Evaluation of the development level of regional startup ecosystems by grey cluster analysis

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Abstract

In recent years, startup ecosystems and their impact on global welfare have become a widely discussed phenomenon. To increase startups' performance, venture institutions and policymakers should consider the geographical diversity of ecosystems related to entrepreneurial potential. Previous research suggested eight major startup ecosystem parameters. This paper attempts to evaluate regional startup ecosystems' development level using concepts of grey clustering with five main parameters offering a more robust model. Grey clustering focuses on collecting information with small samples, allowing management decision making with limited data. We use data from 116 regional startup ecosystem cities to test the method and derive insights from ecosystem development's geographical distribution. Results show that only two are developed; one is developing, while the rest are undeveloped.

Keywords: Startup ecosystem, grey clustering, regional development, venture creation, innovations

Introduction

In the new global economy, startup firms have been considered a key player in economic development. Their significance is their contributions to job creation and economic growth at the regional, national, and industrial levels. Startups have generated several breakthrough innovations and huge businesses.

The elements of such an environment need to interact together as an ecosystem that can nurture the creation of successful startups (Motoyama and Watkins, 2014; Roundy et al., 2018;). Startup ecosystems are rapidly developing in all corners of the World. Aspiring founders and disruptive business models emerge everywhere, making attempts to find unique ways to build a stable product-market fit and grow the companies. However, innovative ideas can only thrive within a system that is built to support them. The innovators need a fostering environment to launch new ventures that could lead to local economic growth and support society's sustainable development. Startups are usually founded in a specific context as parts of an entity – a network, a system – much more significant than themselves (Spigel, 2017; Subramaniam et al., 2019; Cohen et al., 2019). Entrepreneurs are surrounded by a community of teams, organizations, and other startups that surround them. Such activities are what refers to as a startup ecosystem (Tripathi et al., 2019). The members of a startup ecosystem collaborate to develop innovation in their local community – be that a specific city, a province, or a designated development zone – and use the pool of resources available to them to create and scale new businesses (Tripathi et al., 2019; Znagui and Rahmouni, 2019; Madsen, 2020).

The Russian startup market started to thrive in the last decade ("Venture Russia", 2020; "The Global Startup Ecosystem", 2020). Although there were already several startup companies, funds, and accelerators, the rise began to develop in this decade. The startup ecosystem is broad and diverse, spread across various sectors and types of business models. However, the venture activities are highly concentrated in only one geographical region, 76% of all Russian startups are located in Moscow, followed by Saint Petersburg, with 6% (Venture Russia, 2020). While this type of clustering is evident in many developing nations, it highlights the need to diversify further into the regions and spread tech entrepreneur activity. Taking this into account, regional startup ecosystems should be analyzed separately.

This study attempts to evaluate the development level of regional startup ecosystems using concepts of the grey theory. The grey systems theory was developed by Deng (1985) to cope with situations where the information is unclear, or the data samples are small (Liu et al., 2017). This theory works with uncertain systems in which only partial or low-quality data are available (Gong and Forrest, 2014), allowing the decision-maker to excavate and extract useful information and reach an accurate conclusion.

Models of grey clustering evaluations

In grey systems theory, a system with totally unknown information is called a black system, while a system with fully known information is a white system. In between, we find grey systems with partially known information (Tseng, 2009), with small samples and insufficient information (Liu et al., 2017). Similarly, a grey number is a number whose value lies within an interval but whose exact value is unknown. In this context, whitenization weight functions are used to determine the preference a grey number has over the interval of values it might take by describing what is known (Liu et al., 2017).

Grey clustering evaluations are important contents of the grey system. The first method is developed to classify observation objects into classes using either grey incidence or whitenization weight functions (Liu et al., 2017). The second method is mainly used to control whether objects belong to predefined classes (Liu et al., 2017).

To propose the results of grey clustering evaluations for startup ecosystems evaluation, several definitions of whitenization weight function and grey clustering are given as follows.

Definition 1. Assume that there exist n objects to be clustered according to m cluster criteria into s different grey classes. The clustering method based on the observational value of the ith object, $i = 1,2, \dots, n$, at the jth criterion, $j = 1,2, \dots, m$, the ith object is classified into the kth grey class, $1 \leq k \leq s$, is called a grey clustering.

Definition 2. All the s grey class formed by the n objects, defined by their observational values at criterion j, are called the j-criterion subclasses. The whitenization weight function of the kth subclass of the j-criterion is denoted $f_j^k(\cdot)$.

