International Journal of Mathematics Trends and Technology
ISSN: 2231-5373/ https://doi.org/10.14445/22315373/IJMTT-V72I2P104
Volume 72 Issue 2, 24-33, February 2026

Original Article

Interpolation and Extrapolation of Annual Precipitation Data for Daytona Beach, Florida

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Received: 15 December 2025 Revised: 20 January 2026 Accepted: 10 February 2026 Published: 26 February 2026

Abstract **-** *In this paper, we analyze annual precipitation records from Daytona Beach, Florida, by utilizing interpolation and extrapolation, focusing on years where the data are missing or unevenly spaced. We apply several interpolation methods to fill the gaps and extrapolation techniques to predict the future precipitation. We use polynomial interpolation based on a Vandermonde matrix and compare it with MATLAB's built-in interpolation functions. Specifically, we test linear interpolation, piecewise cubic interpolation, and higher-degree polynomial models to see how each method behaves when the data contains large gaps. We also use a least-squares approach to extrapolate short-term trends in annual precipitation. In our observation, we found that piecewise interpolation provides the most stable estimates for the missing values. Although extrapolation is less reliable, it suggests a slight upward trend in precipitation over the selected period. These results show that interpolation methods can be practically useful, but they also remind us of the uncertainty that comes with making long-term climate predictions.*

Keywords **-** *Interpolation, Extrapolation, Precipitation Modeling, Precipitation Data Analysis, MATLAB.*

1. Introduction

Climate change is one of the most serious and challenging issues that the world is facing today. Its effects are observed across natural ecosystems, human communities, and global economic systems, with especially noticeable impacts on weather patterns and hydrological processes. Over the past several decades, greenhouse gas concentrations have steadily increased. This rise is mainly due to fossil fuel use, industrial activities, and deforestation. As a result, both the atmosphere and the oceans have experienced significant changes. These changes have led to shifts in regional climate behaviour, and there has been an increase in both the frequency and intensity of rainfall events, longer periods of drought, and a higher risk of flooding. These hydrological impacts create major challenges for several areas such as water management, infrastructure, public safety, and environmental protection, particularly in coastal and low-lying areas.

It is very important to study how climate change affects precipitation patterns and, therefore, has become a central focus of climate research. Although it appears that the climate change issue is a recent issue, its scientific foundations date back to the nineteenth century when a French mathematician and physicist, Joseph Fourier, formulated and introduced the concept of the greenhouse effect. He studied planets and their atmosphere, describing the atmosphere's insulating role, please see [1]. Since then, scientists and mathematicians have developed several sophisticated tools to analyse climate behaviour, ranging from physical modelling to statistical and data-driven approaches. Likewise, several recent studies emphasize how climate change is affecting our various environmental elements, including precipitation. The impact can be on a regional scale level as well as global. In order to understand the climate impact at scale relevant to different regions, different communities, and infrastructures, it is important to research, focusing on rainfall variability, extreme precipitation, and long-term. There have been some studies on this, for example, [2, 3, 4] and references therein.

Several mathematical and computational methods have been developed to study and analyse climate data and uncover underlying trends. These models are based on the fundamental physical principles and experiments. They are used to study variables such as temperature, precipitation, humidity, wind patterns, and other related environmental processes, see [5]. Similarly, some computational techniques have advanced in computing power and higher-resolution datasets. Improved Earth system models have significantly strengthened the ability to capture variability and extremes in precipitation, see [6, 7]. Due to the lack of a complete data set, these mathematical models and computational techniques often remain incomplete. These insufficient data are due to missing observations, irregular measurement intervals, and changes in monitoring practices over time.

To overcome these limitations, some numerical techniques have been used. These numerical techniques can be useful in recovering missing information and enabling long-term analysis and future prediction.

