Assessment of Seasonal Variability of Precipitation under Climate Change and Its Importance for Urban Water Infrastructure Management: A Model-Based Approach using the Example of Kostanay City

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Abstract: - Under conditions of growing climate instability and the simultaneous ageing of urban water infrastructure, the question of how precipitation is distributed across seasons is no longer a purely descriptive climatological issue but a practical planning problem. Cities located in sharply continental climate zones are especially exposed to this challenge: precipitation is uneven within the year, interannual fluctuations are substantial, and short periods of excess rainfall may alternate with extended dry intervals. In such settings, engineering water systems operate under structurally variable loads, which increases both operational uncertainty and long-term investment risk. This study examines the seasonal and interannual behavior of monthly precipitation in the city of Kostanay and develops a forecast framework based on a Seasonal autoregressive integrated moving average specification. The empirical analysis relies on long-term hydrometeorological observations, which make it possible to distinguish persistent seasonal regularities from irregular stochastic deviations and extreme monthly anomalies. Particular attention is given to how these variations translate into uneven stress on drainage and water-management systems rather than being treated as abstract statistical noise. Model identification and parameter selection were conducted step-by-step, with separate evaluation of seasonal structure, autocorrelation patterns, and forecast error behavior. Validation results demonstrate a high level of agreement between observed and estimated values across different years, including periods with atypical precipitation distribution. This indicates that seasonal stochastic time-series models of this class can serve as a reliable analytical instrument for short- and medium-term precipitation forecasting at the city level. From a practical standpoint, the results support the inclusion of model-based seasonal precipitation forecasts in urban water-infrastructure planning, climate risk assessment, and adaptation policy design. The proposed approach is intended not as a purely theoretical exercise but as a decision-support tool for municipal and sectoral planning under conditions of climatic uncertainty.

Key-Words: - water resources, precipitation variability, seasonal patterns, urban infrastructure, urban water management, climate risk.

Received: September 29, 2025. Revised: January 14, 2026. Accepted: June 11, 2026. Published: July 20, 2026.

1 Introduction

Urban water supply infrastructure is usually described in terms of annual totals, design standards, and nominal capacity limits. In practice, the load on the system is formed differently. The decisive role is played not by the annual total itself, but by its internal distribution. In countries with a sharply continental climate, of which Kazakhstan is an example, precipitation is uneven; at times it is concentrated within a narrow seasonal window, at times it decreases for extended periods. A significant share of the annual water input falls within a small number of months, while other months may be dry. Such a climatic feature requires explicit consideration when ensuring the reliability of engineering systems.

In the northern regions of Kazakhstan, the monthly structure of precipitation repeatedly demonstrates this imbalance. A shifted seasonal maximum or a dry early period changes the pattern of runoff formation and water accumulation in such a way that it cannot be compensated later by arithmetic averaging. Hydraulic systems react first to sequence and concentration, and only afterwards to totals. It is also important that a large share of the networks was built long ago, when urban infrastructure did not assume such load growth, and climatic conditions were somewhat different. Gradual urban expansion, partial reconstruction, and uneven modernization have degraded hydraulic system performance. Under such conditions, precipitation statistics move from descriptive background data into the category of calculation parameters. Forecasting is required here not for reporting purposes but for advanced adjustment of operating regimes.

The absence of smooth precipitation time series and the changing amplitude of the seasonal structure together require analytical instruments of a different class, capable of separating seasonal recurrence from stochastic disturbances. These include seasonal autoregressive time-series models, since dependence structure and seasonal memory are preserved in explicit form. The usefulness of such models is connected not only with forecasting results but also with parameter interpretability.

As a representative example, the Kostanay region was selected, since seasonality is present there, interannual spread is noticeable, and the observation data are consistent. In the study, a quantitative reconstruction of the seasonal structure was carried out, and a reproducible Seasonal autoregressive integrated moving (SARIMA) model was built, making it possible to forecast load periods, reserve requirements, and vulnerability intervals.

2 Literature Review

Research on water management has gradually moved away from narrowly technical interpretations and is now treated as a field where climatic processes, institutional arrangements, and patterns of resource use are tightly interwoven.

The origins of sustainable water management stem from the concept of Integrated Water Resources Management [1], according to which environmental, economic, and social factors must be taken into account in decision-making. A significant contribution to the development of this direction was made by studies devoted to water security. In particular, a number of works introduced the concepts of “water stress” [2], “water deficit” [3], and “hydropolitical tension” in transboundary basins [4].

According to a number of researchers, water scarcity depends not only on natural and climatic factors, [5], [6], [7]. Their studies demonstrate that water deficit may arise even under more favorable climatic conditions if governance institutions in a region are weak. For example, outdated water-management infrastructure combined with insufficient coordination of water-use measures may lead to a deficit. The same works also note that effective management is possible where developed forecasting and monitoring systems are in place. Recent studies, including those by [8], [9], expand the fundamental ideas of IWRM by focusing on SDG-6, technological innovation, public–private partnerships, and the digitalization of the water sector. These authors find that addressing water challenges requires strategies that mix innovation with public–private cooperation. In short, analysts argue that modernizing infrastructure, conserving water, and improving cross-border agreements are all needed for water security, [3].

For example, study [10] links precipitation and temperature changes to long-term climate trends. The projected global temperature increase of 1.8 to 3.7°C by the end of the 21st century indicates significant negative consequences for ecosystems and urban areas, [11]. More frequent and intense heatwaves, shifts in the character and intensity of precipitation, and accelerated melting of glaciers and polar ice are projected to occur, [12]. These climate trends are expected to increase disasters (flash floods, storm surges, etc.) worldwide, [13].

A number of studies focus on documented changes in weather patterns, such as the increasing frequency of temperature extremes and shifts in precipitation regimes, which are largely linked to rising anthropogenic emissions from agriculture, livestock production, and industrial sectors. Comprehensive assessment reports of the IPCC (2007, 2014, 2021) indicate that global climate change contributes to a higher occurrence of extreme precipitation events, droughts, and floods,

[14]. Comparable findings have also been presented in more recent empirical studies, [15], [16], [17], [18], [19]. These results suggest that climate change can no longer be viewed as a purely regional process. Changes in large-scale atmospheric circulation patterns lead to variations in both the intensity and timing of precipitation across different regions of the world, [20]. High temporal and spatial resolution of precipitation data enables improved numerical model evaluation and more detailed studies of extreme precipitation variability, [21].

Urban water infrastructure also has a substantial research base. Many scholars propose concepts of water security for natural–economic systems as a factor of sustainable development, analyze stages of water-crisis formation in relation to water-use evolution, propose solutions to water scarcity, and consider priorities of national water-security strategies:

1) improving inter-state water allocation systems in transboundary basins;

2) rationalizing the use of domestic renewable water resources based on conservation and territorial redistribution of river runoff.

Effective water-resource management is a key component of national water policy, and under the transition toward sustainable water use, forming an adequate management system becomes critically important, [22]. Successful water-resource governance is essential for achieving multiple Sustainable Development Goals, [23], [24]. Particular attention is paid to factors influencing the formation and implementation of countries' institutional water-management policies. A multidimensional approach is considered necessary – enhancing water-resource management practices, increasing investments in infrastructure and technology to strengthen water security, and implementing widespread educational and public-awareness campaigns to inform communities about the importance of water conservation and the risks associated with climate change, [9]. Water legislation regulates relations in the use and protection of national water assets, management of water funds, and water-management systems.

Rapid population growth combined with the expansion of urban areas exerts increasing pressure on water resources and significantly complicates the achievement of long-term sustainable development objectives, [25]. Water resources are one of the fundamental prerequisites for economic development and sustainable growth, having a direct impact on the standard of living and social well-being of the population, [26]. Limited freshwater availability, together with the low effectiveness of existing water-management instruments, poses serious risks for sustainable development and environmental quality, [27]. Urban water-supply infrastructure forms a basic element of city systems, providing drinking water, sanitation, and wastewater treatment, which are essential for stable urban functioning. Long-term reliability of these systems depends on the timely modernization of drainage and sewerage networks, regular control of water quality, and the ability of cities to cope with increasingly frequent and intense extreme weather events.

Recent studies further develop these approaches by proposing modern solutions based on nature-based technologies and digital systems, [28].

Various strategies and methods for water-resource management have long been developed, [29]. Climatic parameters – such as air temperature, wind patterns, and precipitation – substantially influence the thermal structure of natural and artificial water bodies, chemical composition, phytoplankton growth, sediment transport, and nutrient levels, ultimately affecting water quality, [30]. Climate-change projections, urbanization, and population growth are expected to increase pressures on the environment and human infrastructure and threaten water-resource sustainability, [31]. As climate dynamics become a more dominant driver of the hydrological cycle, precipitation regimes are increasingly shaped by atmospheric variability. At the same time, the interaction of climatic processes with socio-economic development contributes to a growing risk of flooding, particularly within urban environments, [32]. Under these conditions, the implementation of early-warning mechanisms and real-time flood forecasting systems based on soft-engineering approaches becomes an essential tool for reducing potential adverse impacts, [33], [34].

The study [35] presents proposals for water resources management solutions. Among the priority directions for addressing the identified problems are measures aimed at introducing the principles of integrated water resource management, improving state policy in this field, strengthening institutional and human-resource capacity, and mastering and applying new technical tools and technologies. At the same time, an analysis of scientific publications shows that water resource management is closely interconnected with the objectives of protecting and restoring natural ecosystems and cannot be considered in isolation from them. Within such a systemic approach, particular importance is attached to measures based on the use of natural processes, which serve as a practical foundation for the development of scientifically grounded and applied strategies aimed at reducing the adverse impacts of climate change and ensuring long-term adaptation of economic systems.

