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TYPOLOGIZATION OF THE ECONOMIC POTENTIAL AND DEVELOPMENT CHARACTERISTICS OF THE DISTRICTS OF SURKHANDARYA REGION BASED ON STATISTICAL AND NEURAL NETWORK APPROACHES

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Abstract: This article develops a multidimensional typology of the economic potential and development characteristics of the districts of Surkhandarya region based on statistical data for 2010-2024. In the study, indicators reflecting the economic condition and development dynamics of the territories were standardized, and the Ward method, K-means clustering, and Self-Organizing Map (SOM) approaches were applied. The results show that the territories of the region are divided into three main typological groups: industrialized districts with high entrepreneurial activity, districts dominated by an agrarian orientation, and territories with relatively high levels of efficiency and growth rates. The scientific novelty of the study lies in the deeper identification of interterritorial economic disparities by integrating traditional statistical clustering methods with the SOM-based neural network approach.

Key words: investment activity, economic disparities, territorial typology, district clustering, economic potential, K-means, Self-Organizing Map.

Аннотация: В данной статье разработана многомерная типология экономического потенциала и особенностей развития районов Сурхандарьинской области на основе статистических данных за 2010–2024 годы. В исследовании были стандартизированы показатели, отражающие экономическое состояние и динамику развития территорий, а также применены методы Уорда, кластеризация K-means и подход Self-Organizing Map (SOM). Результаты показали, что территории региона подразделяются на три основные типологические группы: индустриализированные районы с высокой предпринимательской активностью, районы с преобладанием аграрной направленности и территории с относительно высокими показателями эффективности и темпов роста. Научная новизна исследования заключается в более глубоком выявлении межтерриториальных экономических различий посредством интеграции традиционных статистических методов кластеризации с нейросетевым подходом на основе SOM.

Ключевые слова: инвестиционная активность, экономические различия, территориальная типология, кластеризация районов, экономический потенциал, K-means, Self-Organizing Map.

INTRODUCTION

Regional development processes do not proceed at the same pace or in the same direction, either at the national level or within individual regions. Each district differs from others in terms of its economic potential, sectoral specialization, labor resources, entrepreneurial activity, and growth opportunities. Therefore, assessing all districts within a region according to the same criteria does not fully reveal their internal disparities, existing opportunities, and specific development characteristics. From this perspective, in recent years, the typologization of territories based on multidimensional economic indicators has been recognized as an important scientific and methodological tool for developing differentiated regional policy.

The relevance of the study is determined by the strategic importance, in the context of the Republic of Uzbekistan, of effectively utilizing the economic potential of territories, directing available resources in a targeted manner, and reducing interregional economic disparities. The “Uzbekistan-2030” Strategy identifies ensuring sustainable economic growth, increasing the investment attractiveness of regions, and fully mobilizing the development potential of each territory based on its existing opportunities as priority objectives [1]. This indicates the need to assess regional development not only through general indicators, but also by taking into account the internal economic characteristics, existing potential, structural features, and development trajectory of each territory.

Surkhandarya region is considered one of the important territorial objects for studying this issue. According to the data of the National Statistics Committee, as of January 1, 2026, 31,225 enterprises and organizations were operating in the region. In 2025, the volume of market services increased by 14.1%, agriculture, forestry and fisheries by 3.8%, and the real total income of the population by 9.0% [2]. In addition, in January-December 2025, the gross regional product of Surkhandarya region amounted to UZS 66,186.5 billion at current prices, with a growth rate of 106.6%. The region’s share in Uzbekistan’s gross domestic product was 3.6% [3]. Although these indicators demonstrate an increase in economic activity in the region, they also indicate that the level of economic development, sectoral structure, and opportunities for utilizing economic potential are not uniform across districts.

The necessity of this study arises from the need to conduct an in-depth analysis of economic disparities among the districts of Surkhandarya region and to group territories on a scientific basis according to their development characteristics. The districts of the region differ significantly from one another in terms of the level of industrialization, the share of the agrarian sector, the development of the service sector, investment activity, the scale of small business, and labor productivity. Under such conditions, assessing territories solely on the basis of general growth indicators does not fully reveal their existing opportunities, weaknesses, and prospective development directions. Therefore, classifying districts into typological groups based on economic potential, structural composition, efficiency, and growth dynamics is necessary for a deeper assessment of regional development and for the formulation of targeted political and economic decisions.

In forming territorial typologies, cluster analysis—particularly Ward’s hierarchical method and the K-means algorithm—is widely applied. These methods make it possible to identify similarities and differences among territories on the basis of multidimensional economic indicators. However, traditional statistical clustering methods do not always sufficiently reveal topological proximity, intermediate states, and hidden grouping patterns within the structure of the data. Therefore, in recent years, unsupervised neural network methods such as the Self-Organizing Map (SOM) have been used as an effective complementary tool for visualizing territorial structures, identifying intermediate economic types, and providing a deeper interpretation of cluster boundaries.