Definition 3. Assume that the whitenization weight function $f_j^k(\cdot)$ of a j-criterion kth subclass is shown in Figure 1. Then the points $x_j^k(1), x_j^k(2), x_j^k(3), x_j^k(4)$ are called turning points of

$f_j^k(\cdot)$.

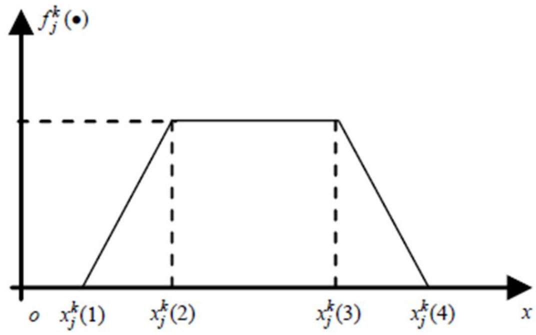

Figure 1. A typical whitenization function

Definition 4.

1. If the whitenization weight function $f_j^k(\cdot)$ above does not have the first and the second turning points $x_j^k(1)$ and $x_j^k(2)$, as shown in Figure 2, then $f_j^k(\cdot)$ is called a whitenization weight function of lower measure.

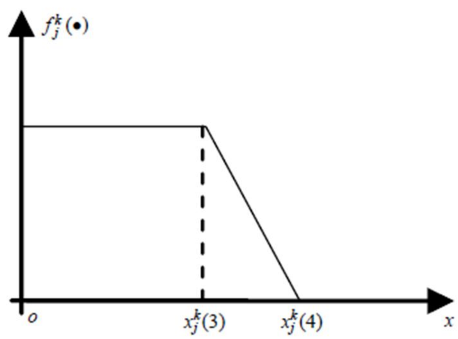

Figure 2. A whitenization function of lower measure

2. If the second $x_j^k(2)$ and the third $x_j^k(3)$ turning points of the whitenization weight function $f_j^k(\cdot)$ as in Figure 1 coincide, as shown in Figure 3, then $f_j^k(\cdot)$ is called a whitenization function of moderate measure.
3.

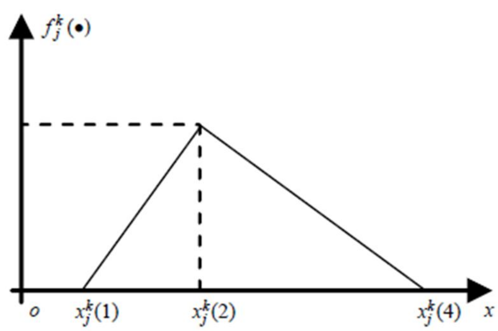

Figure 3. A whitenization function of moderate measure

4. If the whitenization weight function $f_j^k(\cdot)$ does not have the third and fourth turning points, as shown in Figure 4, then $f_j^k(\cdot)$ is called a whitenization weight function of upper measure.

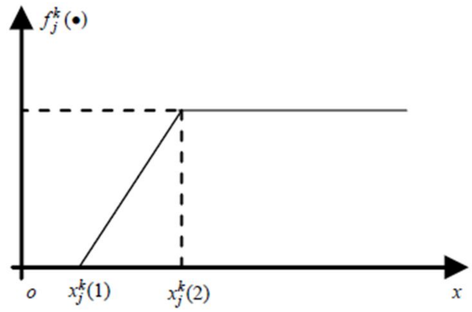

Figure 0. A whitenization function of upper measure

The typical whitenization weight function, as shown in Figure 1, is given by:

$$f_j^k(x) = \begin{cases} 0, & x \notin \left[x_j^k(1), x_j^k(4)\right] \\ \dfrac{x - x_j^k(1)}{x_j^k(2) - x_j^k(1)}, & x \in \left[x_j^k(1), x_j^k(2)\right] \\ 1, & x \in \left[x_j^k(2), x_j^k(3)\right] \\ \dfrac{x_j^k(4) - x}{x_j^k(4) - x_j^k(3)}, & x \in \left[x_j^k(3), x_j^k(4)\right] \end{cases} \tag{1}$$

The whitenization weight function of lower measure, as shown in Figure 2, is given by:

$$f_j^k(x) = \begin{cases} 0, & x \notin \left[0, x_j^k(4)\right] \\ 1, & x \in \left[0, x_j^k(3)\right] \\ \dfrac{x_j^k(4) - x}{x_j^k(4) - x_j^k(3)}, & x \in \left[x_j^k(3), x_j^k(4)\right] \end{cases} \tag{2}$$