Issues of water-resource governance within this framework have been widely discussed in the literature, [36], [37], [38].

Despite the substantial body of both fundamental and recent studies, a number of unresolved issues can still be identified. In particular, existing research provides limited evidence on the application of statistical modeling techniques, including SARIMA, for the analysis of regional precipitation dynamics.

Summarizing the conducted review, it can be concluded that the role of seasonal precipitation modeling in regional urban infrastructure planning remains insufficiently disclosed. Operational forecasting tools that could be directly used for effective water-resource management are not sufficiently developed. Statistical time-series analysis methods are widely known in climatology, but their applied use for diagnosing seasonal instability and short-term precipitation changes in specific cities is still sporadic and methodologically heterogeneous. The connection between forecast precipitation models and the functional resilience of drainage and water-management infrastructure is frequently mentioned, but only rarely quantified within a reproducible modeling framework. In particular, for Kazakhstan, empirically grounded model-based assessments of seasonal precipitation behavior remain limited, which creates a gap between observational climate analysis and engineering-oriented planning practice. The present study is intended to partially fill this gap by combining seasonal stochastic modeling with an explicitly urban management perspective.

3 Research Methods

We forecast monthly precipitation in Kostanay using a seasonal ARIMA (SARIMA) model. The model structure was defined step by step, with separate identification of seasonal and non-seasonal lag orders and subsequent parameter estimation following the Box-Jenkins approach. Model diagnostics were conducted manually, without reliance on fully automated procedures. This approach provides a step-by-step procedure for time-series modelling and ensures transparency in the construction and interpretation of the selected model. This careful approach ensures we select an appropriate model and produce reliable forecasts – crucial when dealing with climate data that varies by season and year. The key reasons for selecting SARIMA were:

- its ability to account for trend, seasonal components, and autocorrelation structure without the need for external regressors;
- high predictive accuracy on relatively small samples, which is particularly relevant for regional climate studies;
- statistical interpretability and reproducibility of results, aligning with scientific and applied requirements;
- robustness to noise and anomalous outliers in climate data.

Table 1 (Appendix) compares these models. It shows that SARIMA achieves the best mix of accuracy and stability for our short, noisy rainfall records.The construction of the SARIMA model for forecasting monthly precipitation in the Kostanay region was conducted manually using the classical seasonal ARIMA methodology. The analysis included initial data processing, the construction of error tables, and the calculation of statistical accuracy measures (MSE, RMSE, MAE, MAPE, R^2), which were performed using Microsoft Excel. This workflow was selected to maintain clarity and consistency of the calculations and to simplify subsequent forecast verification. When relatively short time-series are used, such an approach makes it possible to closely track seasonal patterns and autoregressive relationships within the model. To evaluate forecast accuracy, key metrics were calculated:

- MSE (Mean Squared Error), measuring the average squared deviation between observed precipitation values and model outputs;
- RMSE (Root Mean Squared Error), reflecting the typical scale of forecast errors and expressed in millimeters;
- MAE (Mean Absolute Error), used to estimate the mean absolute difference between predicted and observed values, independent of direction;
- MAPE (Mean Absolute Percentage Error), applied to evaluate relative forecast accuracy in percentage terms;
- R^2 (coefficient of determination), used to determine the extent to which the model explains the variability of the observed precipitation series.

In summary, our SARIMA model fits the data with very high precision (low errors). It remains robust across different data subsets.

4 Results

The analysis of long-term changes in key climatic indicators, such as precipitation, air temperature, and humidity, makes it possible to identify changes in precipitation patterns in a specific region and to assess probable future trends. These indicators for Kazakhstan are presented in Figure 1 (Appendix), based on official meteorological data, [39].

As can be seen from Figure 1 (Appendix), the annual precipitation in Kazakhstan deviates noticeably from the long-term average level. It is also easy to observe a fairly sharp alternation of wet and dry years. At the same time, this pattern is not trend-based, since the identified individual outliers are random. This indicates the instability of the precipitation regime in Kazakhstan. In this connection, these indicators cannot be used directly in calculations for urban water-resource planning.

According to the data, ongoing climatic changes are observed. As shown by our calculations, the average annual precipitation for 2010-2023 amounted to 352.64 mm, which lies within the regional climatic norm. It is noteworthy that the minimum precipitation was recorded in 2020 – 270.7 mm, and the maximum in 2016 – 439.6 mm. The median value was 314.95 mm. The standard deviation amounted to 44.4 mm. This indicates a substantial spread of values, that is, an asymmetric distribution of precipitation.

Let us consider the dynamics of average annual precipitation (Figure 2, Appendix). The curve is uneven; in some years, the deviations from the typical level are quite pronounced, and the amplitude of these fluctuations changes continuously. On this basis, the absence of a stable long-term trend can be stated.

Maximum monthly precipitation by year is listed separately (Figure 3, Appendix). The data show that peak precipitation values varied from year to year. At the same time, the timing of these peaks also varied. Accounting for peak precipitation values and their timing is crucial for seasonal modeling of watershed loads and for subsequent response measures.

Using the example of the city of Kostanay, a region of Kazakhstan with an unstable precipitation pattern and vulnerable water supply infrastructure, forecast calculations were carried out using the SARIMA model. These results are valuable for climate analysis and for guiding practical water management decisions. The interpretation of the trend-seasonal model can be summarized as follows:

- a positive trend means precipitation in Kostanay is increasing over time;
- a negative trend indicates decreasing precipitation;
- a weak trend means long-term stability;
- if the model consistently identifies July as the wettest and February as the driest, seasonality is strong;
- a stable trend allows forecasting future precipitation with confidence;
- high model fit ensures high forecast accuracy.

Figure 4 (Appendix) presents the main indicators used in the trend-seasonal precipitation analysis, based on historical precipitation data, [39].

The average annual precipitation in Kostanay for 2010–2024 is approximately 369 mm. At the same time, the yearly values themselves cannot be considered even, since within the period under review, they change noticeably and at times quite sharply. The observation series looks irregular rather than smoothed. The minimum for the period was recorded in 2010 – 221 mm. Higher precipitation totals were observed in 2013, 2016, 2018, 2020, and 2023, with the maximum reached in 2023 – 446 mm.

If adjacent years are compared pairwise, it can be seen that the difference in annual totals often reaches 100–150 mm. For practical calculations, this is not a minor adjustment but a substantial discrepancy. This indicates an alternation of wetter and drier years. It can also be stated that no stable long-term trend in precipitation change is observed here. These conclusions are relevant for assessing water availability and for planning agricultural activity. Seasonal differences between months are shown in Figure 5 (Appendix).

From the data in Figure 5 (Appendix), a pronounced structure of monthly precipitation distribution can be observed, and the average monthly precipitation amount is 31.7. The highest values occur in mid-summer, mainly in July and August. It's worth noting that March, April, and December see the least amount of precipitation. While the spring months see very little precipitation, the opposite is true in the summer months. Autumn and early winter show more moderate conditions.

These seasonal features are relevant for water-management planning and climate risk assessment. At the next stage, monthly and annual precipitation volumes in Kostanay were analyzed (Figure 6, Appendix).

The analysis shows fluctuations in the total annual precipitation from 320 to 450 mm. At the same time, in May, July, and August, a large amount of precipitation may fall, or it may be low in different years. Here, it is necessary to pay attention to the high risk for crop farming. In spring periods, dryness, and in late summer and early autumn, a large amount of precipitation is крайне unfavorable for the harvest. Therefore, in Table 2 (Appendix), trend values for individual years were calculated by us.

The trend–seasonal model of precipitation in Kostanay provides the following insights:

1) Trend component. Estimates obtained using the least squares method indicate a weak downward tendency in total annual precipitation in Kostanay. The continued high interannual variability of precipitation cannot be ignored. For example, while annual precipitation in 2021 was 317 mm, by 2023 it had increased to 446 mm. Such a difference within a short time interval indicates the prevalence of short-term fluctuations over a stable long-term trend.

2) Seasonal component. The annual precipitation distribution is characterized by pronounced seasonality and unevenness. For example, December–February saw the lowest monthly precipitation, while from March to May it steadily increased. The maximum precipitation falls in the summer months. In autumn, overall precipitation decreases, although short-term increases can occur

3) Random component. We removed trends and seasonal components to conduct an adequate analysis. The results revealed the presence of volatile short-term weather anomalies. In particular, in April 2023, precipitation was extremely low – 0.5 mm – while July 2021 saw the maximum monthly precipitation – 104 mm.

The trend-seasonal model combined with these random deviations is shown in Figure 7 (Appendix).

Based on the constructed trend-seasonal model for precipitation in Kostanay, the following conclusions can be formulated:

1) The annual precipitation regime in Kostanay follows a clearly pronounced seasonal pattern, with the highest precipitation amounts concentrated in the summer months and the lowest values typically occurring during the winter–spring period.

2) An examination of the long-term precipitation series points to a weak downward tendency in average annual totals. While this tendency is not strong, it may be associated with gradual phase-related changes in regional climatic conditions.

3) The heaviest precipitation was most often observed in May and July, but in some years this pattern was not observed.

To obtain more accurate forecasts, additional parameters can be included in the model. These may include air temperature, wind speed and direction, and other atmospheric circulation parameters. In addition to visual analysis, forecast reliability was assessed using the coefficient of determination (R^2) and root mean square error (RMSE) calculations, which allow for a consistent assessment of forecast reliability.