Although the existing literature extensively covers issues of territorial typology and clustering, there is still a lack of studies that assess economic potential, structural indicators, efficiency, and growth dynamics within a unified system at the district level of Surkhandarya region, while also integrating statistical clustering methods with a SOM-based neural network approach. This scientific gap further increases the relevance and methodological significance of the present study. Therefore, the main objective of this article is to typologize the districts of Surkhandarya region according to their economic potential and development characteristics using statistical and neural network approaches based on statistical data for 2010-2024.

REVIEW OF LITERATURE ON THE SUBJECT

The assessment of regional development processes based on multidimensional indicators and the classification of territories into typological groups have been widely studied in recent years within the fields of regional studies, analysis of interregional economic relations, and urban analytics. In international studies, unsupervised learning methods, particularly clustering algorithms, are considered effective tools for identifying hidden similarities and differences among territories. In their systematic review within the field of urban studies, J. Wang and F. Biljecki demonstrated that clustering methods are widely used for grouping urban and regional systems [4]. Arribas-Bel, D. Kourtit, and P. Nijkamp substantiated that the Self-Organizing Maps (SOM) approach is useful for visualizing and benchmarking complex territorial typologies [5].

From a methodological perspective, hierarchical clustering and K-means methods are widely used for grouping territories. A. Rao and V. Srinivas demonstrated that a hybrid clustering approach is effective in classifying territorial units into homogeneous groups [6]. At the same time, classical clustering methods do not always fully capture topological proximity and intermediate states in multidimensional data. For this reason, unsupervised neural network approaches such as SOM are increasingly being used as important complementary tools for deepening clustering results and providing their visual interpretation. A. Ruiz-Varona et al. showed that SOM can be used to assess regional development trajectories [7], while P. Hajek and R. Henriques substantiated the possibility of visualizing the structure of regional innovation systems through SOM [8]. M. Tonini et al. also demonstrate that the typology of the rural-urban continuum can be classified more accurately using a neural network approach [9].

In studies conducted within the CIS and post-Soviet context, the statistical assessment of regional development and the identification of interregional disparities based on factors such as investment activity, industrialization, the labor market, and infrastructure are regarded as important research directions. However, these studies predominantly employ classical statistical methods, composite indices, and clustering approaches, while the issue of identifying topological proximity among regions through neural network methods such as SOM has been addressed relatively insufficiently.

Existing studies on Uzbekistan have also examined issues of regional development and economic potential using statistical and econometric methods. B. Begalov and H. Berdiyeva demonstrated the methodological significance of grouping the regions of Uzbekistan on the basis of factor and cluster analysis [10]. Z. Abdalova and I. Islomov analyzed the relationship between investment activity and regional economic development [11]. M. Pardayeva assessed the economic development trends of Surkhandarya region using econometric and statistical methods [12]. However, these studies are mainly focused on general analysis at the regional level or on the dynamics of individual indicators.

The analysis of the existing literature shows that the scientific significance of clustering and SOM approaches in territorial typologization has been sufficiently substantiated in international studies. However, in the context of Uzbekistan, there is a lack of comprehensive studies that assess the economic potential, structural characteristics, efficiency, and growth dynamics of the districts of Surkhandarya region within a unified system of indicators and jointly apply Ward's hierarchical clustering, K-means, and SOM approaches.

The strength of this study lies in the fact that the districts of Surkhandarya region are typologized on the basis of multidimensional indicators reflecting economic potential, sectoral structure, labor productivity, and development dynamics. In addition, traditional statistical clustering methods are integrated with a SOM-based neural network approach, which creates an opportunity for a deeper interpretation of internal similarities among territories, intermediate economic types, and cluster boundaries.

RESEARCH METHODOLOGY

In this study, statistical and neural network approaches were applied in an integrated manner in order to conduct a multidimensional assessment and typologization of the economic potential and development characteristics of the districts of Surkhandarya region. The general research algorithm included the stages of data collection and preparation, formation of derived indicators, standardization, determination of the number of clusters, construction of the final typology based on K-means, and additional neural network-based validation using SOM.

Official statistical data for the districts and cities of Surkhandarya region covering the period 2010-2024 were used. Territorial units, namely districts and cities, were adopted as the units of observation. Termez district and Termez city were treated as separate units of observation. For Bandikhan district, data were accepted only for the years in which they were available, and missing values for earlier periods were not artificially imputed.