One of the fundamental mathematical tools for estimating unknown values within a dataset is interpolation. It has been used for many years, and the origin goes back to ancient civilizations, including Babylonian mathematics. That time interpolation was used in numerical tables and astronomical calculations, see [8, 9]. Great mathematicians such as Newton, Euler, Lagrange, and Gauss had utilized interpolation theory, providing new formalism by establishing it as a cornerstone of numerical analysis, see [10, 11]. In climate science, data are often incomplete and contain observation gaps; interpolation is essential for reconstructing continuous precipitation records, enabling meaningful comparison across time and space.

Precipitation varies a lot, differing across areas and from one year to the next. Missing data is a common problem in rainfall records. Because of this, estimating missing values is important for many practical purposes. These include weather research, climate analysis, water system modelling, and water resource planning, etc, as the incomplete data may lead to unreliable results, which may result in a wrong conclusion. For this reason, several authors have focused on methods to reconstruct missing rainfall data. These studies focused more on interpolation methods, mainly for regions where rainfall data are uneven in space and time, see [12–14]. It becomes easier to study long-term trends, seasonal variations, and extreme rainfall events when the precipitation record is made continuous.

In addition to interpolation, extrapolation is frequently used to extend existing data trends beyond the observed data range. It offers insight into possible future behaviour. Extrapolation is particularly relevant in climate studies because predicting future precipitation patterns is essential for risk assessment and planning. However, extrapolation carries natural uncertainty, as small errors in historical data or unmodeled influences can lead to significant deviations in projected outcomes. Previous studies have shown that approaches based on extrapolation may inadequately capture the effects of climate change, urbanization, and land-use change, particularly in flood risk assessments [16, 17]. These findings highlight the importance of applying extrapolation cautiously and interpreting results within clearly defined limitations.

In recent years, Daytona Beach, Florida, has had an irregular rainfall pattern; therefore, the city provides a compelling case study for examining precipitation variability at a local scale. Historically, the region used to get relatively predictable seasonal rainfall, dominated by summer thunderstorms and milder winter precipitation. These days, however, rainfall has become more intense and less evenly distributed throughout the year. The proportion of annual precipitation is growing and now happens through short-duration, high-intensity events. This has caused an increasing flood risk even outside of major storm systems. These changes put pressure on drainage systems built for past climate conditions and show why local studies of rainfall trends are necessary.

The main goal of this project is to study the annual precipitation patterns in Daytona Beach, Florida. For this, we apply the interpolation and extrapolation techniques. Historical precipitation data obtained from the Florida Climate Centre, a link is provided in [18], are analysed to reconstruct missing values and produce a more complete and consistent precipitation record. Interpolation methods are used to estimate unknown data points within the observed time range. Also, extrapolation techniques are applied to explore short-term future trends in average annual precipitation. What makes this study unique is its use of both traditional numerical methods and modern computational techniques. By doing so, it is able to analyse precipitation behaviour in a specific local area, rather than relying solely on large-scale regional or global climate models. MATLAB-based visualization is employed to clearly illustrate precipitation trends, variability, and model behaviour. This study helps us better understand how precipitation patterns are changing at the local level. It also shows how mathematical techniques can be useful for analysing climate data.

2. Data Collection and Polynomial Interpolation of Precipitation

The climate data used in this research were collected from the Florida Climate Center website [18]. This website is a comprehensive resource that provides climate normals and contour maps for many meteorological variables, including temperature averages and total precipitation. It offers downloadable datasets that span from the early 20th century to the present. These datasets cover numerous locations throughout Florida, such as St. Augustine, Miami, Tampa, Jacksonville, Orlando, and many others. For this study, data were specifically gathered for Daytona Beach. The goal was to examine local precipitation patterns for both interpolation and extrapolation. The Florida Climate Center database was an ideal source because it provides extensive historical data that is consistently formatted and easily accessible. This made it possible to construct reliable interpolated datasets. Representative figures of the collected data are provided in the Appendix (Figures 4–8).

