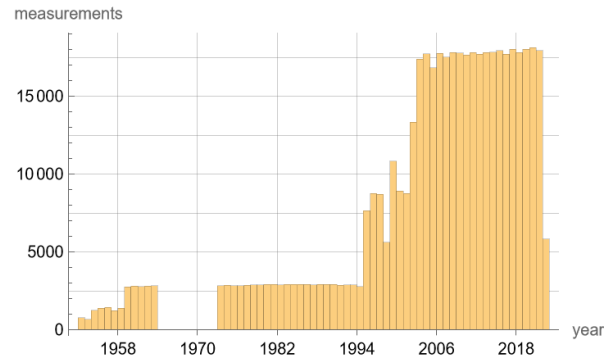


Fig. 6: Date histogram of recorded wind speed measurements on Wolfram data center in Ostrava 1951–2022.

The function **Histogram** [24] has been used to draw a distribution of wind speed on the scale of the density function of the probability function. It can be seen that the normal distribution cannot be used in this case. Fortunately, the Mathematica function **FindDistribution** [20] can automatically find the most suitable distribution and estimate its parameters. Mathematica has many integrated distribution functions. In that case **WeibullDistribution** [19] was applied. The result is shown in Fig. 7.

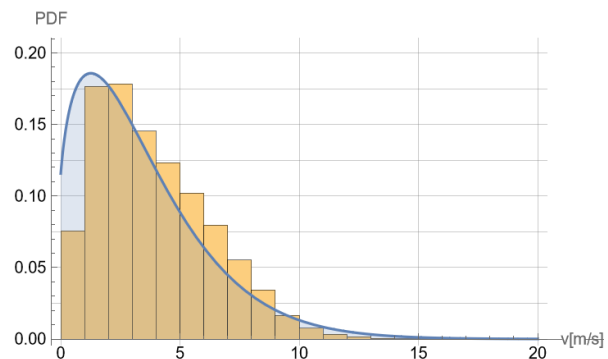


Fig. 7: Histogram wind speed in Ostrava 1951–2022 estimated by Weibull Distribution with  $\alpha = 1.3475$ ,  $\beta = 3.95005$  and  $\mu = -0.184607$

Weibull distribution has the following function PDF (1):

$$\text{PDF}(\alpha, \beta, \mu, x) := \begin{cases} \frac{\alpha e^{-\left(\frac{x-\mu}{\beta}\right)^\alpha} \left(\frac{x-\mu}{\beta}\right)^{\alpha-1}}{\beta} & x > \mu \\ 0 & x \leq \mu \end{cases} \quad (1)$$

Figure 7 shows that most of the wind speed values are below  $10\text{m/s}$ . Speed exceeding  $15\text{m/s}$  is very rare. The maximum value  $24\text{m/s}$  has been observed only once since 1951 and within 501249 measurements. This is less than the Fundamental Basic Wind Velocity equal to  $25\text{m/s}$  given in the Czech Republic Annex to Eurocode 1-4 [3]. This means that the design rules used in Czechia are probably conservative enough.

It should be noted that the data analyzed above were recorded recently in intervals of 30 minutes in the conditions of terrain described in EN1991-1-4 (airport), but we cannot be sure if it is the 10 minutes mean wind velocity. More details can be obtained from the weather station.

## 5. Wind direction

For proper building design, urban planning, and ventilation, the direction of the wind is also very important.

The function **WeatherData** [12] with the option **"WindDirection"** can be used to obtain these data. This is an alternative to the dedicated function **WindDirectionData** [13].

```
WeatherData[{"Ostrava CITY", "WindDirection",
  {Mon 1 Jan 1900, Sun 1 May 2022}}]
```

According to the data stored by Wolfram Research Inc. the most common wind direction is due south-west, it is shown in Fig. 8. In this drawing, a function **SmoothHistogram**[26] has been used to accompany the traditional bar chart histogram.

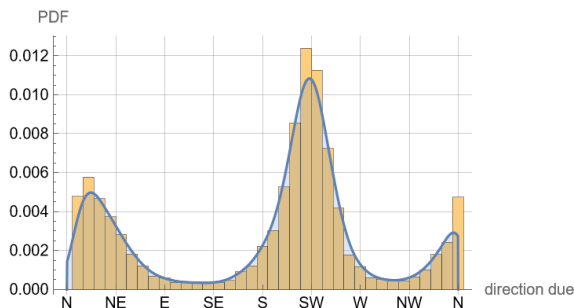


Fig. 8: Histogram of wind direction in Ostrava 1951–2022.

