

Scientific article

TYOLOGY OF CALENDAR YEARS AND THERMAL REGIME DYNAMICS UNDER GLOBAL WARMING: RISK ASSESSMENT FOR ALMATY

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KEY WORDS

Almaty climate, multivariate statistical analysis, factorization, clustering, year typology, recurrence dynamics, change point, Pettitt test, Mann–Kendall test, climate risks, adaptation.

ABSTRACT

The aim of this work was to develop a statistically substantiated typology of thermal conditions of calendar years for Almaty and a quantitative analysis of its transformation against the background of ongoing climate change. A two-stage approach was used for the study. The first stage: dimensionality reduction using principal component analysis (PCA) followed by k-means clustering to identify integral year types. The second stage: analysis of the recurrence dynamics of the obtained types using nonparametric statistics (Pettitt test, Mann–Kendall test, Theil–Sen estimator). The PCA results (KMO = 0.764) revealed four latent factors (61.6 % of variance) characterizing the main seasonal regimes. Cluster analysis based on these factors allowed the identification of 5 statistically stable types (classes) of calendar years with a classification accuracy of 95.8 % as confirmed by discriminant analysis (LDA). Dynamic analysis recorded a statistically significant change point in the climate regime in 1993 (Pettitt test, $p < 0.001$). Exceptionally high rates of transformation were established: the frequency of the warmest type (mild winter, very warm summer) increases by +8.4 % per decade, while the frequency of the coldest type decreases by –7.1 % per decade. In the modern period (2001...2025), a new climatic norm has formed, with the warmest type accounting for 68 % of years. The resulting typology and quantitative estimates of its dynamics serve as a practical tool for detailed climate diagnostics, assessment of complex risks (heat waves, air quality deterioration, infrastructure load), and the development of targeted adaptation strategies for a metropolis in a global warming hotspot region.

1. INTRODUCTION

Large urban agglomerations such as Almaty (population over 2 million people) represent a critical focus of synergistic interaction between global climate trends and local anthropogenic factors [1...3]. The Central Asian region is officially recognized by the international expert community as one of the key modern 'hotspots', where the growth rates of surface air temperature significantly outpace global average values [4...6]. The local Urban Heat Island (UHI) effect, superimposed on the geomorphological features of the Ili intermontane basin, further exacerbates challenges related to urban ecosystem survival, municipal energy infrastructure resilience, and the development of adverse environmental conditions [2, 3].

Analysis of long-period climate changes requires strict consideration of the complex structure of time series, which, according to fundamental theory, includes trend, cyclical (wave oscillation), and random components [7...9]. As demonstrated in classical hydrometeorological literature, excluding the wave (cyclical) component from climatological analysis is categorically impermissible, since quasi-periodic natural rhythms of varying duration reflect the fundamental thermodynamics of the atmosphere-ocean system [10, 11]. At the same time, traditional analysis focused on fixed sliding 30-year 'climate normals' encounters a profound methodological

bottleneck: secular warming causes an upward 'baseline drift', artificially underestimating the magnitude of real thermal anomalies and depriving instruments of physical contrast (the phenomenon of 'thermal blindness' in models) [10, 12, 13]. Resolving this problem requires neutralizing the background trend and transitioning to the concept of digital twins of natural systems and relative dynamic baselines [14...18].

To objectively identify discrete, physically determined thermal regimes without introducing human subjectivity, non-linear machine learning and multidimensional statistical methods are most effective [19...23]. Preliminary dimensionality reduction of initial monthly hydrometeorological matrices using Principal Component Analysis (PCA) with adequacy control via the Kaiser–Meyer–Olkin (KMO) criterion and Bartlett's test of sphericity ensures the minimization of multicollinearity and the extraction of latent seasonal factors [24]. Subsequent clustering using the k-means algorithm automatically groups multi-year calendar years into stable classes [19...22], while Linear Discriminant Analysis (LDA) guarantees statistical verification of the separability of the obtained phase states [25].

To quantitatively evaluate the transformation of the climate regime, identify structural break points (bifurcations), and calculate the rate of change in sliding frequencies of year types, a transition to robust non-parametric statistics invariant to data distribution and extreme outliers is required [26...29]. The homogeneous non-parametric Pettitt test provides precise localization of the calendar year of regime shift [27], the Mann–Kendall sign test proves the directional statistical significance of trends [26, 29], and Sen's slope estimator determines the actual rate of restructuring of the year type structure [%/decade] [28].

The objective of this study is to develop a multidimensional statistical typology of thermal regimes of calendar years for Almaty over a 95-year period (1931...2025), mathematically localize the structural climate shift point, and quantitatively evaluate the non-linear dynamics of year type occurrence to form a scientific basis for adaptation strategies of Almaty's municipal economy in a global warming 'hotspot' region [5, 6, 23].