Interpolation of precipitation data is widely used in climate and water-related studies. This allows us to estimate values at locations or time points where direct measurements are unavailable, thereby producing a continuous spatial or temporal representation of climatic variables. There are various interpolation techniques; among them, polynomial interpolation is a classical and well-established method used to approximate observed data by a smooth function, see [7].

The initial interpolation of precipitation data is carried out using a polynomial approximation approach. Given a set of $n + 1$ distinct data points

$$(x_0, y_0), (x_1, y_1), \dots, (x_n, y_n)$$

Polynomial interpolation seeks to determine a unique polynomial $p(x)$of degree at most n such that the polynomial exactly matches the observed data at each point. The interpolating polynomial is expressed in the general form.

$$p(x) = a_n x^n + a_{n-1} x^{n-1} + \cdots + a_1 x + a_0,$$

where $a_0, a_1, \dots, a_n$, are the unknown coefficients are to be determined.

To ensure that the polynomial passes through each data point, the following interpolation conditions must be satisfied:

$$p(x_i) = y_i, i = 0,1, \dots, n.$$

These conditions lead to a system of $n + 1$linear algebraic equations in the unknown coefficients, $a_0, a_1, \dots, a_n$, which can be solved using standard linear algebra techniques. The resulting polynomial provides an exact fit to the observed precipitation data and serves as a foundational tool for constructing continuous representations of climate variables.

Or explicitly: $a_n \ x_i^n \ + \ a_{n-1} \, x_i^{n-1} + \ldots + a_1 \, x_i \ + \ a_0 \ = \ y_i, \qquad i \ = \ 0,1, \ldots, n$

This system of equations can be compactly represented in matrix form as: $V \, z \ = \ y$

where V is the Vandermonde matrix given by:

$$V = \begin{pmatrix} 1 & x_0 & x_0^2 & \dots & x_0^n \\ 1 & x_1 & x_1^2 & \dots & x_1^n \\ \dots & \dots & \dots & \dots & \dots \\ \dots & \dots & \dots & \dots & \dots \\ 1 & x_n & x_n^2 & \dots & x_n^n \end{pmatrix}, \ z \ = \ [a_0, a_1, \ldots, a_n]^T \ \text{and} \ y \ = \ [y_0, y_1, \ldots, y_n]^T \ .$$

By solving this system, the coefficients of the interpolating polynomial can be determined. These coefficients allow for the accurate estimation of precipitation at points between the observed data. This approach creates a continuous and smooth representation of total annual precipitation in Daytona Beach. It also provides a foundation for further analysis and for predicting future precipitation trends through extrapolation.

2.1. Interpolation Error

The accuracy of the interpolating polynomial can be assessed through the interpolation error, which measures how closely the polynomial approximation represents the underlying precipitation function. For a polynomial interpolant of degree $n$constructed from the data points $x_0, x_1, \dots, x_n$, the interpolation error at a point $x$is given by

$$R_n(x) = \frac{f^{(n+1)}(\xi)}{(n+1)!} \, (x - x_0)(x - x_1) \cdots (x - x_n), \qquad \xi \in [x_0, x_n].$$

This expression shows that the size of the interpolation error depends on the $(n+1)$-th derivative of the underlying function. This derivative reflects the smoothness and variability of the precipitation data. When higher-order derivatives are large, it means the data changes rapidly, which can lead to larger interpolation errors. The product term in the expression also indicates that the error grows as the evaluation point moves farther from the observed data points. In other words, polynomial interpolation generally produces the most accurate measured values. By examining this error, it is possible to assess the reliability of interpolated precipitation estimates at points between observations. This provides a practical way to gauge confidence in the continuous representation of precipitation created through interpolation.