Initially, the data were structured in panel format, that is, in the form of "territory-year." At the next stage, for the purposes of typological analysis, these panel data were aggregated by territory, and a separate economic profile was formed for each territorial unit.

A number of derived indicators were calculated to represent the economic potential of the territories. First, in order to reflect the total volume of the main sectors of the territorial economy, the indicator of the volume of key economic sectors was calculated using the following formula:

$$ATH_i = SANOAT_i + QX_i + XIZMAT_i \quad (1)$$

where: ATH_i - denotes the volume of key economic sectors in territory i, $SANOAT_i$ - denotes the volume of industrial output, QX_i - denotes the volume of agricultural output, $XIZMAT_i$ - denotes the volume of services.

To reflect the formation of territorial economic outcomes relative to the population size, the volume of key economic sectors per capita was calculated:

$$JBATH_i = \frac{ATH_i}{AHOLI_i} \quad (2)$$

where: $JBATH_i$ - the volume of key economic sectors per capita in territory i, $AHOLI_i$ - the population size in territory i,

To represent efficiency across territories, the labor productivity indicator was determined as follows:

$$MU_i = \frac{ATH_i}{BAND_i} \quad (3)$$

where: $BAND_i$ - the number of employed persons in the territory.

In addition, to represent the development dynamics of the territories, the compound annual growth rate (CAGR) was calculated for the volume of key economic sectors and the volume of services:

$$CAGR = \left(\frac{Y_{t_n}}{Y_{t_0}}\right)^{\frac{1}{n}} - 1 \quad (4)$$

where: Y_{t_0} - denotes the value in the initial period, Y_{t_n} - denotes the value in the final period, n - denotes the length of the period.

In addition, to represent the development dynamics of the territories, the compound annual growth rate (CAGR) was calculated for the volume of key economic sectors and the volume of services:

$$SU_i = \frac{SANOAT_i}{ATH_i} \quad (5)$$

$$QXU_i = \frac{QX_i}{ATH_i} \quad (6)$$

where: $SANOAT_i$- denotes the volume of industrial output in the territory,

As a result, the following final indicators were selected for the typological analysis: investment volume, the volume of key economic sectors, labor productivity, the CAGR of the volume of key economic sectors, the CAGR of the volume of services, the share of industry, and the share of agriculture.

Since the indicators included in the analysis are expressed in different units of measurement and scales, their direct use in clustering methods is not methodologically appropriate. Therefore, all final indicators were standardized using the z-score method:

$$z_{ij} = \frac{x_{ij} - \bar{x}_j}{s_j} \quad (7)$$

where: x_{ij} - denotes the value of territory i for indicator j, $\bar{x}_j$ - denotes the mean value of indicator j, s_j - denotes the standard deviation of indicator j

This stage made it possible to bring the indicators to a common scale, reduce the excessive influence of variables with large numerical values on the clustering results, and ensure a methodologically correct comparative assessment of territories (Table 1).

Table 1. Descriptive statistics of the main indicators before standardization[1]

No.	Indicators	N	Mean	Standard deviation	Minimum	Maximum	Unit of measurement
1	Population size	15	168,43	75,96	79,75	366,9	thousand persons
2	Investment volume	15	456,34	343,59	149,53	1550,57	billion UZS
3	Number of small business entities	15	1074,37	660	532,75	3035,53	units

1 Author's calculations based on data from the Surkhandarya Regional Department of Statistics and the National Statistics Committee of the Republic of Uzbekistan.

4	Volume of key economic sectors	15	1752,11	784,28	943,18	3706,86	billion UZS
5	Per capita volume of key economic sectors	15	10,33	3,11	6,52	17,96	million UZS/person
6	Labor productivity	15	28,36	12,55	17,22	67,16	million UZS/ employed person
7	CAGR of the volume of key economic sectors	15	22,2	2,31	16	26	%
8	CAGR of the volume of services	15	26,73	3,08	21	31	%
9	Share of industry	15	14,33	6,18	7	26	%
10	Share of agriculture	15	61,47	19,24	1	72	%

The data presented in Table 1 indicate a significant differentiation of indicators across territories. In particular, the dispersion is relatively high in terms of investment volume, the volume of key economic sectors, labor productivity, and the share of agriculture, which confirms that dividing the territories into multidimensional typological groups is methodologically justified.

Before clustering, the relationships among the indicators were examined using the Pearson correlation coefficient. The main purpose of this stage was to identify indicators that could conceptually duplicate one another and to simplify the final model. As a result, several variables with very strong correlations were excluded, and the seven most meaningful indicators were retained for clustering and SOM analysis (Figure 1).