## 6. Relative humidity

Relative humidity is a quantity bounded by the interval  $(0, 1)$ . In Ostrava, its distribution according to the measurements is shown in Fig. 9.

For such a bounded quantity, Mathematica has, among others, the non-central Beta distribution. [17].

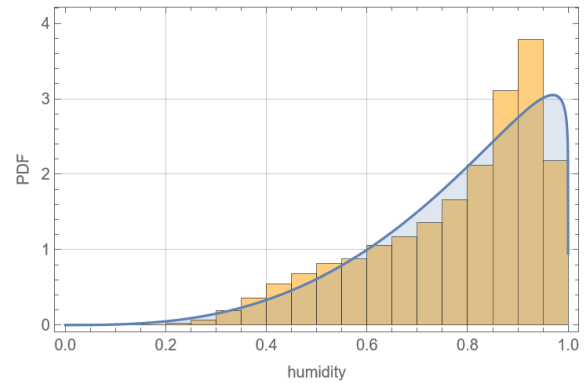


Fig. 9: Histogram of relative humidity in Ostrava 1951–2022 estimated by Noncentral Beta distribution with  $\alpha = 3.80157$ ,  $\beta = 1.0881$ ,  $\gamma = 3.59188 \times 10^{-9}$

Its parameters can be computed with **FindDistributionParameters** [9].

```
FindDistributionParameters[hum,
  NoncentralBetaDistribution[α, β, γ]]
```

```
{α → 3.80154, β → 1.08809, γ → 3.23899 × 10-15}
```

This distribution has a very sophisticated expression that describes the probability density function (2):

$$\text{PDF}(\alpha, \beta, \gamma, x) := \begin{cases} \frac{e^{-\delta/2} x^{\alpha-1} (1-x)^{\beta-1} {}_1F_1(\alpha+\beta; \alpha; \frac{x\delta}{2})}{B(\alpha, \beta)} & 0 < x < 1 \\ 0 & \text{Otherwise} \end{cases} \quad (2)$$

where  ${}_1F_1(a; b; z)$  is the Kummer confluent hypergeometric function [25] and  $B(a, b)$  is the Euler beta function [22].

## 7. Air pressure

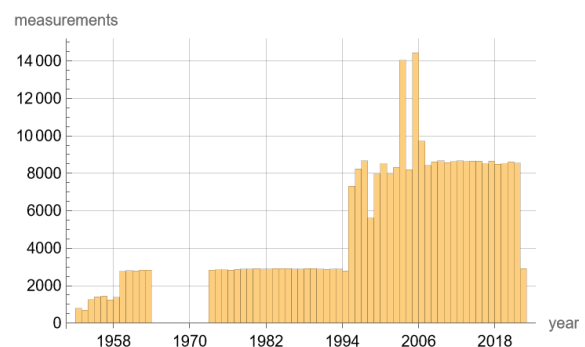
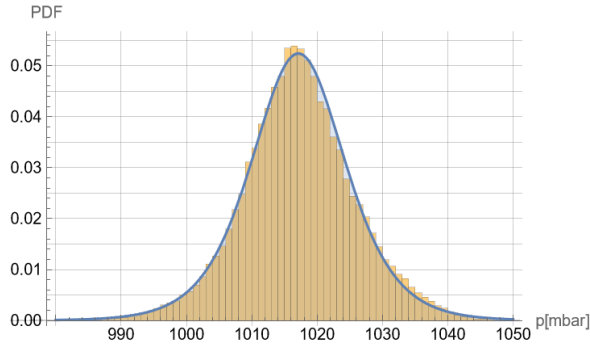


Fig. 10: Histogram of recorded air pressure measurements on Wolfram data center in Ostrava 1951–2022.

Air pressure seems to have a histogram distributed in a way similar to the normal distribution (Gauss) used the most frequently by researchers. Mathematica has

instead proposed the logistic distribution. Figure 11 shows that really **LogisticDistribution** [15] fits the histogram almost perfectly.