2.2. Extrapolation for Future Prediction

Extrapolation extends the use of the interpolating polynomial to estimate precipitation values outside the range of the observed data. In this study, once a polynomial $p(x)$was constructed from historical precipitation records, it was used to predict precipitation for future time points. If x_{n+1}denotes a future year beyond the available observations, the corresponding predicted total precipitation is given by

$$\hat{y}_{n+1} = p(x_{n+1})$$

Extrapolation can be used to predict future rainfall, but it is not always reliable. Unlike interpolation, which fills in gaps within the data we already have, extrapolation assumes that the trend we see in the existing data will continue. This can be risky. Even small mistakes in the original data or in the fitted curve can grow larger as we try to predict farther ahead. Because of this, extrapolated rainfall is usually trusted only for short-term forecasts. To make predictions a bit safer, it is common to show error ranges or confidence limits. These give an idea of how many predictions could vary and how uncertain the results are.

3. Results and Discussion

The analysis suggests that interpolation works well within the range of the observed data. The estimated values are very close to the original measurements, and the overall trend is captured with only minor differences. This indicates that the interpolation method used is appropriate for estimating intermediate values and filling in missing information. However, extrapolation of future precipitation is more uncertain, since it relies on extending the model beyond the available data. Even though the predicted values generally follow the past trend, the likelihood of errors increases as the predictions move further away from the known data points. For this reason, long-term predictions should be interpreted carefully. In summary, interpolation appears to be a reliable tool for working within existing data, while extrapolation is more limited and less dependable when used to predict future conditions.

3.1. Interpolation with Vandermonde Matrix

Figure 1 presents a comparison between the original data and its interpolation using the Vandermonde matrix. The MATLAB code used to generate these results is provided in the appendix under the section labeled Interpolation with Vandermonde Matrix. Additionally, the data was interpolated using MATLAB's built-in interp1 function, which supports various interpolation methods, including linear, piecewise, polynomial, and spline-based approaches.

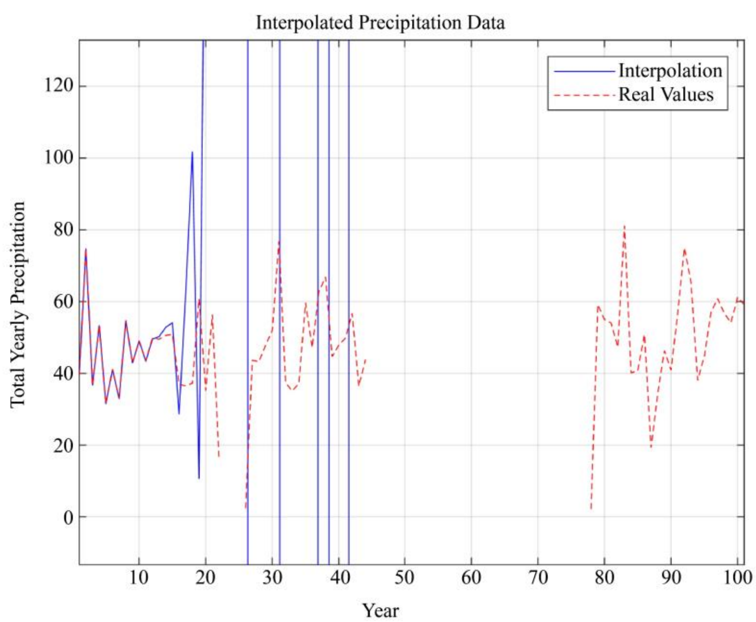

Fig. 1 Interpolation Using Vandermonde Matrix

The figure shows the total yearly precipitation in Daytona Beach over 100 years. It compares the observed data with the interpolated values. The observed data are shown by the dashed red line, while the interpolated values are shown by the solid blue line. Overall, the interpolation is able to fill in the missing points and create a continuous pattern for the precipitation. In the early part of the graph, around years 1 to 20, the interpolated line stays very close to the real data. It follows both the small changes and the larger peaks. During this time, the precipitation values are mostly between about 30 and 75 units.