Analysis of statistical model parameters:

1) The coefficient of determination equals −1.49. This demonstrates the significant role of random fluctuations in precipitation dynamics. For this reason, a model specification relying solely on the trend component does not provide an adequate description of the observed series.

Since the RMSE is high (37.47), this indicates a significant difference between the actual observed data and the model estimates. These discrepancies can be attributed to nonlinear climate variability and the limited data set. This justifies the need for more flexible modeling approaches, such as SARIMA, using optimal parameters. Accuracy was evaluated using commonly applied statistical measures:

- The mean square error (MSE) was 1.3875, indicating that the overall model error remains relatively small:

$$\text{MSE} = \frac{1}{n}\sum_{i=0}^{n} \quad (Yi - \hat{Y}i) \tag{1}$$

where:
Yi - actual data;
Ŷi - values predicted by the model;
Ŷ mean value of the actual data;
n - number of observations.

$$\text{MSE} = \frac{1+0{,}25+0{,}09+0{,}25+1+0{,}64+1+2{,}25+0{,}04+0{,}25+0{,}09+0{,}04}{12} = \frac{8{,}23}{12} = 1{,}3875$$

- RMSE is calculated according to the standard expression.

$$\Sigma(Yi - \hat{Y}i)^2 = 8{,}23 \tag{2}$$

$$RMSE = \sqrt{MSE} \tag{3}$$

$$RMSE = \sqrt{1{,}3875} \approx 1{,}178$$

The obtained value allows us to confirm that the average discrepancy between the model's calculated estimates and actual precipitation values remains small. Now let's calculate the coefficient of determination (R^2):

$$R^2 = 1 - \frac{\Sigma(Yi - \hat{Y}i)^2}{\Sigma(Yi - \hat{Y})^2} \tag{4}$$

where:
$\Sigma(Yi-\hat{Y}i)^2$ - is the sum of squared differences between predicted and observed values (numerator);

$\Sigma(Yi-\hat{Y})^2$ - is the sum of squared deviations of the observed values from their mean (denominator).

1) Let's estimate the average value of the series of observed precipitation::

$$\hat{Y} = \frac{45 + 15 + 15 + 32 + 31 + 51 + \ +56 + 72 + 10 + 9 + 39 + 6}{12} = 31{,}75$$

2) Next, we determine the total sum of squared deviations of actual precipitation values from their average level. The calculation is based on monthly observations: the deviation from the average is found for each month, after which the resulting squared deviations are summed over the entire period under consideration.

$$\begin{aligned} SST = {} & (45 - 31{,}75)^2 + (15 - 31{,}75)^2 \\ & + (15 - 31{,}75)^2 + (32 - 31{,}75)^2 \\ & + (31 - 31{,}75)^2 + (51 - 31{,}75)^2 \\ & + (56 - 31{,}75)^2 + (72 - 31{,}75)^2 \\ & + (10 - 31{,}75)^2 + (9 - 31{,}75)^2 \\ & + (39 - 31{,}75)^2 + (39 - 31{,}75)^2 \\ & + (6 - 31{,}75)^2 = 6065{,}7 \end{aligned}$$

Using these values, the coefficient of determination is calculated:

$$R^2 = 1 - \frac{8{,}23}{6065{,}7} = 1 - 0{,}00136 = 0{,}998 = 99{,}8\% \ .$$

Additionally, the model's quality was tested using standard forecast error metrics – RMSE, MAE, and MAPE. Data for 2024 were used in the calculations, while observations for 2023 served as a control sample. Monthly precipitation totals for these two years were directly compared with estimates obtained using the SARIMA model. The final comparisons are summarized in Table 3 and Table 4 (Appendix).

The total discrepancy between observed and model-predicted values was 21.14 squared. Converted to error terms, this yields an MSE of 1.7617 and an RMSE of 1.327 mm. In other words, the average deviation of the forecast from actual precipitation remains small.

The sum of the squared deviations of actual values from the mean is 8468.61, with $R^2 = 0.9975$. This means that the SARIMA model reproduces monthly precipitation variability closely to observed data.

A comparison of monthly values (Table 4, Appendix) shows that in most cases, the discrepancy is within 1–2 mm, and the relative error is a few percent. There is an exception in April, when there was virtually no precipitation – 0.5 mm. Since even a small absolute difference in this situation results in an inflated percentage error, this does not indicate a model failure.

The MAPE is 13.84%. This high value was achieved by months with very low precipitation totals. Considering the MAE is 1.02 mm and the RMSE is 1.33 mm, this is quite normal. This level of accuracy is considered acceptable and workable for climate calculations.

To assess the stability and performance of the SARIMA model, validation was carried out for two consecutive years – 2023 and 2024. For ease of analysis and subsequent use, the results are summarized in the final Table 5 (Appendix), which presents the values of all three metrics for each observation year, allowing for a comparable conclusion regarding the model's performance under varying interannual precipitation variability.

The indicators presented in Table 5 (Appendix) made it possible to quantitatively assess the model's accuracy, the stability of its forecasts under interannual variability, and its ability to reproduce both average and extreme precipitation values. RMSE was used to describe the average dispersion of forecast errors in millimeters, while MAE reflects the mean absolute deviation irrespective of its direction. MAPE, expressed in percentage terms, provides an assessment of relative forecast accuracy and is particularly sensitive in situations where monthly precipitation values are very low, which is common in climate data analysis.

A comparison of the two analysed years shows differences in forecast accuracy. These differences can be explained by anomalous precipitation patterns in 2023, while precipitation in 2024 was more regular. Even accounting for these changes, the modeled indicators for these periods were stable and statistically significant.

In general, the results of the comparative analysis indicate that the SARIMA model provides a reliable basis for practical monthly precipitation forecasting in the Kostanay region and can also be used for scenario-based assessments of potential changes in seasonal precipitation patterns.

Model stability and generalization capability were additionally assessed using cross-validation with a rolling-origin (expanding window) scheme. This procedure is particularly appropriate for time-series data, as it preserves the temporal structure of observations and prevents information leakage between the training and validation samples.

According to the results summarized in Table 5 (Appendix), the cross-validation metrics averaged over the two validation windows indicate consistently low forecast errors.

First, in all cases, the absolute errors remain small: RMSE is 1.33 mm for 2023 and 1.18 mm for 2024, while MAE is 1.02 and 0.65 mm, respectively. This means that, on average, the model deviates by less than 1–1.5 mm in monthly precipitation totals, which is an excellent result for climate time series of this nature.

In absolute terms, the model performs smoothly in both years, producing precipitation values close to actual ones. No significant deterioration in millimeter-level accuracy is observed. Noteworthy differences in MAPE values are related not so much to the quality of the model as to the distribution of precipitation within each year.

Third, the comparison of the two analyzed years indicates that the SARIMA model remains stable under conditions of interannual variability. The comparison of the two years shows that the SARIMA model maintains stable performance under contrasting precipitation regimes. Comparable accuracy is observed both in years with smoother seasonal patterns and in years with pronounced monthly anomalies. No deterioration in predictive accuracy is detected in the subsequent period.

Overall, the comparative results suggest that the SARIMA approach provides reliable forecasts and shows stable performance across two independent evaluation periods. These findings support the use of the model for practical forecasting of monthly precipitation in the Kostanay region and for scenario-based assessments of potential changes in the seasonal structure of precipitation.

The stability and generalization performance of the SARIMA model were additionally examined through cross-validation based on a rolling-origin (expanding window) scheme. This procedure is suitable for time series data because it preserves the chronological order of observations and prevents information leakage between the estimation and validation steps. Based on the results presented in Table 5 (Appendix), the aggregated (averaged over the two validation windows) cross-validation metrics are as follows:

This procedure is suitable for time series data because it preserves the chronological order of observations and prevents information leakage between the estimation and validation steps. The cross-validation results are presented in Table 5 (Appendix).

$$RMSECV = \frac{1.33 + 1.18}{2} = 1{,}26\, mm$$

$$MAECV = \frac{1.02 + 0.65}{2} = 0{,}84\, mm$$

$$MAPECV = \frac{13.84 + 2.45}{2} = 8{,}15\, mm$$

In accordance with the obtained results:
The obtained RMSE(CV) and MAE(CV) values, on the order of 1–1.3 mm and below 1 mm, respectively, indicate that error levels remain similar across validation intervals. This suggests stable model behavior when applied to adjacent time periods.

The relatively higher average MAPE value in cross-validation (around 8%) is primarily due to the specific precipitation distribution in 2023, discussed earlier. In 2024, the intra-annual precipitation distribution was smoother. Without extremely small values, the percentage error decreases; the MAPE remains at around 2.45%. Under these conditions, the accuracy estimate is more stable and better reflects the actual quality of the approximation.

The RMSE and MAE values do not significantly deviate between validation windows. In other words, the model is not "overfitted" to a single year, but reproduces the interannual variability of monthly precipitation within the working range.

The SARIMA specification used can be applied to applied calculations of monthly precipitation forecasts for the Kostanay region. A comparison of observed and calculated values for 2023 and 2024 is shown in Figure 8 (Appendix).

The use of two independent validation periods, 2023 and 2024, shows that model performance remains stable across different time horizons. The RMSE and MAE values change only slightly when the validation window is shifted, and the spread of the values is small. This suggests the model is stable.