Корреляции

		aholi_soni	investitsiya_hajmi	kichik_biznes_subyektlari_soni	asosiy_tarmoqlar_hajmi	jon_boshiga_asosiy_tarmoqlar_hajmi	mehnat_unumdorligi	cagr_asosiy_tarmoqlar_hajmi	cagr_xizmatlar_hajmi	sanoat_ulushi	ulush_qx
aholi_soni	Корреляция Пирсона	1	-,074	,447	,828	-,340	-,344	-,127	-,519	,158	-,052
	знач. (двухсторонняя)		,792	,095	<,001	,215	,210	,652	,048	,575	,853
	N	15	15	15	15	15	15	15	15	15	15
investitsiya_hajmi	Корреляция Пирсона	-,074	1	,275	,057	,072	-,103	,254	-,289	,017	-,263
	знач. (двухсторонняя)	,792		,321	,841	,798	,715	,362	,295	,951	,344
	N	15	15	15	15	15	15	15	15	15	15
kichik_biznes_subyektlari_soni	Корреляция Пирсона	,447	,275	1	,748	,347	-,017	,006	-,702	,505	-,863
	знач. (двухсторонняя)	,095	,321		,001	,205	,953	,982	,004	,055	<,001
	N	15	15	15	15	15	15	15	15	15	15
asosiy_tarmoqlar_hajmi	Корреляция Пирсона	,828	,057	,748	1	,205	,062	,131	-,555	,366	-,410
	знач. (двухсторонняя)	<,001	,841	,001		,464	,827	,642	,032	,180	,129
	N	15	15	15	15	15	15	15	15	15	15
jon_boshiga_asosiy_tarmoqlar_hajmi	Корреляция Пирсона	-,340	,072	,347	,205	1	,877	,462	,049	,283	-,470
	знач. (двухсторонняя)	,215	,798	,205	,464		<,001	,083	,862	,306	,077
	N	15	15	15	15	15	15	15	15	15	15
mehnat_unumdorligi	Корреляция Пирсона	-,344	-,103	-,017	,062	,877	1	,383	,218	,100	-,119
	знач. (двухсторонняя)	,210	,715	,953	,827	<,001		,159	,434	,723	,673
	N	15	15	15	15	15	15	15	15	15	15
cagr_asosiy_tarmoqlar_hajmi	Корреляция Пирсона	-,127	,254	,006	,131	,462	,383	1	,449	,118	-,030
	знач. (двухсторонняя)	,652	,362	,982	,642	,083	,159		,094	,675	,917
	N	15	15	15	15	15	15	15	15	15	15
cagr_xizmatlar_hajmi	Корреляция Пирсона	-,519	-,289	-,702	-,555	,049	,218	,449	1	-,241	,521
	знач. (двухсторонняя)	,048	,295	,004	,032	,862	,434	,094		,387	,047
	N	15	15	15	15	15	15	15	15	15	15
sanoat_ulushi	Корреляция Пирсона	,158	,017	,505	,366	,283	,100	,118	-,241	1	-,657
	знач. (двухсторонняя)	,575	,951	,055	,180	,306	,723	,675	,387		,008
	N	15	15	15	15	15	15	15	15	15	15
ulush_qx	Корреляция Пирсона	-,052	-,263	-,863	-,410	-,470	-,119	-,030	,521	-,657	1
	знач. (двухсторонняя)	,853	,344	<,001	,129	,077	,673	,917	,047	,008	
	N	15	15	15	15	15	15	15	15	15	15

Figure 1. Correlation matrix of the research indicators [2]

Hierarchical clustering was applied to determine the optimal grouping level of the territories. At this stage, Ward's method and the squared Euclidean distance were used. This approach is aimed at minimizing within-cluster variation and makes it possible to identify overall similarities and differences among territories.

Based on the agglomeration schedule and dendrogram, the step-by-step merging process was analyzed in order to determine the most appropriate clustering solution. As a result of this analysis, it was found that dividing the territories into three main groups is the most methodologically appropriate option.

2 Source: Author's calculations based on SPSS software.

ANALYSIS AND RESULTS

The results of hierarchical clustering made it possible to identify multidimensional economic similarities and differences among the territories. At the initial stage, the step-by-step merging process of the territories was analyzed using a dendrogram. This figure not only visually illustrates the degree of proximity among the territories, but also serves as an important analytical basis for selecting the optimal number of clusters (Figure 2).