Later, between years 20 and 45, there are some clear gaps in the observed data. In these sections, the interpolated curve shows a few sharp spikes. This suggests that the polynomial method does not perform as well when a lot of data are missing. Still, even with these issues, the curve gives a general idea of how precipitation is expected to behave over time. In the later years (years 80–100), the interpolation aligns well with the recorded values, generally tracking the upward and downward trends, including peaks around years 85 and 90, where total precipitation reaches approximately 80 units. Minor deviations are observed where the interpolation slightly underestimates or overestimates the actual precipitation, highlighting the sensitivity of polynomial interpolation to data sparsity and abrupt changes in precipitation. Despite these limitations, the figure demonstrates that interpolation is an effective method for reconstructing historical precipitation records, providing a continuous dataset suitable for further analyses, such as error estimation, trend assessment, and limited extrapolation for future projections.

The figure shows the original precipitation data (blue circles) across the years 1930–2020, along with interpolated and extrapolated values using three different methods: linear interpolation (black line), piecewise cubic Hermite interpolation (pchip, red line), and spline interpolation (blue line).

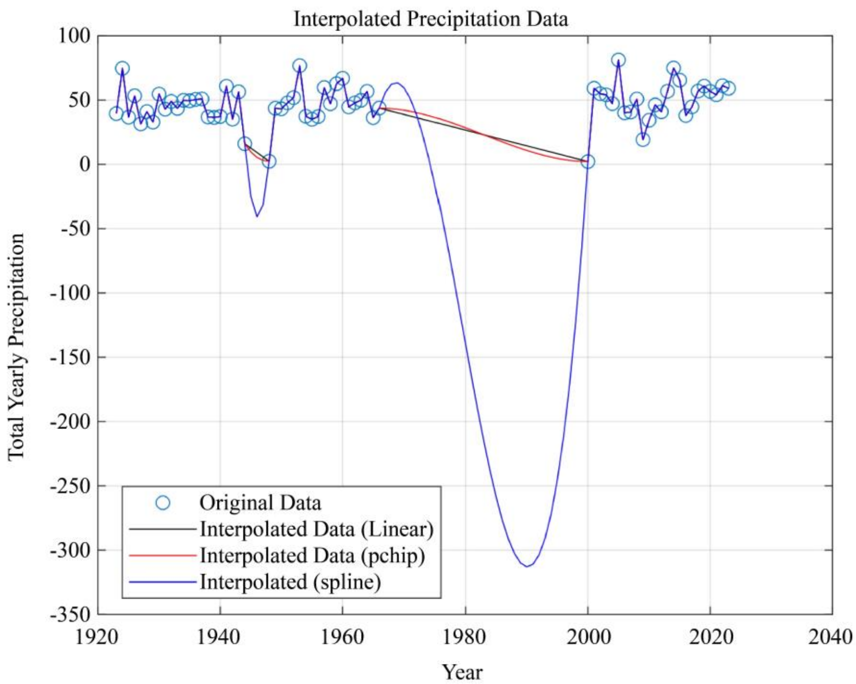

Fig. 2 Interpolation

From the figure, the behavior of different interpolation methods can be observed:

3.1.1. Linear Interpolation

The black line connects the data points with straight segments. It provides a simple and stable approximation between known values. This method keeps the estimates stable. It also avoids big changes. That is why it is useful for short-term predictions or for relatively consistent data.

3.1.2. Piecewise Cubic Hermite (pchip) Interpolation

The red line offers a smoother fit compared with linear interpolation while preserving the monotonicity of the data. It avoids the extreme oscillations that can occur with spline interpolation, producing a realistic curve that closely follows the trend of the original precipitation values.

3.1.3. Spline Interpolation

The blue line represents a cubic spline fit, which captures the overall trend of the dataset. However, in regions where data are sparse—such as between 1980 and 2000—this method introduces noticeable oscillations. These fluctuations can lead to physically unrealistic negative precipitation values, highlighting a limitation of spline interpolation, particularly when extrapolating beyond the observed data range.