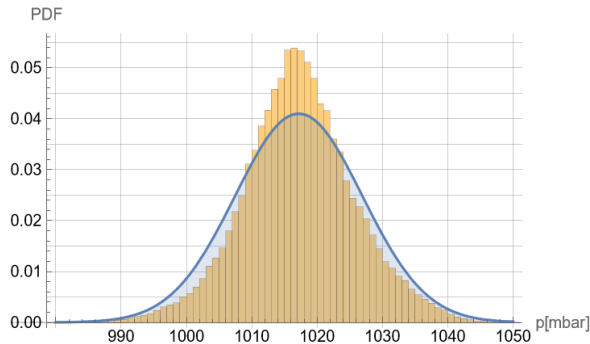


**Fig. 11:** Histogram of probability density function of air pressure in Ostrava 1.1.1951–3.5.2022 estimated with logistic distribution  $\mu = 1017.13$ ,  $\beta = 4.76889$ .

For logistics distribution, Probability Density Function (PDF) is defined with (3):

$$\text{PDF}(\mu, \beta, x) := \frac{e^{\frac{\mu-x}{\beta}}}{\beta \left( e^{\frac{\mu-x}{\beta}} + 1 \right)^2}. \quad (3)$$

It can be checked that **NormalDistribution** [18] is less suitable; see Fig. 12.



**Fig. 12:** Histogram of probability density function of air pressure in Ostrava 1.1.1951–3.5.2022 estimated with normal distribution  $\mu = 1017.19$ ,  $\beta = 9.7324$ .

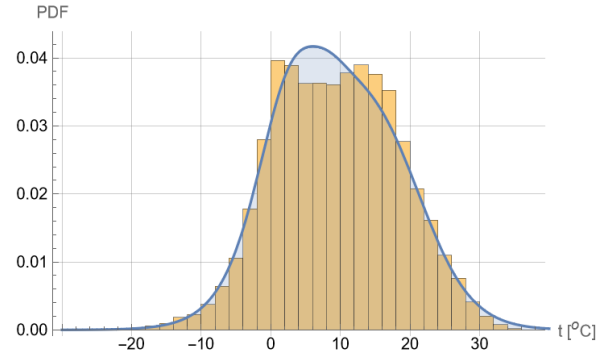
For this well-known normal distribution, the probability density function (PDF) is defined by (4):

$$\text{PDF}(\mu, \beta, x) := \frac{e^{-\frac{(x-\mu)^2}{2\sigma^2}}}{\sqrt{2\pi}\sigma}. \quad (4)$$

## 8. Air temperature

In the case of temperature histograms in our climatic zone, they usually have two maxima; see Fig. 13.

In that case, Mathematica proposes the distribution mixture defined with **MixtureDistribution** [16].



**Fig. 13:** Histogram of probability density function of air temperature in Ostrava 1.1.1952–3.5.2022 estimated with mixture distribution.

```
MixtureDistribution[
{0.503839, 0.227163, 0.268998},
{LogisticDistribution[3.08387, 3.47807],
NormalDistribution[10.7129, 3.88395],
InverseGaussianDistribution[20.1512, 302.591]}]
```

PDF function for the inverse Gaussian distribution is defined by (5):

$$\text{PDF}(\mu, \lambda, x) := \begin{cases} \frac{\sqrt{\frac{\lambda}{x^3}} e^{-\frac{\lambda(x-\mu)^2}{2\mu^2 x}}}{\sqrt{2\pi}} & x > 0 \\ 0 & x \leq 0 \end{cases}. \quad (5)$$

For normal and logistic distribution functions PDF, definitions have already been shown, (4) and (3), respectively.

## 9. Climate prophecy

In this section, we will analyze a part of the Mathematica notebook showing the analysis of temperature data taken from Wolfram | Alpha.

This script is prepared to be applied to every place on Earth for which climatic data are available on Wolfram servers. First, we establish that this place is Ostrava.