Порядок агломерации (кластеров)

Этап	Объединенный кластер		Коэффициенты	Этап первого появления кластера		Следующий этап
	Кластер 1	Кластер 2		Кластер 1	Кластер 2	
1	3	6	,228	0	0	7
2	2	13	,523	0	0	6
3	8	15	1,505	0	0	9
4	11	14	2,737	0	0	8
5	9	12	4,497	0	0	7
6	2	10	6,348	2	0	12
7	3	9	8,625	1	5	8
8	3	11	12,659	7	4	10
9	7	8	22,136	0	3	11
10	3	4	32,246	8	0	13
11	1	7	43,244	0	9	14
12	2	5	55,258	6	0	13
13	2	3	72,369	12	10	14
14	1	2	98,000	11	13	0

Figure 2. Results of determining the number of clusters based on the agglomeration schedule [3]

According to the data presented in Figure 2, the agglomeration coefficient increased gradually as the clusters were successively merged. However, a sharp increase in the coefficient was observed at the final stages. In particular, the rate of increase became substantially more pronounced during the transition from Stage 12 to Stage 13 and from Stage 13 to Stage 14. This indicates that forcing the territories into two clusters or a single cluster would eliminate the natural differences among them. Therefore, dividing the territories into three clusters was accepted as the most appropriate solution.

Based on the results of hierarchical clustering, the final typology of the territories was formed using the K-means algorithm. The K-means method is aimed at minimizing the following objective function:

$$J = \sum_{k=1}^{K} \sum_{x_i \in C_k} ((x_i - \mu_k)) \tag{8}$$

Where: C_k - denotes the set of observations belonging to cluster k, μ_k- denotes the cluster centroid

In the study, K=3 was adopted. As a result of the K-means algorithm, the cluster membership of each territory, cluster centroids, and the mean values of the main indicators by clusters were obtained. This stage formed the statistical typology of the territories (Figure 3).

Конечные центры кластеров

	Кластер		
	1	2	3
Zscore (investitsiya_hajmi)	,09268	,18470	-,41590
Zscore (asosiy_tarmoqlar_hajmi)	1,07929	-,49263	-,21719
Zscore (mehnat_unumdorligi)	-,11210	-,46220	,92094
Zscore (cagr_asosiy_tarmoqlar_hajmi)	-,19908	-,36195	,83250
Zscore (cagr_xizmatlar_hajmi)	-1,07803	-,03473	1,13880
Zscore(sanoat_ulushi)	1,16012	-,47848	-,32278
Zscore(ulush_qx)	-,98257	,40050	,28170

Figure 3. Final cluster centroids according to K-means[4]

3 Source: Compiled by the author based on agglomerative cluster analysis using SPSS 26 software.
4 Source: Results calculated by the author based on the K-means clustering method.

The final cluster centroids obtained using the K-means algorithm are presented. The results of the Figure indicate that there are significant differences among the clusters in terms of economic volume, structural composition, efficiency, and growth dynamics. In particular, the first cluster is characterized by dominant positive standardized values for the volume of key economic sectors and the share of industry, whereas the second cluster has a relatively higher share of agriculture and lower economic volume indicators. The third cluster, in turn, is characterized by higher values of labor productivity and growth rates. These results confirm that the economic development profiles of the territories differ from one another and that their classification into separate typological groups is methodologically justified (Figure 4).

Принадлежность к кластерам

Номер наблюдения	Кластер	Расстояние
1	1	2,872
2	2	1,346
3	2	1,156
4	3	2,448
5	2	2,910
6	3	1,267
7	1	2,658
8	1	1,556
9	3	1,397
10	2	2,401
11	2	1,840
12	3	1,172
13	2	1,343
14	2	2,049
15	1	1,929

Figure 4. Final distribution of territories by clusters[5]

The final distribution of territories by clusters is presented. According to the results, the territories of Surkhandarya region were divided into three main groups. The first cluster included relatively large, industrialized territories with a high level of entrepreneurial activity. The second cluster mainly consisted of territories with a dominant agrarian orientation and relatively lower indicators of economic volume and efficiency. The third cluster brought together territories characterized by higher labor productivity and growth rates. This distribution indicates that the economic potential and development characteristics of the districts of Surkhandarya region are not uniform and that a differentiated approach is required in regional policy (Figure 5).