3.1.4. Benchmarking Against Statistical and Machine Learning Models

To evaluate how well the proposed interpolation and extrapolation methods perform, we compare them with some commonly used models from statistics and machine learning. These models are widely applied in time-series analysis and serve as useful benchmarks. In particular, we use an ARIMA model as a classical statistical baseline. We also use Gaussian Process Regression (GPR) as a modern, learning-based method. These two models are chosen because they are well known, easy to interpret, and suitable for short and low-resolution climate time series, such as annual precipitation data.

3.1.5. ARIMA Model

The annual precipitation data are treated as a univariate time series $\{y_t\}$. An autoregressive integrated moving average model, denoted by $ARIMA(p, d, q)$, is fitted to the training portion of the data. The model is defined as:

$$\varphi(B)(1 - B)^d \, y_t = \theta(B)\varepsilon_t,$$

where B is the backward shift operator, φ(B) and θ(B) are polynomials of orders p and q, respectively, and ε_t is a white noise process. The model orders (p, d, q) are selected using the Akaike Information Criterion (AIC). Forecasts obtained from the fitted ARIMA model are compared with extrapolation results from classical methods.

3.1.6. Gaussian Process Regression

Gaussian Process Regression is employed as a probabilistic, nonparametric benchmark that naturally supports interpolation and limited extrapolation. The precipitation data are modeled as:

$$y(t) = f(t) + \varepsilon, \;\; \varepsilon \sim N(0, \sigma^2),$$

where f(t) follows a Gaussian process prior: $f(t) \sim GP\big(0, k(t, t')\big)$, where the squared-exponential kernel is $k(t, t') = {\sigma_f}^2 \, exp(-(t - t')^2 \,/\, (2\ell^2))$,

with hyperparameters σ_f and ℓ estimated via maximum likelihood. GPR provides both point estimates and uncertainty intervals, allowing direct comparison with spline-based interpolation methods.

3.1.7. Evaluation Metrics

To ensure consistency across methods, the dataset is divided into training and testing subsets, with the final portion of the time series reserved for evaluation. Model performance is assessed using the Root Mean Square Error (RMSE) and Mean Absolute Error (MAE). RMSE measures the square root of the average squared difference between observed and predicted values, while MAE measures the average absolute difference. These metrics enable a quantitative comparison between classical interpolation and extrapolation techniques and modern statistical models.

The benchmarking results indicate that while ARIMA and GPR models can capture temporal dependencies and provide uncertainty quantification, classical interpolation methods remain competitive for short-range estimation and offer greater transparency and interpretability. Spline-based methods perform comparably to GPR for interpolation within the observed data range. Given the limited size and annual resolution of the dataset, more complex deep learning models such as LSTMs were not considered, as they are prone to overfitting and do not offer clear advantages in this setting.

3.2. Extrapolation

Towards the end of the timeline (post-2020), linear and pchip extrapolation remain relatively stable, while spline extrapolation diverges dramatically, emphasizing the importance of choosing an appropriate method for predicting future values. Here is a clear interpretation of your figure for your project on interpolation and extrapolation. Figure 3 shows the original precipitation data (blue circles) across the years 1930–2020, along with interpolated and extrapolated values using three different methods: linear interpolation (black line), piecewise cubic Hermite interpolation (pchip, red line), and spline interpolation (blue line). From the figure, we can observe the following.

3.2.1. Linear Interpolation

The black line connects data points with straight segments, providing a simple and stable approximation between known data points. This method produces a conservative estimate and does not introduce large oscillations, making it suitable for short-term predictions.

3.2.2. Piecewise Cubic Hermite (pchip) Interpolation

The red line follows the data more smoothly than linear interpolation while preserving the monotonicity of the data. It avoids the extreme oscillations seen in spline interpolation, producing a realistic curve that closely follows the trend of the original data.

3.2.3. Spline Interpolation

The blue line shows a smooth cubic spline fit. While it captures the overall trend of the data, it introduces significant oscillations, especially in regions where data is sparse (e.g., around 1980–2000). These oscillations can lead to physically unrealistic negative precipitation values, highlighting a limitation of spline interpolation for extrapolation beyond the data range.