The whitenization weight function of moderate measure, as shown in Figure 3, is given by:

$$f_j^k(x) = \begin{cases} 0, & x \notin \left[x_j^k(1), x_j^k(4)\right] \\ \dfrac{x - x_j^k(1)}{x_j^k(2) - x_j^k(1)}, & x \in \left[x_j^k(1), x_j^k(2)\right] \\ 1, & x = x_j^k(2) \\ \dfrac{x_j^k(4) - x}{x_j^k(4) - x_j^k(2)}, & x \in \left[x_j^k(2), x_j^k(4)\right] \end{cases} \tag{3}$$

The whitenization weight function of the upper measure, as shown in Figure 4, is given by:

$$f_j^k(x) = \begin{cases} 0, & x < \mathrm{x}_j^k(1) \\ \dfrac{x - x_j^k(1)}{x_j^k(2) - x_j^k(1)}, & x \in \left[\mathrm{x}_j^k(1), x_j^k(2)\right] \\ 1, & x \geq \mathrm{x}_j^k(2) \end{cases} \tag{4}$$

Definition 5.

1. For the whitenization wight function of the kth subclass of the j-criterion, as shown in Figure 1, define:
$$\lambda_j^k = \frac{1}{2\left[x_j^k(2) + x_j^k(3)\right]} \tag{5}$$
2. For the whitenization weight function of the kth subclass of the j-th criterion, as shown in Figure 2, let:
$$\lambda_j^k = x_j^k(3) \tag{6}$$
3. For the whitenization weight function of the kth subclass of the j-th criterion, as shown in Figure 3 and 4, let:
$$\lambda_j^k = x_j^k(2) \tag{7}$$

Then λ_j^k is called the critical value for the kth subclass of the j-criterion.

Definition 6. Assume that λ_j^k is the critical value for the kth subclass of the j-criterion. Then $\eta_j^k = \lambda_j^k / \sum_{j=1}^{k} \lambda_j^k$ is called the weight of the j-criterion to the kth subclass.

Definition 7. Assume that x_{ij} is the observational value of object i to criterion j, $f_j^k(\cdot)$ the whitenization weight function of the kth subclass of the j-criterion, and η_j^k – the weight of the j-criterion to the kth subclass. Then $\sigma_i^k = \sum_{j=1}^{m} f_j^k(x_{ij}) \cdot \eta_j^k$ is said to be the clustering coefficient of variable weight for object i to belong to the kth grey class.

Definition 8. The following:
$$\sigma_i = \left(\sigma_i^1, \sigma_i^2, \dots, \sigma_i^k\right) = \left(\sum_{j=1}^{m} f_j^1\left(x_{ij}\right) \cdot \eta_j^1, \sum_{j=1}^{m} f_j^2\left(x_{ij}\right) \cdot \eta_j^2, \dots, \sum_{j=1}^{m} f_j^3\left(x_{ij}\right) \cdot \eta_j^3,\right) \tag{8}$$
is called the cluster coefficient vector of object i.

Definition 9. If
$$\sigma_i^{k^*} = \max_{1\le k\le s}\{\sigma_j^k\}, \tag{9}$$
then we say that object i belongs to the grey class k^*.

Data description

To evaluate regional startup ecosystems' development, five quantitative parameters are proposed: financial organizations, networking organizations, business infrastructure, ecosystem population and number of startups (Tripathi et al., 2019).

Financial organizations parameter quantify interest in investments in terms of the presence of the number of VC funds headquarters and regional offices, private VC investors, governmental programs of venture investments, and other entities that perform various forms of VC investments.

The ecosystem population parameter represents a city's population, showed in thousands, which is used under an assumption, that the more people the city has, the more connections they may produce and the more involved they are in the startup ecosystem.

Networking parameter represents an ecosystem's development in providing places and opportunities for its members to meet, discuss and collaborate, thus comprise the number of organizations, which support productive networking: high-level universities, business schools, and startup accelerators.

Business infrastructure assesses the development of logistic, rental market, ease of access for machinery and production houses. The parameter is taken as a part of The Urban Environment Quality Index (n.d), which the Ministry of Construction has calculated, Housing and Utilities of the Russian Federation.