A comparison of precipitation data for 2023–2024 in the Kostanay region reveals significant differences in hydrometeorological conditions. In 2024, precipitation totals were higher in most months than in the previous year. The most pronounced differences were observed in January (45 mm versus 15 mm), April (32 mm versus 0.5 mm), and certain summer months—July and August. This indicates a shift in seasonal patterns, with moisture being distributed unevenly throughout the year.

However, the pattern is different in the autumn and winter. For example, from September to December 2024, values in several months were lower than in 2023. In August, precipitation decreased from 104 to 72 mm, and in December, from 36 to 6 mm. Not only the overall volume but also the monthly distribution of precipitation is changing.

The Kostanay region's hydrological network is extensive, with approximately 300 small rivers and over 8,000 lakes. Large bodies of water include the Sarykol, Alakol, Kusmuryn, Koybagar, Akkol, and Teniz. The Tobol River and its tributaries, and the Torgai River form the bulk of surface runoff. Changes in precipitation patterns under these conditions directly impact surface water replenishment, the regional water balance, and the operation of water management infrastructure. This sensitivity increases the exposure of water supply systems and agricultural production to precipitation variability.

The precipitation forecast obtained using the SARIMA model is presented in Figure 9 (Appendix). It covers the period 2025-2026 and reflects the preservation of a pronounced seasonal structure of precipitation while allowing for possible deviations from long-term average values. The results obtained make it possible to assess the likely directions of change in precipitation regimes in the medium term and may be used to support management decisions in the field of water resource planning.

Considering that it is very important for agriculture to predict critical periods, we additionally analyzed monthly precipitation estimates (Figure 10, Appendix).

The figure shows that the model evaluation graphs closely match the observed precipitation data. The determination coefficient reaches 99.8%, and the root mean square error is 1.178 mm.

Taken together, this demonstrates the good predictability of the SARIMA model (Figure 11, Appendix), supported by official meteorological forecast data, [40].

The projected amount of precipitation in January 2025, according to the SARIMA model calculations, shows an exceedance of the climatic norm across a significant part of Kazakhstan. The forecast data correlate with the results published by RSE “Kazhydromet,” which confirms the reliability of the developed model and its practical applicability.

According to the obtained estimates, precipitation amounts are expected to exceed long-term averages in some regions of Kazakhstan. Normal precipitation is expected in some areas of the Kostanay, Karaganda, Aktobe, Zhambyl, and East Kazakhstan regions. Spatial heterogeneity of this kind cannot be ignored when making decisions on water use and infrastructure regulation.

Thus, the obtained forecast values not only confirm broader climatic trends but also highlight the need for adaptive water resource management during the winter period, including snowmelt planning, ensuring sufficient capacity of stormwater infrastructure, and forecasting flood risks.

5 Discussion

Our analysis of Kostanay’s seasonal and yearly precipitation patterns uncovers key features that water planners must consider in a changing climate. The constructed models, particularly SARIMA, demonstrated high accuracy in reproducing actual monthly precipitation values and can serve as a reliable tool for short-term forecasting.

The analysis of the model’s statistical indicators confirmed its robustness to interannual data fluctuations. An R^2 value in the range of 0.9975–0.998 indicates that the model explains nearly the entire variance in precipitation, while a root mean squared error (RMSE) below 1.5 mm reflects a high level of precision even under sharp climatic variability.

We note that some years (especially 2023) show high MAPE values. This is largely because a few months had extremely low rain, an arid-region feature that makes percentage errors appear large. When a series includes months with very low precipitation totals, even a difference of a fraction of a millimeter between the calculated and observed values significantly inflates the relative error. Formally, the indicator deteriorates, although in reality the discrepancy remains small. This is due to the mathematics of relative values, not to the model's accuracy.

When comparing 2023 and 2024 in terms of monthly precipitation, it is clear that the seasonal proportions have shifted. In one year, the main contribution shifts to summer, while in another, the autumn-winter period is weaker in terms of total values. It is important to understand the consequences here. For example, heavy precipitation in summer increases the likelihood of localized flooding, while very low precipitation in spring leads to a decrease in soil moisture availability, which is important for agricultural crops.

Forecast results for 2025–2026 obtained using the SARIMA model suggest the preservation of a stable seasonal pattern, alongside a tendency toward above-average precipitation in the winter–spring period.

Notably, our model's predictions match Kazhydromet's official forecasts (Figure 12, Appendix), which gives us confidence in its validity for practical use. The consistency between the results of statistical modelling and available meteorological forecasts increases confidence in the applied methodological approach and confirms its relevance for use in climate-related and infrastructure-oriented analyses.

Importantly, increasing rainfall in winter–spring months will strain stormwater drains and treatment systems further. Given the traditionally low precipitation levels characteristic of the January–March period, existing urban infrastructure may, in some cases, prove insufficiently adapted to the emerging hydrological loads associated with changing climatic conditions. In this regard, the forecast data call for a revision of current water intake regulations, as well as an assessment of the stormwater drainage capacity in Kostanay. Early identification of such deviations enables proactive planning of engineering system upgrades, reducing the risk of flooding and technological failures.

Trend-seasonal forecasting models are helping cities move from reactive to proactive water management. Precipitation forecasts, therefore, help planners respond quickly to weather swings and spot emerging risks early on. This approach is particularly useful in Kazakh cities, where long dry spells suddenly alternate with heavy rains.

In this context, the integration of precipitation forecasts obtained, in particular, using the SARIMA model into water-resource planning systems represents a practical tool for enhancing the resilience of urban infrastructure to climatic loads.

The use of such models contributes to the development of scientifically grounded and flexible solutions in the field of water-resource management, aimed at ensuring environmental safety and improving living conditions for the population.

Figure 13 (Appendix) illustrates the architecture of applying the results of forecasting models within an integrated water and urban management system. The left side shows the input data (precipitation, climatic parameters, water consumption), followed by the forecasting block, where the SARIMA model is implemented with subsequent analysis of output metrics and visualization. The right side of the diagram demonstrates the practical directions of applying the results: optimization of water balances; scenario modeling and risk assessment; adaptation of agriculture and urban systems to predictable anomalies.

A modeling approach of this type, grounded in the results of long-term observations of precipitation regimes, water consumption, and climatic conditions, provides a practical basis for improving the validity and accuracy of water-resource planning. Forecasting models help us interpret climate changes quickly and spot risks early. This creates a basis for the development of adaptive water-resource management approaches. These points are crucial for continental-climate cities like Kostanay, which face long droughts interrupted by heavy rains. Based on this, the following practical measures are proposed for Kostanay:

1) Strengthening monitoring and forecasting of water resources – implementation of local weather stations and automated hydrological posts for accurate tracking of precipitation volumes and water body levels.

2) Improvement of stormwater drainage systems, involving adjustments to urban planning regulations with consideration of the projected increase in precipitation volumes during the winter–spring period, as well as the reconstruction of individual sections of drainage infrastructure in areas exposed to an elevated risk of flooding.

3) Forecasted changes in precipitation patterns should be taken into account when revising water intake and distribution regulations for Kostanay and nearby agricultural areas. If seasonal moisture supply changes, water use patterns should be adjusted accordingly, rather than relying on "old averages."

4) For agriculture, this means a more flexible approach to sowing times and tillage methods, especially for crops that do not tolerate excess moisture and waterlogging in the spring. Precipitation forecasts can then be used as a

practical guide when planning irrigation and drainage measures.

5) Planning of reserve capacities – creating additional storage and diversion systems within the city to reduce the risk of local floods in peak months (e.g., May and July).

6) Integration of models into strategic planning – incorporating trend–seasonal forecasts into regional sustainable development programs and territorial planning documents (master plans, land-use plans, etc.).

The conducted study demonstrates that trend–seasonal modeling of precipitation serves not only as a tool for climate analysis but also as a scientifically grounded basis for managerial decision-making in the field of sustainable urban development and water resource management. Given its high predictive accuracy, the model under consideration can be integrated into municipal and operational management systems, primarily in regions characterized by increased climatic vulnerability, such as the Kostanay region.

To systematize the directions for practical application of the modeling results, Table 6 (Appendix) presents the key segments of urban and water-management infrastructure in which precipitation forecasts can be integrated into planning, operation, and adaptation strategies.

Sustainable water use under conditions of climatic and demographic change increasingly depends on the implementation of systematic and interdisciplinary approaches to water-resource management. Current challenges in this field cannot be addressed through isolated technical solutions alone and instead require coordinated technical and institutional measures. The system of the measures outlined is aimed at improving water-use efficiency, preserving the quality of water resources, and ensuring a balanced allocation of water among economic sectors and regions. In this context, transboundary cooperation in the field of water governance acquires particular significance. Kazakhstan's geographical position predetermines that a substantial share of its water resources is formed outside the national territory, which makes interaction with neighboring states a fundamentally important element of water policy.

Long-term agreements with China, the Russian Federation, and the countries of Central Asia constitute a necessary condition for the coordinated management of transboundary river basins. Such arrangements should be based on internationally accepted principles, including the ecosystem-based approach, as well as the principles of equity and fair allocation of water resources. The integration of international standards into national water governance systems contributes to the harmonization of the regulatory framework and to the formation of transparent and predictable mechanisms of interstate cooperation.

At the national level, the challenge of increasing the efficiency of water resource use remains pressing. In Kazakhstan, agriculture still accounts for a significant portion of water consumption, so it is here that the implementation of more precise irrigation regimes and streamlined water intake is most effective. Technological solutions of this type allow for a reduction in water losses without increasing the volume of withdrawals. Upgrading hydraulic structures and control structures makes the management system more manageable seasonally and reduces dependence on precipitation fluctuations.