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2. MATERIALS AND METHODS

Input Data

A continuous series of monthly mean air temperatures (°C) from the Almaty meteorological station (WMO 36870) for complete calendar years from 1931 to 2025 inclusive (n = 95 years) was used. Data from the Kazhydromet archive underwent standard quality control and homogeneity procedures (Figure 1).

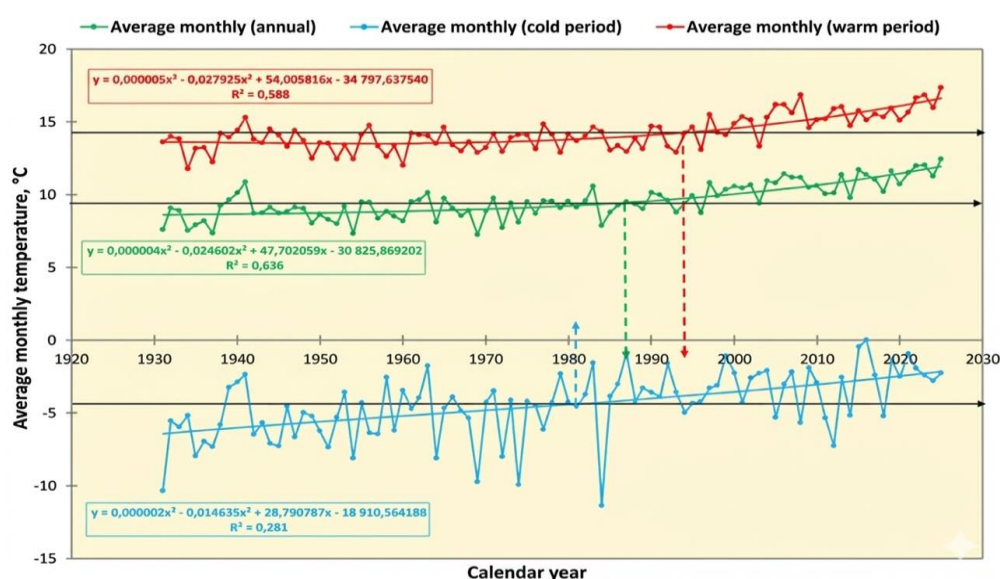


Figure 1. Linear trends of monthly mean temperature for the year, cold and warm periods, indicating the year of deviation onset from the mean value

Two-Stage Methodological Approach

The study was based on a sequential two-stage methodological approach integrating multivariate statistics methods for classification and time series analysis. Practical implementation was carried out using specialized software: IBM SPSS Statistics (version 26) for the typology construction stage and R (version 4.3.2) with necessary packages for the dynamics analysis stage. The overall logic of the approach is presented in the flowchart (Figure 2).

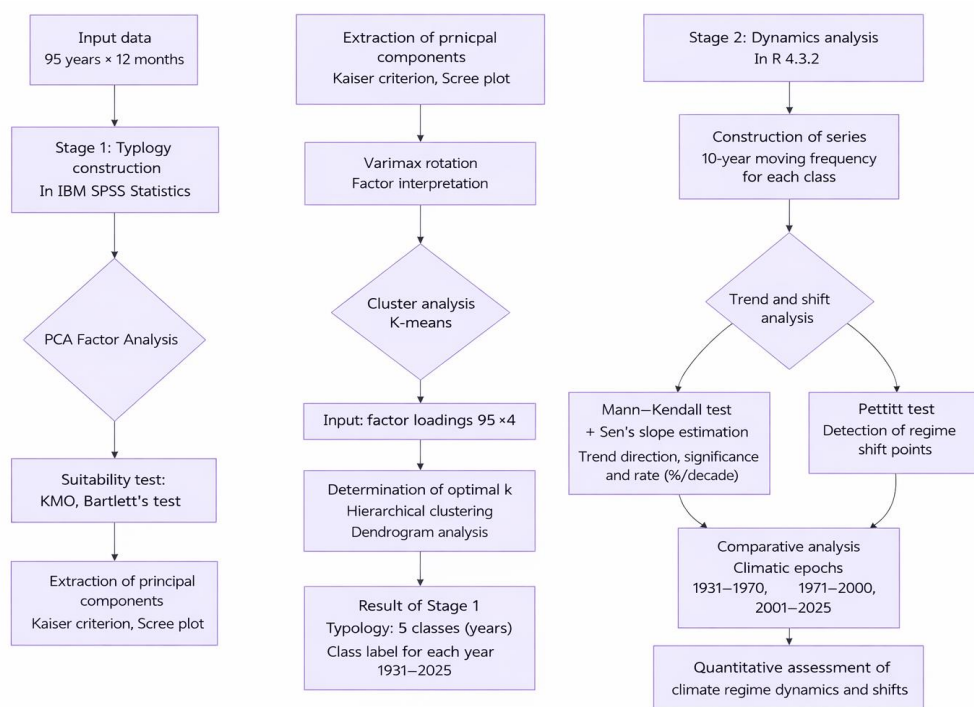


Figure 2. Flowchart of the two-stage methodological approach of the study

Stage 1. Typology Construction

Factor analysis. Principal component analysis with Varimax rotation was applied to the initial 95×12 matrix (years $\times$ months) to reduce dimensionality and identify latent seasonal factors. Data adequacy was confirmed by a high Kaiser-Meyer-Olkin measure ($KMO=0,764$) and the significance of Bartlett's sphericity test ($p<0,001$). The Kaiser criterion and Cattell's scree plot analysis justified the extraction of 4 factors.