Отчет

Номер кластера наблюдения		aholi_soni	investitsiya_hajmi	kichik_biznes_subyektlari_soni	asosiy_tarmoqlar_hajmi	jon_boshiga_asosiy_tarmoqlar_hajmi	mehnat_unumdorligi	cagr_asosiy_tarmoqlar_hajmi	cagr_xizmatlar_hajmi	sanoat_ulushi	ulush_qx
1	Среднее	230,5800	491,2650	1842.667500	2558.080304	10,88869075	27,0500	,21810875	,24295500	,2175000	,4448525
	N	4	4	4	4	4	4	4	4	4	4
	Стандартная отклонения	93,37815	287,31809	906.1175171	881.3477239	3,419162464	4,84178	,003344693	,026705359	,06719899	,29091161
2	Среднее	154,4857	525,9471	781.5157143	1384.237573	8,55808443	22,9586	,21419929	,27062814	,1183514	,6879343
	N	7	7	7	7	7	7	7	7	7	7
	Стандартная отклонения	30,27458	510,65607	129.3615866	429.7740760	1,602521242	4,18029	,030103568	,009130426	,03935040	,04040996
3	Среднее	130,6825	299,5875	818.5700000	1589.919907	12,90451850	39,1225	,24286950	,30175575	,1277725	,6670550
	N	4	4	4	4	4	4	4	4	4	4
	Стандартная отклонения	63,14161	114,42991	265.8943072	489.0974697	3,825872204	18,81867	,011227162	,009728903	,02094386	,04082060
Всего	Среднее	168,4300	456,3360	1074.370667	1752.110923	10,33862853	28,3600	,22288720	,27154933	,1473033	,6175447
	N	15	15	15	15	15	15	15	15	15	15
	Стандартная отклонения	68,72794	376,88914	654.5913074	746.7592297	3,208583983	11,68645	,024002857	,026524740	,06050818	,17575628

Figure 5. Mean values of the main economic indicators by clusters[6]

According to the data presented in Figure, there are significant differences among the clusters in terms of economic volume, structural composition, efficiency, and growth rates. In particular, the territories in Cluster

5 Source: Author's calculations based on the results of K-means clustering.

6 Source: Calculated by the author using the K-means clustering method in SPSS based on the data formed by the author.

1 have relatively high indicators in terms of population size, the number of small business entities, and the volume of key economic sectors, and are distinguished by a higher share of industry. In Cluster 2, the share of agriculture is high, while the volume of key economic sectors and labor productivity are relatively lower. The territories in Cluster 3 demonstrate higher results in terms of the per capita volume of key economic sectors, labor productivity, and the growth rates of the volume of key economic sectors and services. These results indicate that the territories of Surkhandarya region do not share a uniform type of development and that they need to be assessed on the basis of a differentiated approach.

To additionally validate the territorial typology from a neural network perspective, the Self-Organizing Map (SOM) method was applied. SOM is an unsupervised artificial neural network that organizes high-dimensional data into a low-dimensional grid while preserving the topological proximity among observations.

In this study, a 3×2 SOM grid was constructed. The same seven standardized indicators selected for K-means were included in the model. After the training process, the closest neuron, namely the Best Matching Unit (BMU), was identified for each territory. Subsequently, the weight vectors of the SOM neurons were additionally divided into three groups, and the cluster_som indicator was generated. This approach made it possible to compare the SOM results with the K-means results (Table 2).

Table 2. BMU coordinates of the territories of Surkhandarya region and their cluster membership according to SOM[7]

Territory	Termez city	Altinsoy	Angor	Bandikhan	Boysun	Muzrabot	Denov	Jarkurgan	**Kumkurgan**	**Kizirik**	**Sariosiyo**	**Termez**	**Uzun**	**Sherobod**	**Shurchi**
bmu	(2,0)	(0,0)	(0,0)	(0,1)	(2,1)	(0,0)	(1,0)	(1,1)	(0,1)	(0,0)	(1,1)	(0,1)	(0,0)	(1,1)	(1,1)
cluster_som	2	1	1	1	1	1	3	1	1	1	1	1	1	1	1
cluster_kmeans	1	2	2	3	2	3	1	1	3	2	2	3	2	2	2

Table 2 presents the Best Matching Unit (BMU) coordinates of each territory based on the results of the Self-Organizing Map, as well as their cluster membership identified using the SOM approach. The results show that the territories are positioned at different points on the neural network map. The fact that some territories are assigned to the same BMU or to neighboring neurons indicates that their multidimensional economic profiles are similar. At the same time, the placement of some territories in separate neurons suggests that their economic characteristics are relatively distinctive (Figure 6).