**city = "Ostrava"**

In the next step, for the defined city data on average temperature within a period of years 1900 to 2022 are collected from Wolfram|Alpha with the **WolframAlpha** function [21] in the form of **ComputableData**. Next, two time series models are constructed for these data with **TimeSeriesModelFit** [11]. The first uses the seasonal ARIMA model family and the second integrates the ARMA model family [2].

```

tsa = TimeSeriesModelFit[
  WolframAlpha[city~StringJoin~
    " average temperature 1900 to 2022",
    "ComputableData"]][[3, 1, 1]], "SARIMA"]
tsb = TimeSeriesModelFit[
  WolframAlpha[city~StringJoin~
    " average temperature 1900 to 2022",
    "ComputableData"]][[3, 1, 1]], "ARIMA"]

```

For both constructed models, we can now calculate a 29-step model (to 2050) using the function **TimeSeriesForecast** [10].

```

tsf = TimeSeriesForecast[tsa, {29}]
tsfa = TimeSeriesForecast[tsb, {29}]

```

Now, we can estimate the reliability of the calculated forecast. For the model based on the SARIMA model family, we can calculate the forecast bounds with a confidence level equal to 95%. It is done with these lines of code:

```

tsaForecastBounds = TimeSeries[
  Map[tsa["PredictionLimits",
    ConfidenceLevel → 0.95], tsf["Dates"]],
  {"Jan 1st 2021", "Jan 1st 2050"}
]

```

The calculated results are presented in Fig. 14. It is produced with the following procedure:

```

DateListPlot[{tsa["TemporalData"],
  tsf, tsfa, tsaForecastBounds},
  GridLines → Automatic, {PlotStyle →
    {Automatic, Automatic, Magenta, Directive[
      Dashing[{Small, Small}], GrayLevel[0.7] ]}},
  Filling → {4 → {5}}, FillingStyle →
    GrayLevel[0.9], PlotLegends →
    Placed[{"Data", "Forecast (SARIMA)",
      "Forecast (ARIMA)", "Bounds (SARIMA)"},
    Below]], PlotRange → {6, 16},
  PlotLabel → Style["Temperature forecast in " ~
    StringJoin~city, 14],
  FrameLabel → {"Years", "Temperature [°C]"}]

```

As we can see in Fig. 14 we can observe the trend of warming, and according to the forecast, we can expect that in 2050 the average temperature will be  $10 \pm 4^{\circ}\text{C}$  with 95% confidence. Anyway, it could have been more than 70 years ago. Similar analyzes can be performed for other climate parameters.

If we change at the beginning the name of the city, for example NYC we will obtain data for this place, NYC is known as New York City by Wolfram|Alpha. The result is shown in Fig. 15.

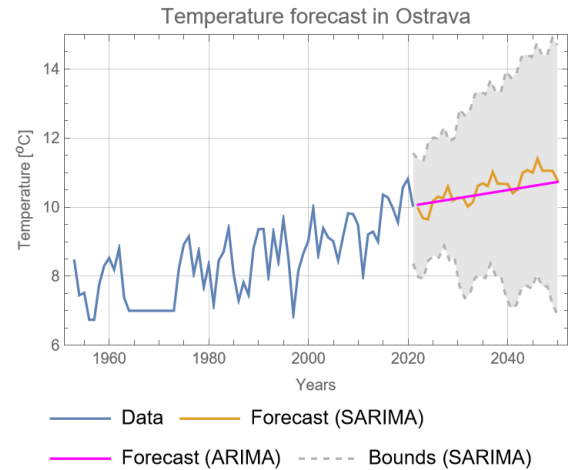


Fig. 14: Warming forecast in Ostrava.

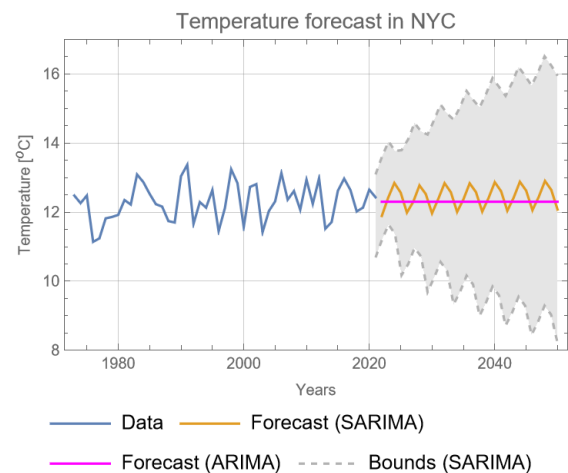


Fig. 15: (No)warming forecast in New York City.