Cluster analysis (k-means). The resulting factor loadings (95×4 matrix) were used as input for the iterative k-means algorithm. This eliminates the influence of multicollinearity of the original monthly temperature values. The optimal number of clusters ($k=5$) was determined based on dendrogram analysis of hierarchical agglomerative clustering and qualitative interpretability.

Classification validation. The stability and accuracy of the clustering were verified using linear discriminant analysis (LDA). The proportion of correctly classified cases and Wilks' lambda were calculated.

Stage 2. Dynamics and Trend Analysis

Time series construction. Based on class labels for each year, moving 10-year frequencies (in %) were calculated for each of the 5 calendar year types.

Change point detection. For the frequency series of the warmest type, a nonparametric Pettitt test was applied to detect a statistically significant breakpoint.

Trend assessment. For each moving frequency series, direction, statistical significance (Mann–Kendall test), and rate of change (robust Theil–Sen slope estimator) were calculated. Results are expressed in % per decade (%/decade).

Comparative analysis of epochs. The distribution of year types was compared across baseline (1931...1970), transitional (1971...2000), and modern (2001...2025) periods to visualize the scale of changes.

Detailed Description of Stages

Stage 1: Construction of Statistical Typology (implemented in IBM SPSS Statistics)

Factor analysis. Data preparation and verification of their suitability for factor analysis were as follows. The initial 95×12 data matrix (years $\times$ monthly mean temperatures) was standardized, and the suitability of the data for factor analysis was assessed. The Kaiser-Meyer-Olkin measure of sampling adequacy ($KMO = 0,764$) indicated "good" suitability of the data for factorization. Bartlett's sphericity test showed statistical significance ($\chi^2 = 259,5$; $p < 0,001$), rejecting the hypothesis of an identity correlation matrix and confirming significant relationships between variables. Four factors were extracted using principal component analysis, determined by the Kaiser criterion (eigenvalue > 1). Visual analysis of Cattell's scree plot showed a break after the fourth principal component. To improve interpretability, orthogonal Varimax rotation was performed. Rotation minimizes the number of variables with high loadings on a single factor, contributing to a clearer semantic separation of seasonal regimes. The result was a matrix of factor loadings of dimension 95×4 , where each row (year) is described not by 12 original temperatures but by 4 new, uncorrelated variables (factor scores) explaining 61,6 % of the total variance.

Cluster analysis. The factor loading matrix was used as input for clustering, which eliminates multicollinearity of monthly temperatures and increases solution stability. To determine the optimal number of clusters (k), hierarchical agglomerative clustering (Ward's method) was preliminarily used. Analysis of the dendrogram and a sharp increase in linkage distance showed the substantive feasibility of partitioning into 5 clusters. Iterative k-means clustering ($k = 5$) was then performed, assigning a final class label (1 to 5) to each year.

Discriminant analysis. To verify the stability and accuracy of the clustering, linear discriminant analysis (LDA) was applied. The result yielded discriminant functions that maximally separate the a priori defined 5 groups (the k-means result). The self-consistency criterion showed that 95.8 % of years were correctly reclassified by these functions into their original cluster. Wilks' lambda value ($\Lambda = 0,052$) and its statistical significance ($p < 0,001$) confirmed the high separability of classes and the reliability of the resulting typology.

The result of Stage 1 was a verified typology of 5 thermally homogeneous classes. Analysis of the temporal distribution of calendar years by classes shows a clear climatic shift, clearly expressed in the form of a color spectrum: from blue and light blue (cold period) in the 1930s and 1940s to the 2000s and 2020s (warm period), indicated by light brown and brown (Figure 2).

Stage 2. The aim of this stage is to present a quantitative assessment of temporal changes in the recurrence of the identified year types. Trend dynamics analysis was implemented in the Python and R (version 4.3.2) software environments.

Distribution of 10-year moving frequencies of identified classes by calendar year. Preparation of material for time series recurrence analysis was carried out based on the sequence of class labels for each year from 1931 to 2025. For each of the 5 classes, a series of moving 10-year frequencies was calculated. For each central year "t", the proportion (percentage) of years belonging to a given class in the window $[t-4; t+5]$ was calculated. This made it possible to obtain smoothed curves reflecting the change in the probability of occurrence of a given year type over time, thereby minimizing the influence of interannual variability.