For urban and industrial areas, the treatment and reuse of wastewater is of primary importance. With high concentrations of consumers, simply withdrawing the resource no longer resolves the balance issue. Here, technological processing of used water and the return of a portion of the volume to the cycle are necessary. Experience shows that the best results are achieved where treatment is combined with regular water quality monitoring and strict discharge restrictions. Maintaining aquatic ecosystems in good condition is also a water management measure, as it is responsible for natural flow regulation.

These areas cannot be implemented on their own and require financial and organizational support. Economic conditions are needed to make reducing water consumption beneficial for users and the implementation of water-saving technologies cost-effective. Infrastructure upgrades, including repairs to existing structures, the introduction of additional regulating tanks, and the development of distribution networks and drainage channels, remain important.

In terms of management, the issue comes down to the distribution of responsibilities and the decision-making process. Since even good technical solutions are ineffective when functions are blurred, it is important to clarify authority, coordinate plans, and establish long-term water use targets. The consistent implementation and use of regulatory and tariff instruments will help regulate water demand.

6 Conclusion

The analysis is based on actual precipitation data and its seasonal distribution in the Kostanay region and considers their significance for water use practices and the sustainability of urban infrastructure in changing climatic conditions. The application of a trend–seasonal approach, implemented on the basis of time-series analysis methods, showed high effectiveness in modeling the dynamics of atmospheric precipitation. The developed SARIMA model, tested using observational data from Kostanay, demonstrated high accuracy of forecast estimates and suitability for water use planning calculations. The resulting approximation is close to the actual series, with a determination coefficient of approximately 0.998, while reproducing both seasonal fluctuations and directional changes over time.

These results provide grounds for using forecast estimates in preparing water management decisions and engineering schemes, taking into account climate uncertainty. In practice, this approach can be used to refine water resource management regimes and reduce the risk of droughts and floods. In Kazakhstan's sustainable development context, this method can inform adaptive water policies and boost the resilience of cities to weather extremes.

Further improvement in forecast accuracy and expansion of the applied capabilities of the model may be achieved by considering an additional set of climatic parameters, including air temperature, wind speed and direction, and atmospheric pressure. The inclusion of these factors will allow a more comprehensive representation of the relationships between meteorological conditions and precipitation dynamics.

An important direction involves the use of external regressors and model extensions, such as ARIMAX, which would provide greater adaptability to diverse conditions. The application of ensemble approaches – combining SARIMA with other methods such as Prophet or machine learning algorithms – also appears promising, as it can improve forecast robustness to external disturbances. To more reliably test the robustness of the proposed model, the number of observations should be increased, and observations from other regions of Kazakhstan with different climatic conditions should be included. In future work, incorporating global climate model projections could help anticipate risks and improve forecast insights. Adaptation of models for operational use – particularly for precipitation forecasting in the interests of municipal services and the agricultural sector, where fast and reliable solutions are required – takes on special importance.

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Contribution of Individual Authors to the Creation of a Scientific Article (Ghostwriting Policy)

Lydia Bekenova was responsible for the conceptualization of the study, methodology development, and overall supervision of the research.
Aksana Panzabekova contributed to the formal analysis, interpretation of results, and preparation of the original draft.
Irina Shtykova carried out data collection, model implementation, and empirical analysis.
Natalia Kuzmina contributed to data processing, visualization, and validation of the results.

Sources of Funding for Research Presented in a Scientific Article or Scientific Article Itself

This research was funded by the Ministry of Science and Higher Education of the Republic of Kazakhstan under Grant No. AP19679641, "Integrated Urban Precipitation Management: Model and Implementation Mechanisms."

Conflict of Interest

The authors have no conflicts of interest to declare that are relevant to the content of this article.

APPENDIX

Table 1. Rationale for selecting SARIMA among alternative forecasting models

№	Model	Capabilities	Limitations	Justification for Selecting SARIMA
1	Holt–Winters (ETS)	Performs well with smooth trends, stable seasonal amplitude, and absence of significant autocorrelation in residuals	Does not capture autocorrelation structure; assumes fixed seasonality; performs poorly during irregular peaks (e.g., heavy August rainfall); often less accurate for noisy climate data.	Accounts for internal autocorrelation (AR and MA components), seasonal dependencies, and the stochastic nature of precipitation
2	Prophet (Facebook/Meta Prophet)	Suitable for social, economic, or web data; automatically captures trend and seasonality; handles large, irregular datasets.	Uses additive or multiplicative approximation without modeling autocorrelation; less accurate on short datasets; requires large data for trend stability; seasonal components are defined by harmonic functions and are less physically representative; tends to smooth extreme rainfall peaks.	Provides stricter statistical structure, performs well on small datasets (unlike Prophet), and models autocorrelation – critical for precipitation, where events often cluster
3	ARIMAX	Can incorporate causal relationships and external climate factors	Requires high-quality, synchronized, extensive datasets for regressors; relevant regressors for climate are unavailable in continuous time; weak regressors lead to instability and overfitting	More reliable, statistically stable, interpretable, and does not require additional data

Source: created by the authors

Table 2. Trend values for each year

Year	Trend Value, mm	Random Component (E), mm.	Note
2020	374	+54	Precipitation shows clear seasonality: maximum in July (61 mm), minimum in April (17.7 mm)
2021	377,45	-60,45	
2022	380,9	-47,9	Random deviations from the trend indicate unstable weather conditions, especially in 2021 and 2023
2023	384,35	+61,15	
2024	387,8	-6,8	

Source: [42]

Table 3. Comparison of actual monthly precipitation values for 2023 and SARIMA estimates

Month	Actual (Yi)	Predicted ($Y\^i$)	Error ($Yi-Y\^i$)	Absolute error ($Yi-Y\^i$)	Squared error ($Yi-Y\^i$)²	Percentage error| $Yi-Y\^i$| / Yi*100, %
January	15	14,8	0,2	0,2	0,04	1,33
February	18	17,5	0,5	0,5	0,25	2,78
March	20	19,6	0,4	0,4	0,16	2,00
April	0,5	1,2	-0,7	0,7	0,49	140,00
May	19	18,5	0,5	0,5	0,25	2,63
June	47	46,2	0,8	0,8	0,64	1,70
July	44	42,7	1,3	1,3	1,69	2,95
August	104	100,5	3,5	3,5	12,25	3,37
September	28	27,4	0,6	0,6	0,36	2,14
October	65	62,9	2,1	2,1	4,41	3,23
November	49	48,3	0,7	0,7	0,49	1,43
December	36	35,1	0,9	0,9	0,81	2,50
Total (Average)				12,2		MAPE ≈13,84

Source: created by the authors

Table 4. Monthly precipitation values for 2024 and SARIMA forecasts

Month	Actual (Yi)	Predicted ($Y\^i$)	Error ($Yi-Y\^i$)	Squared error ($Yi-Y\^i$)²	Percentage error| $Yi-Y\^i$| / Yi*100, %
January	45	44	1	1	2,22
February	15	14,5	0,5	0,25	3,33
March	15	15,3	-0,3	0,09	2,00
April	32	31,5	0,5	0,25	1,56
May	31	32	-1	1	3,23
June	51	50,2	0,8	0,64	1,57
July	56	55	1	1	1,79
August	72	70,5	1,5	2,25	2,08
September	10	9,8	0,2	0,04	2,00
October	9	8,5	0,5	0,25	5,56
November	39	38,7	0,3	0,09	0,77
December	6	6,2	- 0,2	0,04	3,33
Total (Average)					MAPE ≈2,45

Source: created by the authors

Table 5. Summary table of sarima performance metrics

Year	RMSE (mm)	MAE (mm)	MAPE (%)
2023	1,327	1,02	13,84
2024	1,178	0,65	2,45

Source: created by the authors

Table 6. Key areas of applying the results of trend–seasonal model calculations to the urban environment and water resource management

№	Direction	Problem	Solution	Example
1	Stormwater drainage and infrastructure management	If the model shows an increase in precipitation, especially in certain seasons (e.g., summer), this indicates the need to modernize the stormwater drainage system.	– optimization of drainage systems in flood-prone areas; – creation of additional channels for the drainage of surface runoff; – treatment of stormwater before discharge into rivers and water bodies.	If calculations confirm consistently higher precipitation amounts in July, the city will have the opportunity to proactively adapt its infrastructure to the expected increase in load.
2	Water supply and reservoir management	If the trend model shows that summer precipitation is decreasing, this may lead to water shortages for urban supply and agriculture.	– planning water storage in reservoirs during periods of abundant precipitation; – developing water-reuse systems (e.g., for irrigation); – controlling water consumption during dry months.	If model estimates predict a decrease in precipitation in August, local authorities may impose water restrictions in August.
3	Flood prevention and infrastructure protection	In some city areas, precipitation may cause localized flooding, especially if the trend indicates growth in certain months.	– developing an early-warning system for heavy precipitation; – planning construction of backup drainage systems; – creating “sponge city” green zones that absorb water.	If calculations show a sharp increase in precipitation in October, protection of critical infrastructure can be strengthened in advance.
4	Optimization of municipal services	If the model shows that certain months are particularly rainy, the workload on municipal services increases.	– increasing funding for pumping water from low-lying areas; – scheduling stormwater system cleaning during the driest months; – improving weather forecasting and public alert systems.	If winter precipitation increases, municipal services can pre-purchase larger volumes of anti-icing reagents.