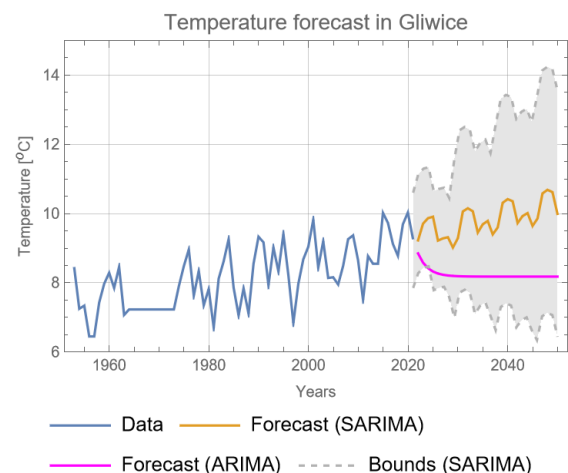


Fig. 16: Warming/cooling forecast in Gliwice.

For most places in the world that I tried to analyze, warming is predicted and New York City is a rare exception. Perhaps because Wolfram|Alpha has fewer records (since 1972, only).



It is also interesting that for my home city Gliwice, the SARIMA model prophets warming, and the ARIMA model cooling of the local climate. see Fig. 16.

But in London(UK) we can expect warming according to both models; see Fig. 17.

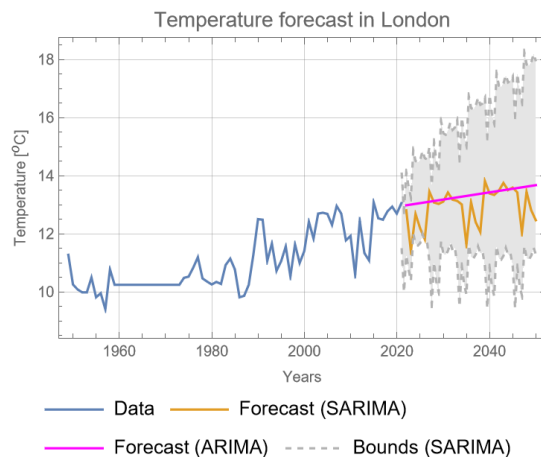


Fig. 17: Warming/cooling forecast in London.

Furthermore, the lower bound of the average temperature with 95% confidence level is not smaller than in the 20<sup>th</sup> century. The expected temperature in 2050 would be 1deg higher than today and 3deg higher than in the middle of the 20<sup>th</sup> century.

## 10. Other local climate properties

Mathematica has the ability to collect and analyze many other data and properties.

For example, the function **WeatherData** allows us to take into account the following characteristics.

**WeatherData["Properties"]**

```
{AlternateStandardNames, CloudCoverFraction,
CloudHeight, CloudTypes, Conditions, Coordinates,
DewPoint, Elevation, Humidity, Latitude,
Longitude, MaxTemperature, MaxWindSpeed,
MeanDewPoint, MeanHumidity, MeanPressure,
MeanStationPressure, MeanTemperature,
MeanVisibility, MeanWindChill, MeanWindSpeed,
Memberships, MinTemperature, NCDCID,
PrecipitationAmount, PrecipitationRate,
PrecipitationTypes, Pressure, PressureTendency,
SnowAccumulation, SnowAccumulationRate,
SnowDepth, StationName, StationPressure,
Temperature, TotalPrecipitation,
Visibility, WBANID, WindChill,
WindDirection, WindGusts, WindSpeed, WMOID}
```

## 11. Conclusions

There was shown how the computational intelligence tools implemented by Wolfram Language and included in Wolfram|Alpha and Wolfram Mathematica can be used to investigate statistical data of climatic loads acting on the structures. Furthermore, it is possible to estimate changes in climatic parameters in the future. Anyway, the presented examples of forecasting global warming or cooling do not return any definite results like any other trial of extrapolation.

Climate change can be analyzed globally and locally. Local analysis is very important because it allows one to improve the reliability of structural mechanics analysis. The design may become "tailored" with the location of the building. It may result in some economic savings.

The results presented could hopefully be an inspiration for other researchers dealing with stochastic and statistical problems in modeling mechanical problems.

## Acknowledgment

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