Detection of climate regime change point. To objectively determine the moment of sharp change in the behavior of the series (shift in mean level), the homogeneous nonparametric Pettitt test was applied. The test, based on rank statistics, was applied to the moving frequency series for Class 3 (the warmest). It identified the year after which the statistical properties of the series changed significantly, indicating a moment of qualitative shift in the climate regime.

Detection and assessment of trend significance were carried out using the nonparametric Mann–Kendall test applied to each moving frequency series to test the null hypothesis of no monotonic trend. Its advantage is robustness to outliers and no requirement for data normality. To assess the rate of detected significant trends, the robust Theil–Sen slope estimator was used. It calculates the median of all possible slopes between pairs of points in the series, making the estimate resistant to anomalies. The result is presented in intuitively understandable units: the percentage change in class recurrence per decade (%/decade).

Comparative analysis of climate epochs. To clearly demonstrate the scale of changes, the distribution of classes was calculated and visualized for three periods:

- Baseline period (1931...1970) – the background "pre-warming" climatic norm.
- Transitional period (1971...2000) – the period of global warming acceleration.
- Modern period (2001...2025) – reflecting the current state of the climate system.

The result of Stage 2 is the quantitative assessment of the rate, direction, and statistical significance of trends in the recurrence of year types, identification of the point of cardinal restructuring of the thermal regime (1993), which clearly demonstrated the scale of the newly formed climatic norm.

Thus, the presented two-stage approach provides a rigorous statistical basis for transitioning from initial climate data to a comprehensive assessment of structural changes in the climate regime, combining classification and time series analysis methods.

3. RESULTS AND DISCUSSION

Factor analysis revealed 4 factors explaining 61,6 % of variance: F1 – "Warm season" (late spring–summer, 24,9 %), F2 – "Severe winter" (13,6 %), F3 – "Autumn–early winter regime" (12,4 %), F4 – "Early autumn" (10,8 %). Clustering of factor loadings identified 5 climatically homogeneous types (table 1). Discriminant analysis confirmed high classification accuracy (95,8 %, Wilks' $\Lambda = 0,052$, $p < 0,001$).

Table 1

Climatic characteristics of five types (classes) of thermal years for Almaty (1931...2025)

Class	Mean annual temperature, °C	Key feature of seasonal regime
1	8,6	Very cold winter, warm summer
2	9,5	Cold winter, warm summer, cold autumn
3	11,3	Mild winter, very warm summer
4	8,6	Moderate winter, coolest summer
5	9,8	Cold winter, warm summer, extremely cold autumn/early winter

Analysis of the temporal distribution of years by classes shows a clear climatic shift, expressed in the form of a color spectrum: from blue and light blue (cold period) in the 1930s...1940s to the 2000s...2020s (warm period), characteristic of global warming (Figure 3).

Calendar year class	Class characteristics	Average annual temperature by class	Distribution of calendar years by class for 95 years between 1931 and 2025.					
I	Very cold winter, warm summer	8,6	1931	1936	1942	1945	1951	1956
			1957	1969	1971	1972	1980	1988
II	Cold winters, warm summers, and cold autumns	9,5	1932	1938	1944	1950	1952	1953
			1961	1962	1963	1966	1975	1976
			1981	1982	1983	1987	2000	2016
			2020	-	-	-	-	-
III	Mild winters, very warm summers	11,3	1997	2001	2004	2005	2006	2007
			2008	2012	2013	2015	2017	2019
			2021	2022	2023	2024	2025	-
IV	Mild winters, coolest summers	8,6	1934	1935	1937	1943	1946	1947
			1948	1949	1954	1958	1959	1960
			1964	1967	1968	1970	1979	1985
			1986	1989	1992	1993	1996	2003
V	Cold winters, warm summers, and extremely cold autumns/early winters	9,8	1933	1939	1940	1941	1955	1965
			1973	1974	1977	1978	1984	1990
			1991	1994	1995	1998	1999	2002
			2009	2010	2011	2014	2018	-

	1931-1940		1951-1960		1971-1980		1991-2000		2011-2020
	1941-1950		1961-1970		1981-1990		2001-2010		2021-2025

Figure 3. Typology of calendar years reflecting the dynamics of the thermal regime of Almaty

Recurrence dynamics and trends. The Pettitt test revealed a statistically significant ($p < 0,001$) regime change point in 1993 for the distribution of 10-year moving frequencies of Class 3. The mean recurrence frequency of the class increased from 14.2 % (before 1993) to 52.8 % (after 1993) (Table 2). The change in thermal regime is clearly shown in Figure 4.