Source: created by the authors

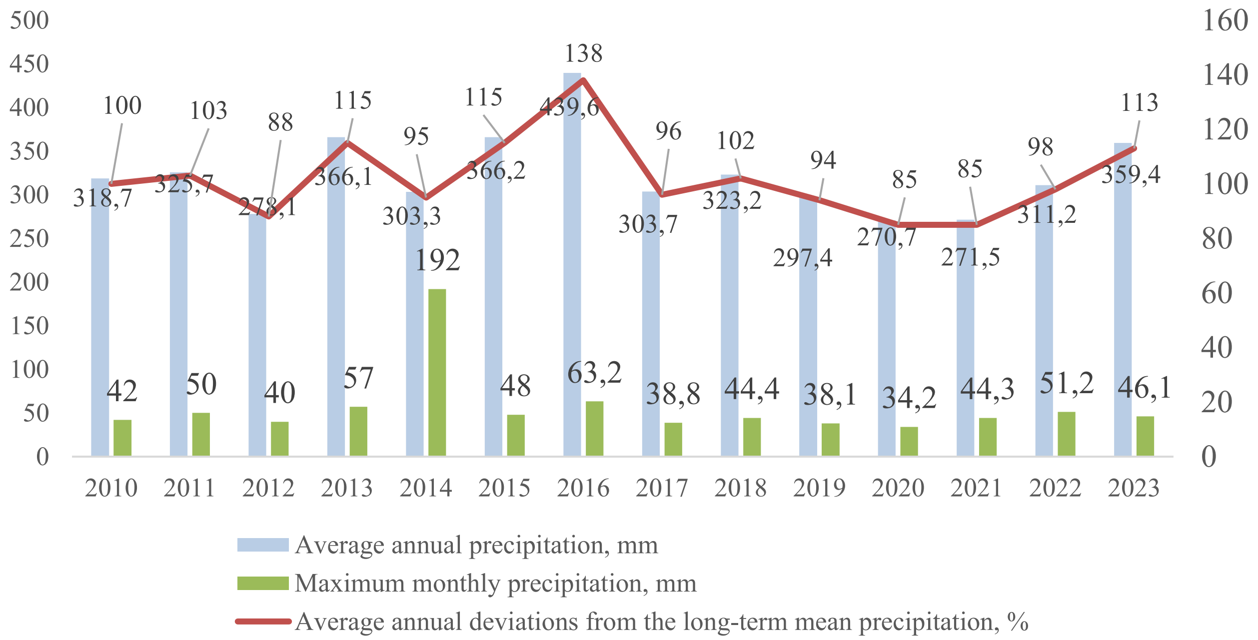


Fig. 1: Multi-year changes in precipitation and principal climatic indicators in Kazakhstan (2010-2023)
Source: [39]

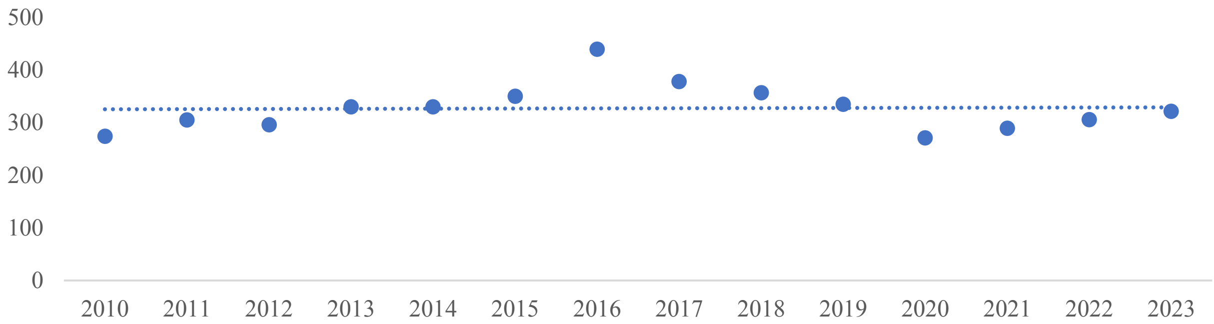


Fig. 2: Annual precipitation dynamics in Kazakhstan over 2010-2023

Source: [39]

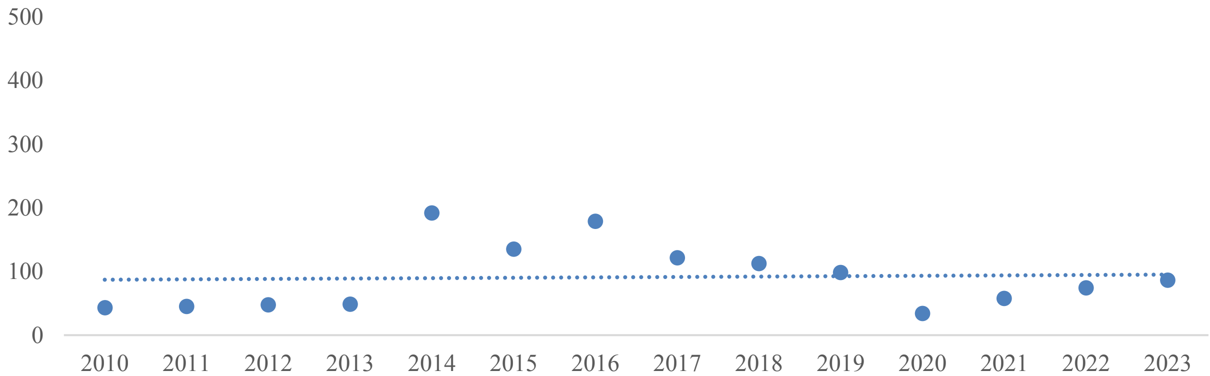


Fig. 3: Interannual distribution of maximum monthly precipitation, 2010-2023

Source: created by the authors

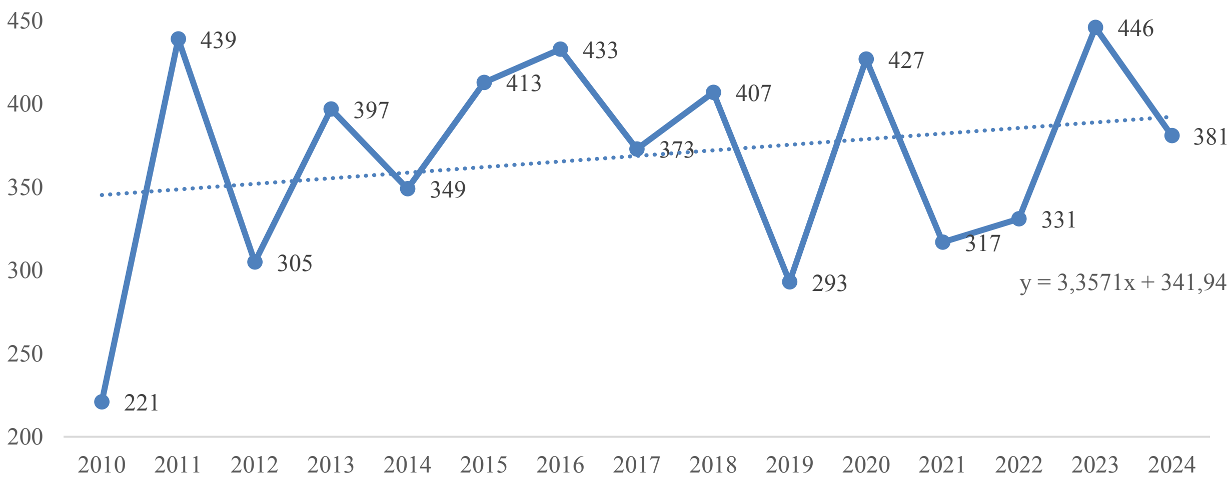


Fig. 4: Change in average monthly precipitation in Kostanay for 2010-2024

Source: [39]