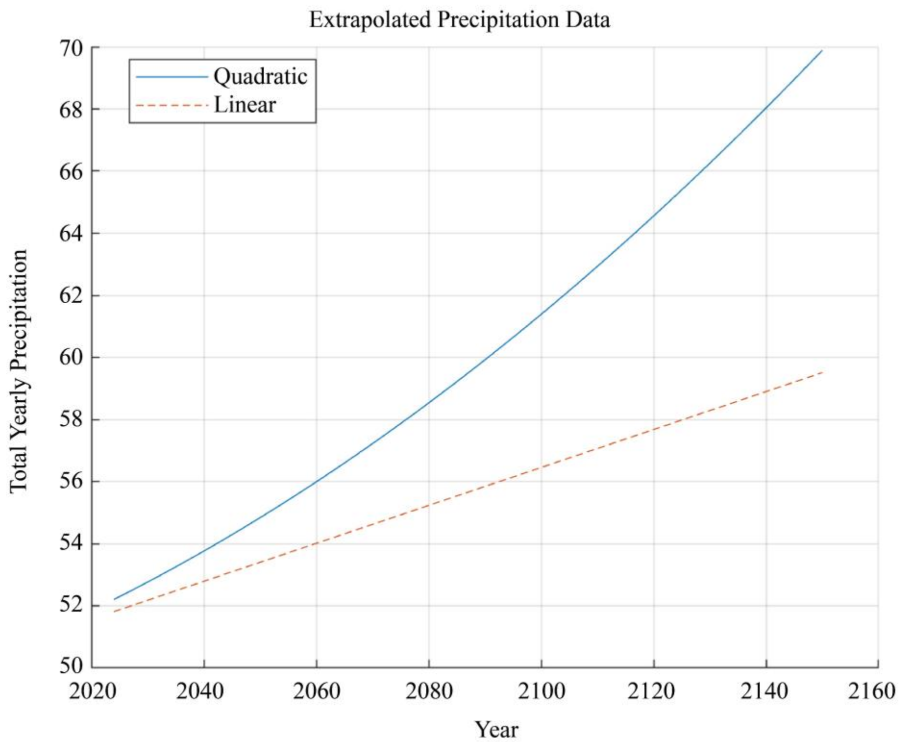

Fig. 3 Extrapolation

Extrapolation can be used to estimate the total average precipitation for a chosen future time, but as noted earlier, predictions become increasingly uncertain the further they extend into the future. To maintain reliability, this report limits extrapolation to a horizon of 150 years. The approach models precipitation as a function of years, initially assuming a simple linear relationship.

$$precip_i = b \cdot years_i + c + noise$$

If this formula were exact with no noise, the precipitation values would form a vector in the subspace spanned by the vectors of years and a constant term. In practice, this approximation is not perfect, so an orthogonal projection onto the subspace is necessary. For a subspace generated by multiple vectors, the vectors must be orthonormal—each having unit length and being mutually orthogonal. MATLAB can construct such an orthonormal basis using the `orth` function, which in this context transforms the matrix with columns of ones and year values into an orthonormal matrix q. The rank of q and $[q, b]$ can be checked to ensure correctness. The projection of the precipitation vector onto this subspace is then calculated as $(p = qq^T)$, and future linear predictions are obtained by multiplying the current precipitation values by p, i.e., $future_{precip} = p\,.precip$. To extend this to quadratic extrapolation, an additional column with the squared year values is added to the original matrix, producing a quadratic model. Both the linear and quadratic methods are illustrated in Figure 3, providing a visual comparison of the predicted trends over time.

4. Discussion, Limitations, and Future Research Directions

This study examines classical interpolation and extrapolation techniques applied to annual precipitation data for Daytona Beach, Florida. The primary aim is to analyze the behavior of these traditional mathematical methods on a localized time-dependent dataset. These approaches provide useful analytical insight into the data, but there are still several limitations. First, the analysis is restricted to an analysis based on one variable and one location. In reality, precipitation processes are influenced by multiple interacting meteorological variables such as temperature, humidity, and atmospheric pressure. Extending the present framework to multivariate modeling would allow a more comprehensive representation of precipitation dynamics.