Table 2

Results of the Pettitt test for the recurrence series of Class 3

Parameter	Value
Change point year (K)	1993
Test statistic (U) $K_{max}=724 > K_{01} = 530$	724
Significance (p)	$< 0,001$
Mean frequency before 1993	14,2 %
Mean frequency after 1993	52,8 %

This breakpoint chronologically coincides with the phase of most intense manifestation of global warming in the region. The change point is visually represented in Figure 4.

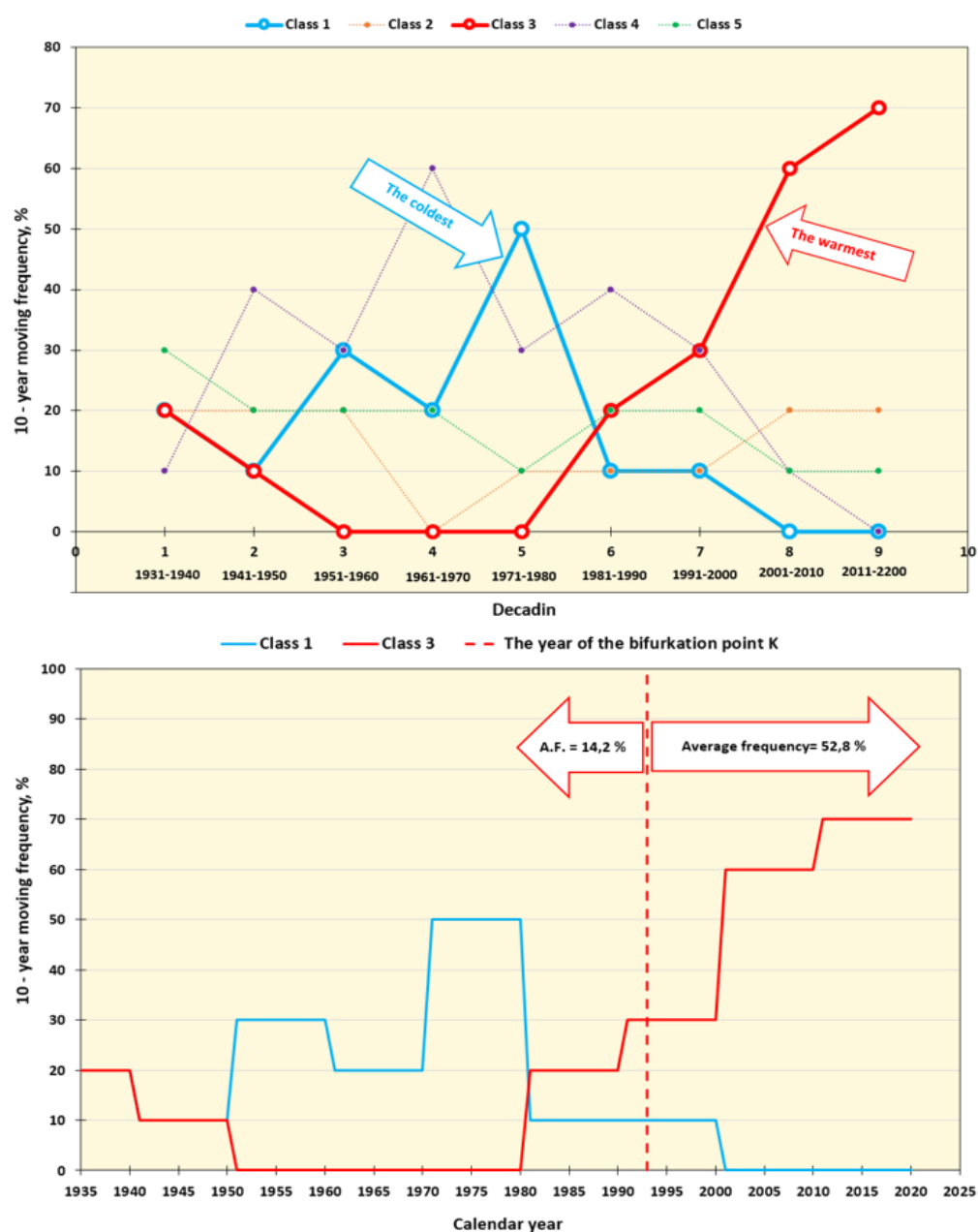


Figure 4. Dynamics of the moving 10-year frequency of Class 1 (coldest) and Class 3 (warmest)

The vertical line marks the regime change point identified by the Pettitt test (1993).

Trend analysis showed (Table 3):

- Class 3 (warm) – significant intense growth (+8,4 %/decade, $p < 0,001$).
- Class 1 (cold) – significant sharp decline (-7,1 %/decade, $p < 0,001$).
- Class 4 – significant moderate decline (-3,2 %/decade, $p = 0,002$).
- Trends for Classes 2 and 5 are statistically insignificant.