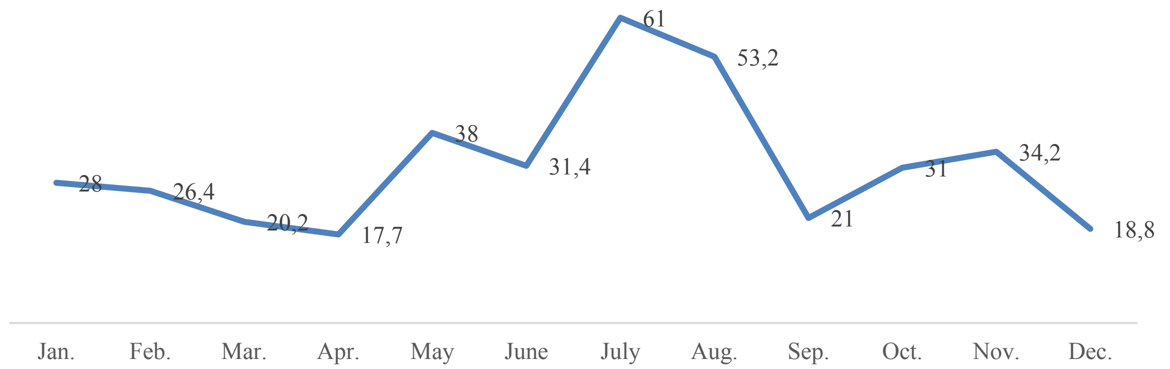
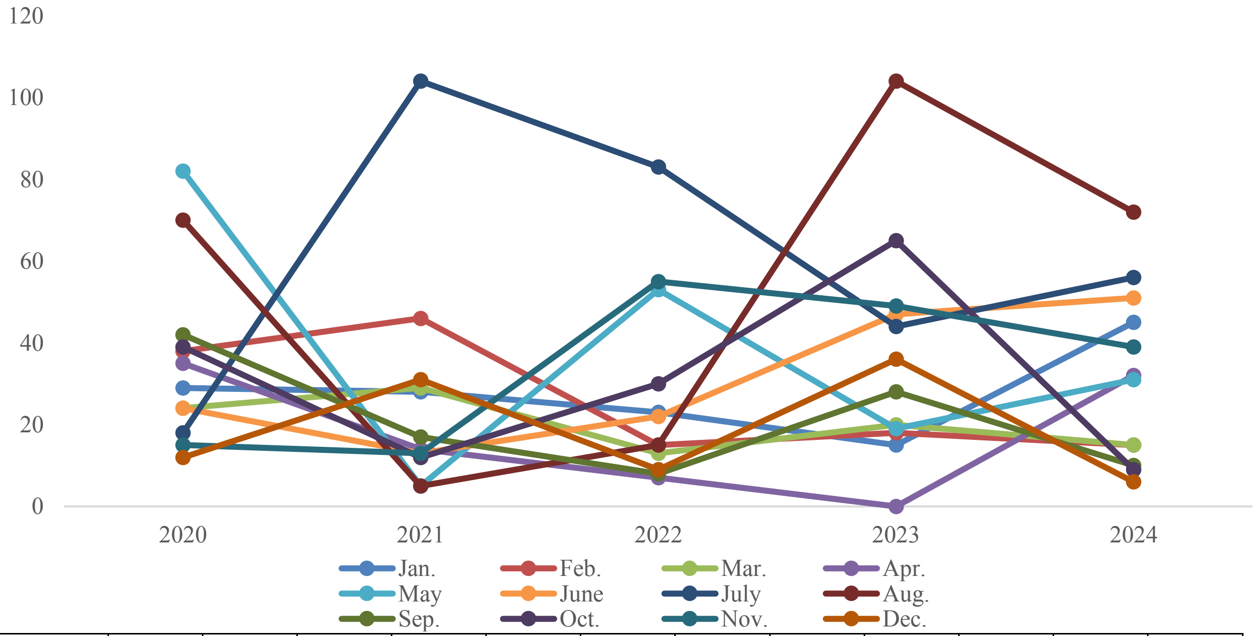


Fig. 5: Seasonal Components for Each Month

Source: [39]



Year	Jan.	Feb.	March	April	May	June	July	Aug.	Sep.	Oct.	Nov.	Dec.
2020	29	38	24	35	82	24	18	70	42	39	15	12
2021	28	46	29	14	5	13	104	5	17	12	13	31
2022	23	15	13	7	53	22	83	15	8	30	55	9
2023	15	18	20	0.5	19	47	44	104	28	65	49	36
2024	45	15	15	32	31	51	56	72	10	9	39	6

Fig. 6: Total Precipitation in Kostanay by month for 2020-2024

Source: [39]

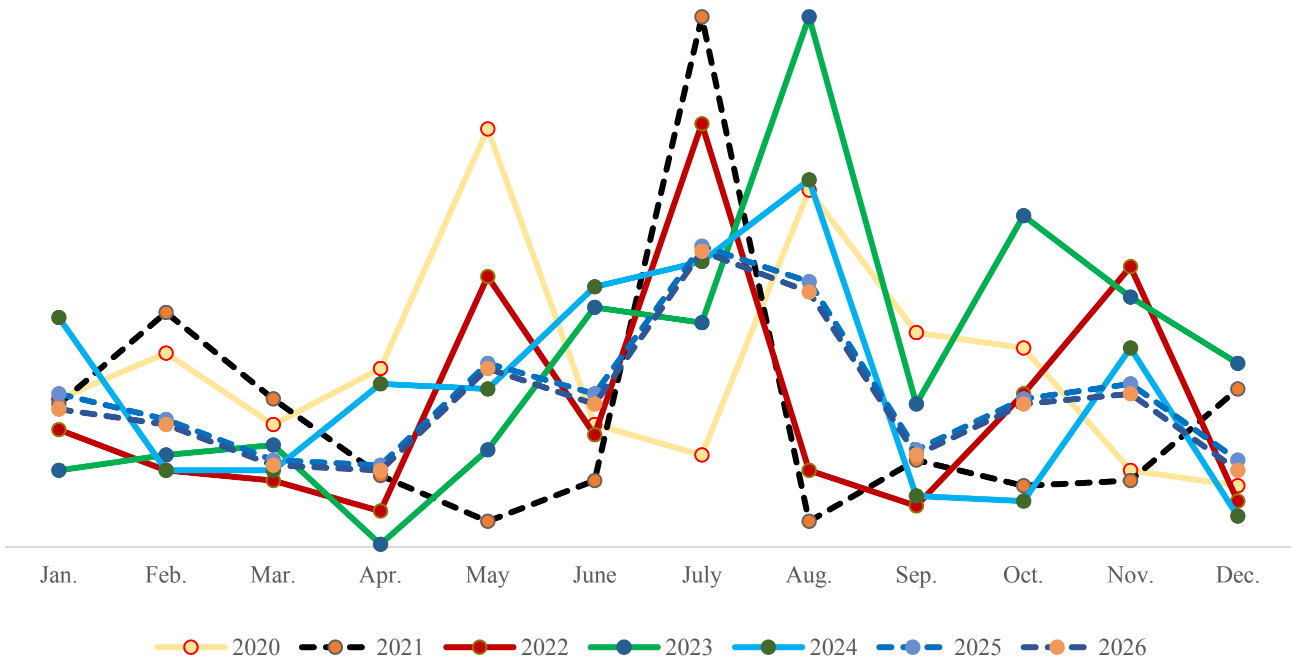


Fig. 7: Trend–Seasonal model of precipitation in Kostanay
Source: created by the authors

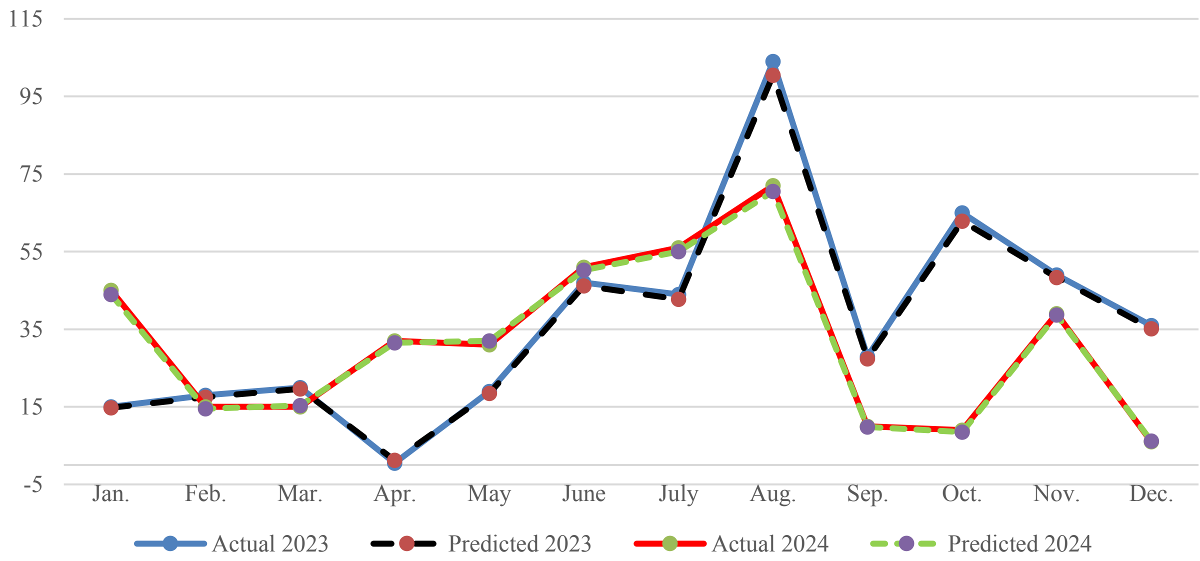


Fig. 8: Actual and estimated changes in precipitation in Kostanay in 2023-2024.
Source: created by the authors

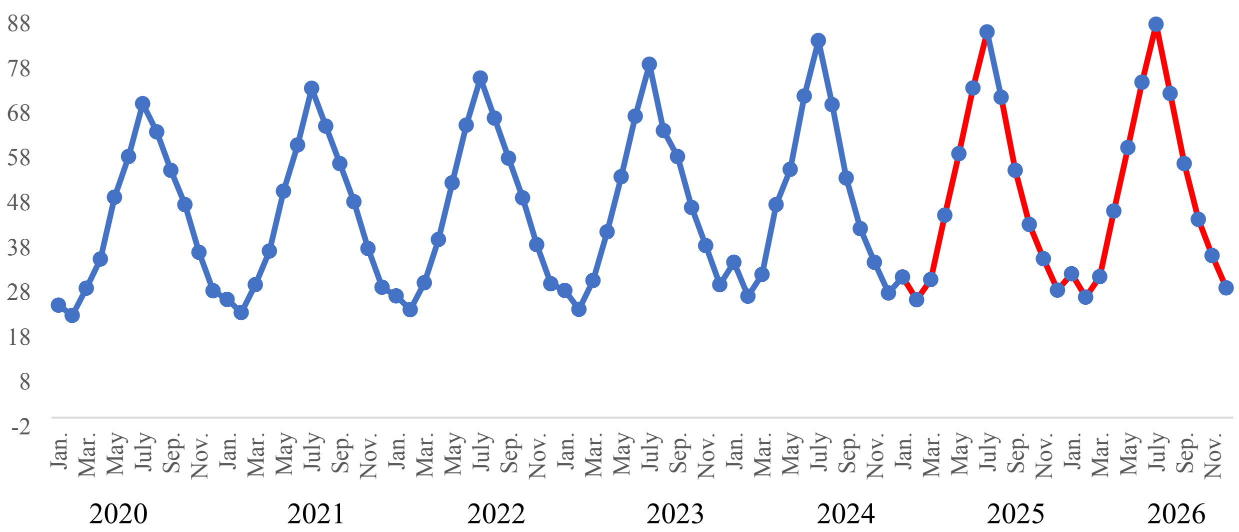


Fig. 9: Forecast of atmospheric precipitation for the city of Kostanay for 2025-2026
Source: created by the authors