The number of startups is a resulting parameter which is the ultimate goal of a startup ecosystem. It shows the number of ventures that are located in an ecosystem. If the startup presents in multiple ecosystems, the headquarters' city is counted. Due to various interpretations of a startup definition, in this research, a startup is considered any new business founded within the last five years and applied an innovative solution.

The data have been collected from startup communities, venture funds' portfolios, startup-accelerators members, popular communication media sites, ranks and lists of companies, job recruitment platforms, and other online resources. The information has been collected using an R programming language with additional libraries (Rvest, Rselenium) using open accessed sources. Information of 648 startups, 458 networking organizations, and 11 financial organizations has been collected. The combined population among observed startup ecosystems exceeds 41 million people, and include 116 regional startup ecosystem cities at various scale.

Application of grey clustering evaluations

Further results are presented as follows where $k = 1$ represents "developed ecosystem", $k = 2$ represents "developing ecosystem", and $k = 3$ represents "undeveloped ecosystem". The data has been normalized: through all the parameters, the large number is good; thus, each value is divided by the maximum in the corresponding column. Corresponding whitenization weight functions are presented in Figure 5 and Formula 10 – 12. The critical values and grey clustering weights are presented in Table 1 and 2.

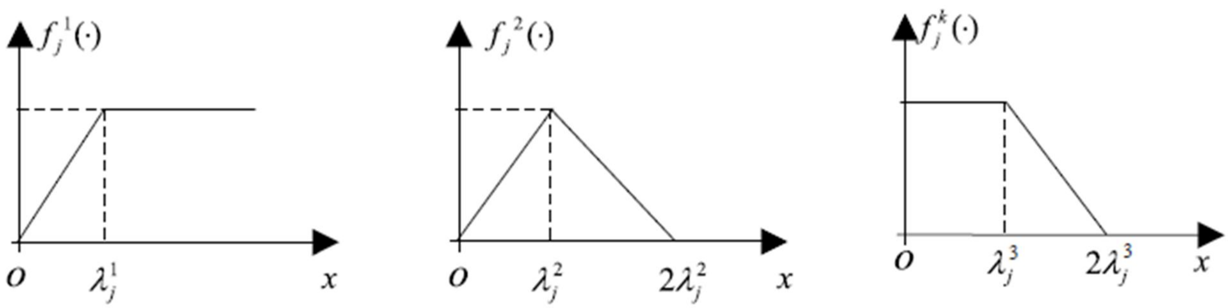

Figure 5. Whitenization weight functions

$$f_j^1(x) = \begin{cases} 0, & x < 0 \\ x/\lambda_j^1, & x \in [0, \lambda_j^1] \\ 1, & x \geq \lambda_j^1 \end{cases}; \qquad (10)$$

$$f_j^2(x) = \begin{cases} x/\lambda_j^2, & x \in [0, \lambda_j^2] \\ \dfrac{2\lambda_j^2 - x}{\lambda_j^2}, & x \in [\lambda_j^2, 2\lambda_j^2] \\ 0, & else \end{cases} \qquad (11)$$

$$f_j^3(x) = \begin{cases} 1, & x \in \left[0, \lambda_j^3\right] \\ \dfrac{2\lambda_j^3 - x}{\lambda_j^3}, & x \in \left[\lambda_j^3, 2\lambda_j^3\right]; \\ 0, & else \end{cases} \tag{12}$$

Table 1. The critical value

Grey class	Critical values			
	λ_1^k	λ_2^k	λ_3^k	λ_4^k
k = 1	1	0.5	0.6	0.45
k = 2	0.6	0.43	0.47	0.34
k = 3	0.2	0.37	0.35	0.28

Table 2. The weights for grey clustering

Grey class	Weights			
	η_1^k	η_2^k	η_3^k	η_4^k
k = 1	0.3921	0.1960	0.2352	0.1764
k = 2	0.3260	0.2336	0.2554	0.1847
k = 3	0.1666	0.3083	0.2916	0.2333

Results and Discussion

The result of the grey cluster of the leading sub-ecosystem is shown in Table 4 (see Appendix); ecosystems are sorted by the number of startups. The evaluation shows that two startup ecosystem cities have been clustered into a "developed" class: Saint Petersburg and Kazan. Yekaterinburg is clustered into "developing", while the rest of the ecosystem cities are "undeveloped".

A small number of developed and developing startup ecosystems indicates a high concentration of startup related entities. The bigger the ecosystem, the more value it can produce; thus, it creates more incentives for ecosystem members who reside in smaller ecosystems to relocate. Leading five regional startup ecosystem cities by the number of startups comprise 55% of observed regional startup number, 63% of observed regional venture capital financial organizations, 34% of the population within regional ecosystems, and 40% of observed regional network organizations. Absolute values of these ecosystems including Moscow (the capital of Russia) are presented in Table 3.