Table 3

Assessment of trends in the recurrence of year types (1935...2020)

Class	Trend direction	Mann–Kendall Z	p-value	Theil–Sen slope (%/decade)
1	Decreasing	-6,87	<0,001	-7,1
2	Not significant	-0,33	0,74	-0,3
3	Increasing	8,34	<0,001	+8,4
4	Decreasing	-3,07	0,002	-3,2
5	Not significant	-0,72	0,472	-0,7

Formation of a new climatic norm. Comparison of periods (Figure 5) shows a radical restructuring:

- 1931...1970: balanced structure, dominance of cold types 1 and 4 (total $\approx 62,5$ %). Class 3 is rare (7,5 %).
- 1971...2000: transitional period, increase in Class 3 share to 20 %.
- 2001...2025: new norm – absolute dominance of Class 3 (68 % of years). Complete disappearance of Class 1 after 1994, sharp reduction in Class 4 share.

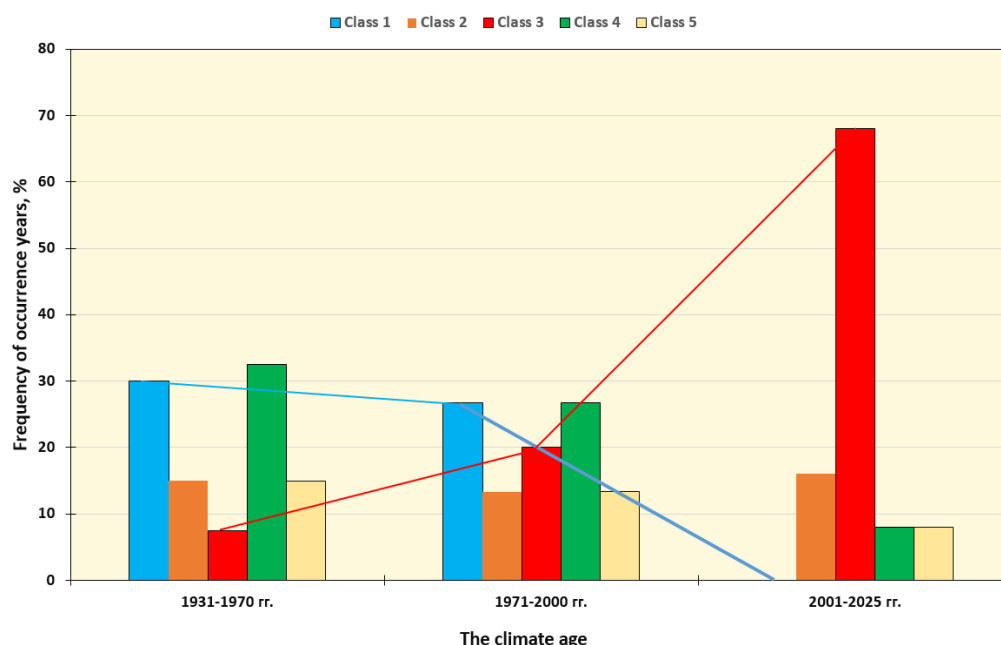


Figure 5. Distribution of thermal year type frequencies by climatic epochs (Almaty)

Discussion and Practical Significance of Results

The developed methodology (factorization + clustering + dynamics analysis) allowed not only to state warming but to identify a qualitative shift in the climate structure – a transition to the dominance of a specific, anomalously warm year type (Class 3). The breakpoint (1993) chronologically coincides with the acceleration phase of global warming. The high rates of change (+8,4 % and -7,1 % per decade) confirm the region's status as a climate "hotspot" and indicate the nonlinear, accelerating nature of the transformation.

The practical significance of the results lies in the transition from stating facts to developing specific, scientifically based adaptation measures. The typology translates global trends into localized and interpretable scenarios for urban management. Based on the identified dynamics, specific adaptation measures for Almaty can be proposed.

Urban planning and infrastructure modernization indicate the need to adjust construction standards (SNIIP, SP). Stricter requirements for building thermal insulation should focus not on average indicators but on the thermal characteristics of Class 3 (mild winter) and Class 5 (extremely cold autumn). Particular attention should be paid to the summer overheating regime: mandatory design of passive cooling (sun shading structures, forced night ventilation, use of high-albedo materials for roofs and facades).

Planning of "cooling corridors" is necessary. Using data on prevailing winds during periods related to Class 3, it is necessary to legally consolidate and restore natural ventilation corridors (e.g., small river valleys), preventing their point development. This is a key measure to mitigate the urban heat island effect.

Adaptation of road and transport infrastructure is required. When designing and repairing roads, it is necessary to use asphalt concrete mixtures resistant to higher summer temperatures (characteristic of Class 3) to avoid wave formation and increased wear.

In the field of healthcare and social protection, it is necessary to implement a Heat-Health Warning System (HHWS). Based on the identification of Class 3 and the forecast of its onset, a multi-level warning system should be created. Threshold values for declaring "yellow," "orange," and "red" danger levels should be calculated specifically for Almaty, taking into account local physiological adaptation of the population and morbidity data.