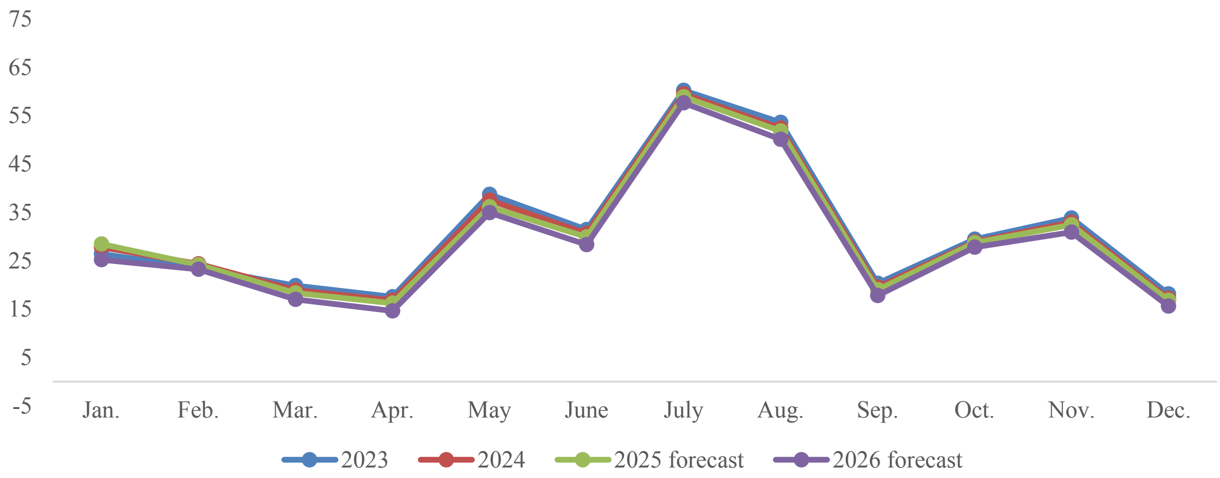


Fig. 10: Monthly Precipitation Forecast for Kostanay.
Source: created by the authors

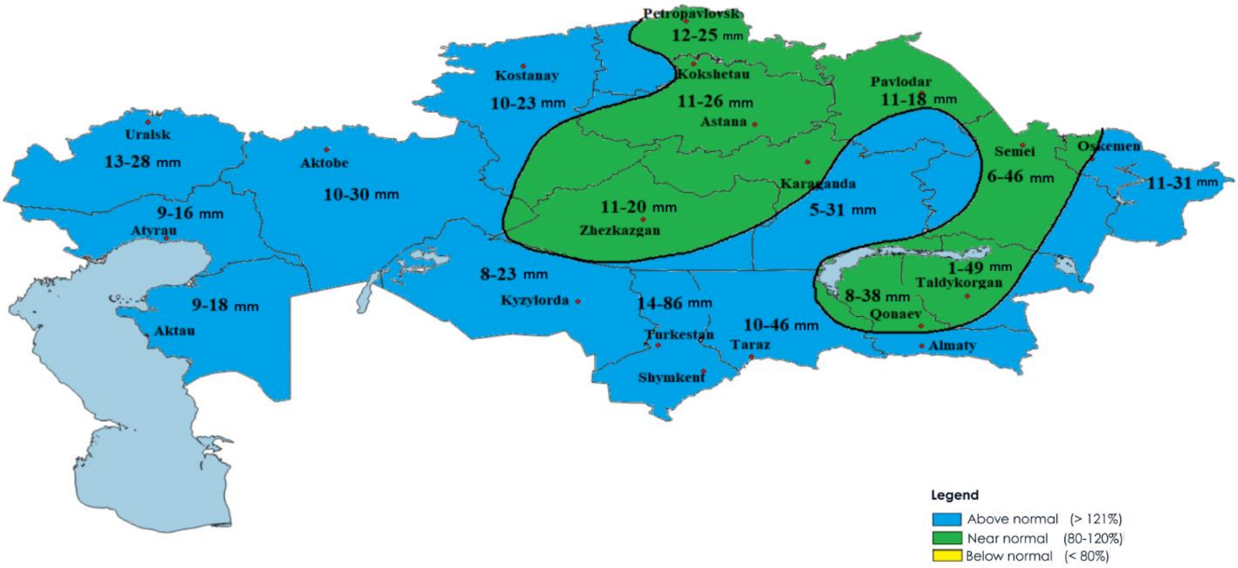


Fig. 11: Deviations of precipitation from the norm in January 2025
Source: [40]

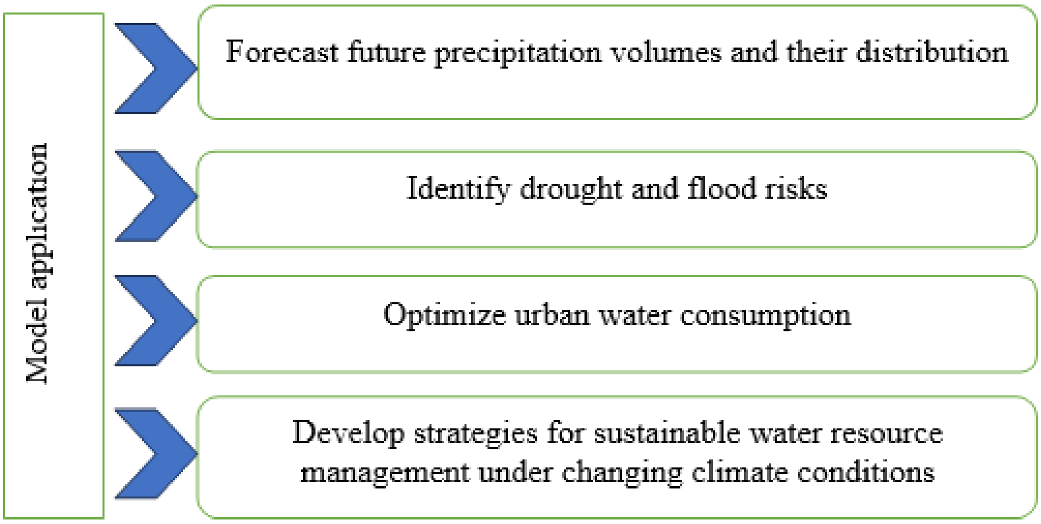


Fig. 12: Application of computational models for assessing precipitation volumes and seasonality in the cities of Kazakhstan
Source: created by the authors

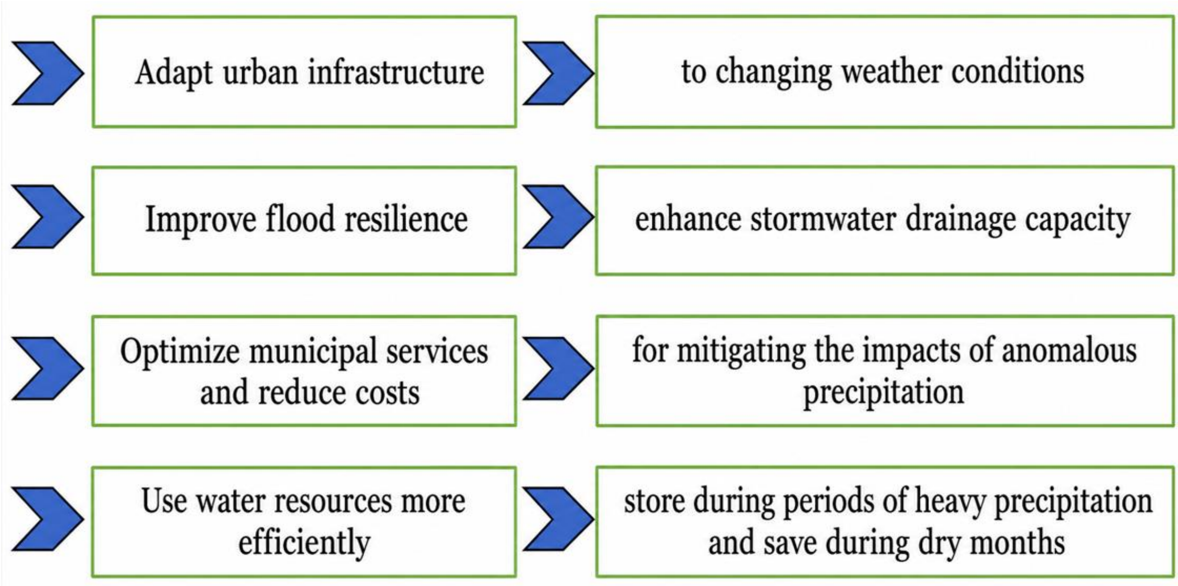


Fig. 13: Use of a trend–seasonal model in urban environment and water resource management
Source: created by the author