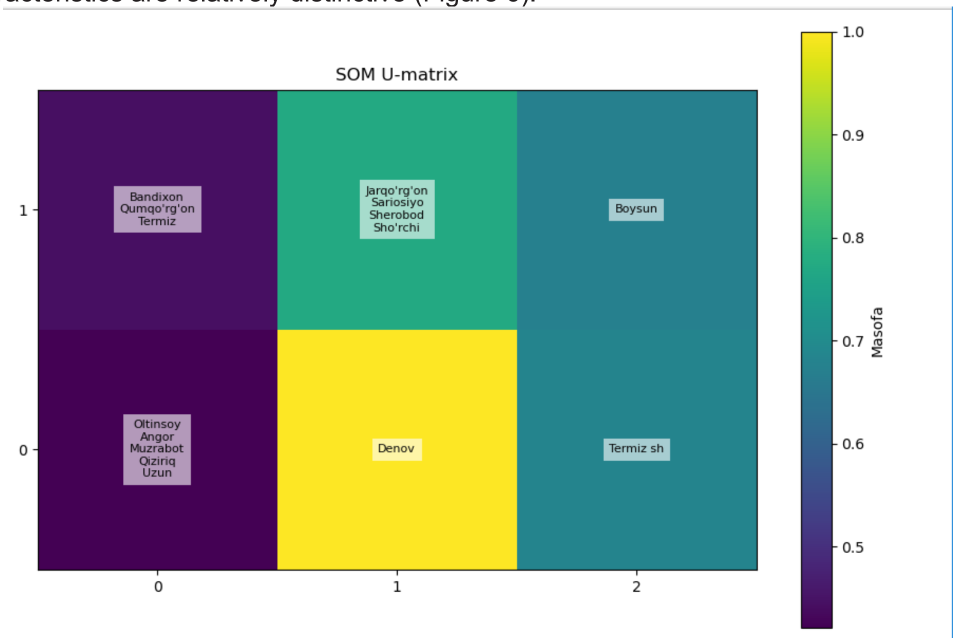

Figure 6. SOM U-matrix for the territories of Surkhandarya region[8]

7 Source: Author's calculations, generated using the Python programming environment based on SOM and K-means algorithms.
8 Source: Calculated by the author using the Self-Organizing Map (SOM) method in Python based on the data formed by the author.

Figure 6 presents the SOM U-matrix, which reflects the topological distances between neurons. An increase in color intensity indicates stronger differences between neurons, whereas lower values indicate a higher degree of similarity among the territories. This figure makes it possible to visually identify internal proximity and boundary cases among the territories. The U-matrix results show that certain territorial groups have similar economic profiles, while others differ significantly from the remaining groups (Figure 7).

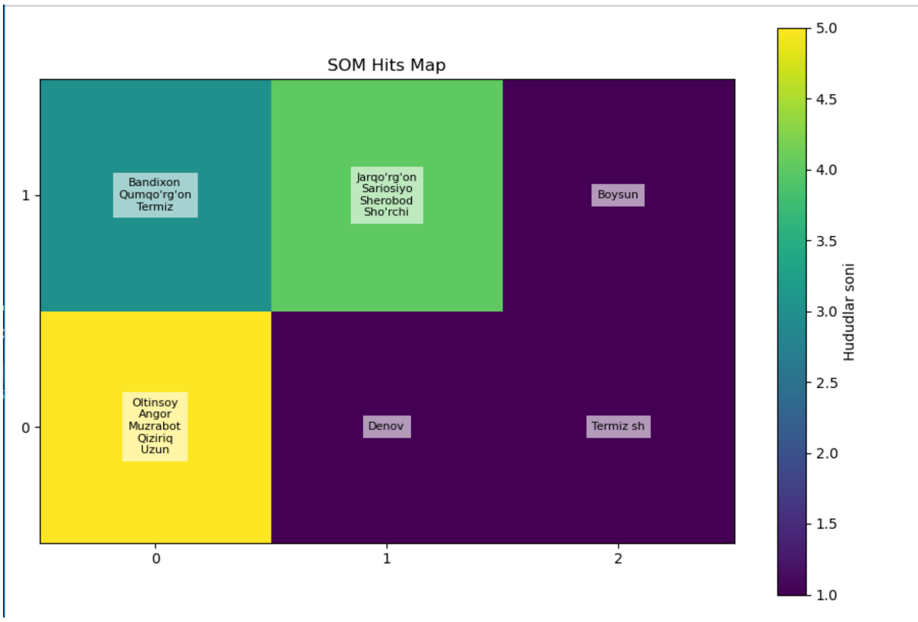

Figure 7. Distribution of the territories of Surkhandarya region according to the SOM Hits map[9]

Figure 7 presents the results of the SOM Hits map, which shows how many territories are assigned to each neuron cell. This map indicates that several territories are concentrated in certain neurons, whereas individual territories are located in separate neurons. This suggests that there are relatively dense groups among the territories, while some territories exhibit relatively distinct development profiles. Thus, the Hits map serves to assess the concentration and distribution of territories within the SOM space.