Creation of vulnerability maps is important. It is necessary to identify urban areas with maximum concentration of vulnerable groups (elderly people, children, persons with chronic diseases) and the least favorable microclimate (dense development, minimal greenery). In these areas, during periods corresponding to Class 3, mobile cooling points should be quickly deployed and patronage services strengthened.

Climate control of social facilities should be ensured. Schools, hospitals, and nursing homes should be prioritized for equipping with air conditioning systems or, at a minimum, powerful forced-air ventilation systems with cooling.

Environmental management and air quality deserve special attention.

A regime of special emission control must be strictly observed. During forecast periods of Class 3 conditions (anticyclonic weather, weak wind), a restriction regime for major stationary pollution sources (CHP plants, industrial enterprises) should be automatically introduced, following the example of systems operating in Beijing or Paris.

A next-generation greening strategy should be developed. Tree planting should be carried out not only for decorative purposes but also for maximum ecosystem effect. Priority should be given to tree species with high transpiration activity and large leaf surface area (e.g., oak, poplar, elm, ash), providing natural cooling and pollutant sequestration. It is necessary to develop green roofs and vertical gardening, especially in the densely built city center.

Creation of a unified digital platform is required, where meteorological data (Class 3 risk), atmospheric air monitoring data, and the epidemiological situation are compared in real time for operational decision-making.

Particular attention should be paid to energy and water use, forecasting peak loads. Energy companies should use scenarios of increasing Class 3 frequency to modernize networks and plan reserve capacities for the summer maximum period associated with the massive use of air conditioners. Co-financing programs for installing solar panels and heat recovery systems in the residential sector should be developed to reduce the load on the network during peak periods.

A special role is assigned to the adaptation of the water management complex. Thus, the increase in warm winters (Class 3) requires adjustment of reservoir filling forecast models dependent on snow supply. It is necessary to develop scenarios for water resource management under conditions of earlier and more intense snowmelt.

Limitations and prospects. The main limitation of the work is the consideration of only the temperature parameter. Promising directions are: 1) creation of a comprehensive typology including data on precipitation, humidity, and atmospheric circulation indices for direct synoptic interpretation of types and forecasting of droughts or floods; 2) expansion of the methodology to other major cities of Central Asia (Bishkek, Tashkent) for comparative analysis of regional climate risks; 3) use of the obtained typology for calibration and verification of regional climate models (RCMs) to develop probabilistic scenarios for the recurrence of identified year types over the next 30...50 years.

Thus, the proposed typology serves not only as a diagnostic but also as a design tool. It allows assessing the effectiveness of existing measures and designing a new, climate-oriented urban development policy, transforming climate risk data into specific action plans for all key sectors of the urbanized environment.

4. CONCLUSION

1. The comprehensive two-stage methodological approach (multivariate statistics + time series analysis) made it possible to create a statistically substantiated typology of 5 thermal year types for Almaty and quantitatively assess its transformation.

2. A cardinal qualitative shift in the climate regime was revealed, expressed in the transition to absolute dominance of the warmest year type (Class 3) after 1993. In the modern period (2001...2025), this type constitutes a new climatic norm (68 % of years).

3. Exceptionally high rates of change were established: an increase in the recurrence of Class 3 by +8.4 % and a decrease in Class 1 by –7.1 % per decade, confirming the high vulnerability of the region.

4. The results obtained are not only diagnostic but also a practical tool. The developed typology and quantitative estimates of its dynamics represent a scientific basis for assessing complex climate risks and developing specific adaptation measures for key sectors of Almaty's urban economy.

DATA AVAILABILITY

The data used is publicly available.

AUTHOR CONTRIBUTIONS

Scientific hypothesis and research methodology – VKKh; Numerical solutions and calculations – YuGB; Writing of the article – YuPD.

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КҮНТІЗБЕЛІК ЖЫЛДАРДЫҢ ТИПОЛОГИЯСЫ ЖӘНЕ ЖАҒАНДЫҚ ЖЫЛЫНУ ЖАҒДАЙЫНДАҒЫ ЖЫЛУ РЕЖИМІНІҢ ДИНАМИКАСЫ: АЛМАТЫ ҚАЛАСЫ ҮШІН ҚАТЕРЛЕРДІ БАҒАЛАУ

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ТҮЙІН СӨЗДЕР

Алматы климаты, көпөлшемді статистикалық талдау, факторлық талдау, кластерлеу, жылдар типологиясы, қайталаным динамикасы, өзгеріс нүктесі, Петтит критерийі, Манн-Кендалл критерийі, климаттық тәуекелдер мен бейімделу