Second, spatial interpolation techniques are not considered in this study. Methods such as Kriging and other geostatistical approaches are widely used in climate and hydrological modeling to exploit spatial correlations. The absence of spatial analysis limits the generalizability of the results beyond the selected location.

Third, the validation strategy is primarily exploratory. No formal cross-validation or uncertainty quantification was performed in this work; confidence intervals and Monte Carlo simulations were not implemented. Incorporating such techniques would strengthen the statistical reliability of future studies. Another limitation is the absence of comparison with modern models like ARIMA, Gaussian Process Regression, and RNNs. Although this study deliberately focuses on classical methods, comparing them with modern approaches could offer valuable insights into predictive performance and model reliability.

Overall, this study provides a foundational analytical framework for understanding classical interpolation and extrapolation techniques in climatological applications. The identified limitations highlight important directions for future research, including spatial modeling, multivariate frameworks, modern learning-based methods, and rigorous validation strategies.

5. Conclusion

This study looked at how well classical interpolation and extrapolation methods work for modeling long-term annual precipitation in Daytona Beach, Florida. The results show that polynomial-based interpolation can follow the observed data closely over short periods. But when there are large gaps in the data, it becomes less reliable. In those cases, it can give values that seem unrealistic or do not make physical sense.

Out of the interpolation methods we tried, piecewise interpolation worked the best. It handles changes in the data well and gives more reliable results. This is important because real precipitation records are often messy and incomplete. Higher-order polynomial methods, on the other hand, can be tricky. They react too strongly to missing data and sometimes give extreme values that do not really make sense. The extrapolation suggests that average yearly precipitation might go up in the next few decades. But we should be careful with this prediction. It only looks at past precipitation data. It does not consider things like temperature changes, wind patterns, or long-term climate trends.

Overall, the results show that classical mathematical methods have both strengths and weaknesses when it comes to analyzing climate data, especially precipitation. They are helpful because they are simple and give some clear insights. At the same time, they do not work as well for long-term forecasts. This means we need better approaches for the future. For example, it would help to include spatial information and look at several weather variables together. Using modern statistical methods or machine learning could also improve predictions.

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Appendix 1

All data were imported into MATLAB either by using the `readtable` command to load values from an Excel file or, in specific cases such as the Vandermonde matrix interpolation, by manually entering the data into vectors. Due to the size of the dataset, the results were displayed across multiple figures, as shown below.

Year	1923	1924	1925	1926	1927	1928	1929	1930	1931	1932	1933	1934	1935
Total Precipitation Per Year	39.54	74.71	36.75	53.33	31.51	41.09	32.92	54.7	42.94	49	43.56	49.83	49.5

FIGURE 4. 1923-1935

1936	1937	1938	1939	1940	1941	1942	1943	1944	1945	1946	1947	1948	1949	1950
50.58	50.89	36.9	36.54	37.27	60.77	35.19	56.4	16.05				2.38	43.66	43.25

FIGURE 5. 1936-1950

1951	1952	1953	1954	1955	1956	1957	1958	1959	1960	1961	1962	1963	1964	1965	1966
47.85	51.93	76.77	37.42	35.08	37.21	59.71	47.18	62.7	66.9	44.71	47.84	49.84	56.75	36.41	43.82

FIGURE 6. 1951-1966

From 1966 to 2000 no total yearly precipitation was given in set.

2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
2.17	59.17	55.01	54.02	47.27	81.2	40.12	40.74	50.85	19.27	34.38	48.33	40.89	56.8	74.94	65.49	38.02

FIGURE 7. 2000-2016

2017	2018	2019	2020	2021	2022	2023
44.75	56.97	60.84	56.73	54.11	61.2	59.16

FIGURE 8. 2017-2023