Table 3. Comparative results of territory classification using K-means and SOM methods[10]

Territory	Termez city	Altinsoy	Angor	Bandikhan	Boysun	Muzrabot	Denov	Jarkurgan	Kumkurgan	Kizirik	Sariosiyo	Termez	Uzun	Sherobod	Shurchi
bmu	(2,0)	(0,0)	(0,0)	(0,1)	(2,1)	(0,0)	(1,0)	(1,1)	(0,1)	(0,0)	(1,1)	(0,1)	(0,0)	(1,1)	(1,1)
cluster_som	2	1	1	1	1	1	3	1	1	1	1	1	1	1	1
cluster_kmeans	1	2	2	3	2	3	1	1	3	2	2	3	2	2	1
Agreement	different	different	different	different	different	different	different	consistent	different	different	different	different	different	different	consistent

Table 3 compares the clustering results obtained for the territories using the K-means and SOM approaches. The results show that the outputs of the two methods are consistent for some territories, while differences are observed for others. This indicates that, although the statistical and neural network approaches to clustering confirm the general tendencies in the grouping of territories, certain territories may represent intermediate or boundary types. Therefore, the SOM results were interpreted as a complementary and deepening tool for the typology obtained on the basis of K-means.

9 Source: Calculated by the author using the Self-Organizing Map (SOM) method in Python based on the data formed by the author.
10 Source: Author's calculations, generated in the Python programming environment based on K-means and SOM algorithms.

Thus, the SOM results visually demonstrated the topological proximity and differences among the territories and made it possible to further deepen the territorial typology obtained on the basis of K-means. While the consistency of the results of the two approaches for some territories confirmed stable typological groups, the differences observed in certain territories indicated the presence of intermediate economic types.

CONCLUSIONS AND SUGGESTIONS

In this study, the territories of Surkhandarya region were assessed from a multidimensional typological perspective in terms of economic potential, structural characteristics, efficiency, and development dynamics. The research findings revealed the existence of significant economic disparities among the territories and showed that assessing them on the basis of a single unified approach is insufficient. The optimal number of clusters was determined through hierarchical clustering, and the final typology of the territories was formed using the K-means algorithm. In addition, the Self-Organizing Map (SOM) method made it possible to provide a deeper interpretation of topological proximity and intermediate states among the territories.

According to the research results, the territories of Surkhandarya region were divided into three main typological groups. The first cluster brought together territories with a relatively large economic volume, a higher share of industry, and strong entrepreneurial activity. The second cluster comprised territories with a high share of agriculture and relatively lower levels of the volume of key economic sectors and labor productivity. The third cluster consisted of territories that demonstrated relatively higher results in terms of economic efficiency, the per capita volume of key economic sectors, and growth rates. These findings confirm that economic development trajectories within the region differ and that the degree to which each territory utilizes its potential is not uniform.

An important scientific result of the study is that territorial typology is formed more comprehensively not only on the basis of economic volume indicators, but also by jointly considering structural composition, efficiency, and dynamic indicators. In addition, the integrated application of statistical clustering and the SOM-based neural network approach made it possible to interpret territorial disparities not only in terms of formal grouping, but also from the perspective of internal topological proximity. In this regard, the findings of the study enrich the methodology of regional economic analysis and provide a practical basis for district-level typological assessment.

From a practical perspective, the obtained results indicate the need to implement a differentiated regional policy in Surkhandarya region. In the territories belonging to the first cluster, the development of industrial cooperation, logistics infrastructure, and high value-added services should be considered priority directions. In the territories of the second cluster, given the continued dominance of the agrarian orientation, it is advisable to strengthen agricultural processing, agrologistics, irrigation efficiency, and the integration of small business with production activities. In the territories of the third cluster, in order to maintain the existing high levels of efficiency and growth rates, it is necessary to support targeted investments, the expansion of the service sector, and technological modernization measures aimed at increasing labor productivity.

On this basis, the following practical recommendations can be proposed. First, regional development programs should be designed by taking into account the specific characteristics of the clusters. Second, in territories with relatively small economic volume but high growth potential, investment incentive mechanisms should be strengthened. Third, in territories where the agrarian orientation predominates, special attention should be paid to accelerating economic diversification and developing the processing industry. Fourth, in industrialized territories, it is advisable to strengthen regional economic stability by expanding the service sector and innovative activities. Fifth, the wider use of statistical monitoring and artificial intelligence-based analytical tools in the regional management system will increase the opportunities for more effective utilization of territorial potential.

This study also has certain limitations. In particular, since the analysis is based on aggregated data at the district level, intra-territorial micro-level differences may not have been fully reflected. In addition, due to the limited completeness of time series for some territories, the results were formed within the scope of available official data. In future research, it would be appropriate to expand the study by conducting a dynamic assessment of territorial typology based on panel data, comparing SOM results with other neural network models, and examining the causal relationship between economic potential and performance in greater depth using econometric modeling.

In general, the research findings showed that the territories of Surkhandarya region can be differentiated into groups according to their economic potential and development characteristics. This typology serves as an important analytical basis for the effective utilization of territorial economic potential, the rational allocation of resources, and the implementation of targeted regional policy.

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