АБСТРАКТ

Осы зерттеудің мақсаты – Алматы қаласындағы күнтізбелік жылдар бойынша жылулық жағдайлардың статистикалық тұрғыдан негізделген типологиясын әзірлеу және қазіргі климаттың өзгеруі жағдайында осы жағдайлардың өзгерісін сандық тұрғыдан талдау болды. Зерттеу барысында екі сатылы тәсіл қолданылды. Бірінші кезеңде негізгі компоненттер талдауы (PCA) арқылы деректердің өлшемділігі қысқартылып, одан кейін k-means әдісімен кластерлеу негізінде күнтізбелік жылдардың типтері анықталды. Екінші кезеңде анықталған типтердің қайталану динамикасы параметрлік емес статистикалық әдістер (Петтит критерийі, Манн-Кендалл критерийі және Тейлор-Сен бағалауы) көмегімен талданды. PCA нәтижелері (КМО = 0.764) жалпы дисперсияның 61,6 %-ын түсіндіретін және негізгі маусымдық заңдылықтарды сипаттайтын төрт жасырын факторды айқындады. Осы факторларға негізделген кластерлік талдау күнтізбелік жылдардың 95,8 % дәлдікпен бес статистикалық тұрғыдан сенімді типін (сыныбын) бар екенін көрсетті, бұл нәтиже сызықтық дискриминанттық талдау (LDA) арқылы расталды. Динамикалық талдау климаттық режимде 1993 жылы статистикалық маңызды бұрылыс нүктесінің бар екенін анықтады (Petit критерийі, $p < 0,001$). Өте жоғары трансформация қарқыны байқалды: ең жылы типтің (жұмсақ қыс, өте жылы жаз) жиілігі әр онжылдықта +8,4 %-ға артып отырса, ең суық типтің жиілігі –7,1 %-ға төмендеген. Қазіргі кезеңде (2001...2025 жж.) жаңа климаттық норма қалыптасқан, мұнда жылы тип жылдардың 68 %-ын құрайды. Алынған типология және оның динамикасының сандық бағалаулары егжей-тегжейлі климаттық диагностика үшін практикалық құрал ретінде қызмет етеді, күрделі тәуекелдерді (жылу толқындары, ауа сапасының нашарлауы, инфрақұрылымға түсетін жүктеме) бағалауға және жаһандық жылынудың «ыстық нүктесі» саналатын аймақта орналасқан мегаполис үшін мақсатты бейімделу стратегияларын әзірлеуге мүмкіндік береді.

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ТИПОЛОГИЯ КАЛЕНДАРНЫХ ЛЕТ И ДИНАМИКА ТЕРМИЧЕСКОГО РЕЖИМА В УСЛОВИЯХ ГЛОБАЛЬНОГО ПОТЕПЛЕНИЯ: ОЦЕНКА РИСКОВ ДЛЯ АЛМАТЫ

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КЛЮЧЕВЫЕ СЛОВА

Климат Алматы, многомерный статистический анализ, факторизация, кластеризация, типология по годам, динамика повторяемости, точка перелома, критерий Петтита, критерий Манна–Кендалла, климатические риски и адаптация

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АБСТРАКТ

Целью данной работы являлась разработка статистически обоснованной типологии тепловых условий календарных лет для г. Алматы, а также количественный анализ их изменений на фоне современных климатических трансформаций. В исследовании применён двухэтапный подход. На первом этапе выполнено снижение размерности данных с использованием метода главных компонент (РСА), после чего проведена кластеризация методом k-средних для выделения типов календарных лет. На втором этапе осуществлён анализ динамики повторяемости выделенных типов с применением непараметрических статистических методов (критерий Петтита, критерий Манна–Кендалла, оценка Тейла–Сена). Результаты РСА (КМО = 0,764) позволили выявить четыре латентных фактора, объясняющих 61,6 % общей дисперсии и отражающих ключевые сезонные режимы. Кластерный анализ, основанный на данных факторах, позволил выделить 5 статистически устойчивых типов (классов) календарных лет с точностью классификации 95,8 %, что было подтверждено дискриминантным анализом (LDA). Динамический анализ выявил статистически значимую точку перелома климатического режима в 1993 г. (критерий Петтита, $p < 0,001$). Установлены исключительно высокие темпы трансформации: частота наиболее тёплого типа (мягкая зима, очень тёплое лето) увеличивается на +8,4 % за десятилетие, тогда как частота наиболее холодного типа снижается на –7,1 % за десятилетие. В современный период (2001...2025 гг.) сформировалась новая климатическая норма, при которой на самый тёплый тип приходится 68 % лет. Полученная типология и количественные оценки её динамики представляют собой практический инструмент для детальной климатической диагностики, оценки комплексных рисков (тепловые волны, ухудшение качества воздуха, нагрузка на инфраструктуру) и разработки целевых стратегий адаптации для мегаполиса, расположенного в регионе, рассматриваемом как «горячая точка» глобального потепления.

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