Table 3. Absolute values of collected parameters

Startup Ecosystem City	VC organizations	Networking organizations	Population, thousand	Startups
Moscow	24	185	17578	1993
Saint Petersburg	2	67	5125	141
Novosibirsk	0	35	2191	64
Yekaterinburg	1	32	2427	60
Kazan	2	24	2727	56
Nizhniy Novgorod	2	26	1644	36
Others	4	274	27115	291

One of the potential development directions is to specify geographical centres among several startup ecosystems and create dedicated "development zones" by providing governmental monetary stimulations and low taxation zones for venture capital institutes and startup founders, encouraging them to relocate from more developed ecosystems. As a result, new members bring knowledge and experience gained from the previous residence; existed acquaintances could spur extra interaction between ecosystems.

Another development direction is to take advantage of the ongoing global pandemic: encourage startup ecosystem elements to transition from local to multi ecosystems. While located in one place, a venture could collaborate with other ventures, investors, teammates, located in another ecosystem. This way, one can benefit from one ecosystem's strengths while mitigating disadvantages by elements of another ecosystem.

Apart from the dedicated introducing of outer stimulations, the promotion of entrepreneurial activities for the non-related residents could raise the ecosystem potential. It can be achieved by organizing business education programs at universities and non-commercial organizations, open lectures and coworking spaces. Ultimately, more people would experiment with venture companies, increasing the number of successful companies.

Limitation and prospects

The major limitation of this study is the evaluation of startup ecosystems as standalone subjects that are encompassed within themselves. Interacting within various ecosystems can vastly increase their performance. The ongoing pandemic encourages companies to work remotely; thus, geographical boundaries play a minor role in a startup performance and survival likelihood. Future studies can investigate such transition of the ecosystem from geographical to digital and other pandemic aftermaths. Besides, this research should be replicated in other countries to construct a general understanding of the startup ecosystem's distribution and their impact on startups success rate.

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Appendix

Table 0.1 The list of the cluster coefficients

σ_i^k	$k = 1$	$k = 2$	$k = 3$	$\max_{1\le k\le 3}\{\sigma_j^k\}$	Grey class
Saint Petersburg	1	0.1086	0	1	1
Novosibirsk	0.5402	0.5387	0.9849	0.9849	3
Kazan	0.8970	0.6787	0.5839	0.8970	1
Yekaterinburg	0.7359	0.8713	0.5194	0.8713	2
Nizhniy Novgorod	0.7702	0.6326	0.8182	0.8182	3
Tomsk	0,4387	0,3974	0,8854	0,8854	3
Perm'	0,3919	0,5381	0,875	0,875	3
Krasnodar	0,4965	0,4563	0,8594	0,8594	3
Kemerovo	0,3848	0,3234	0,9505	0,9505	3
Troick	0,3185	0,1957	1	1	3
Samara	0,4864	0,6644	0,7474	0,7474	3
Tyumen'	0,4436	0,3494	0,8333	0,8333	3
Chelyabinsk	0,4483	0,4106	0,9245	0,9245	3
Vladivostok	0,4403	0,3791	0,8594	0,8594	3
Ufa	0,4292	0,5893	0,8255	0,8255	3
Voronezh	0,4691	0,4391	0,9375	0,9375	3
Izhevsk	0,3875	0,3271	0,9245	0,9245	3
Ul'yanovsk	0,3764	0,3119	0,8984	0,8984	3
Yakutsk	0,3269	0,4488	0,8385	0,8385	3
Astrahan'	0,4663	0,2491	0,75	0,75	3
Odincovo	0,4426	0,1738	0,75	0,75	3
Saratov	0,4333	0,39	0,8854	0,8854	3
Yaroslavl'	0,4842	0,2908	0,75	0,75	3
Krasnoyarsk	0,4193	0,3707	0,9115	0,9115	3
Obninsk	0,408	0,2346	0,8203	0,8203	3
Podol'sk	0,444	0,2157	0,7682	0,7682	3
Ryazan'	0,4083	0,3522	0,8724	0,8724	3

Tambov	0,3605	0,2901	0,8854	0,8854	3
Tol'yatti	0,3771	0,3128	0,9115	0,9115	3
Himki	0,4274	0,1604	0,75	0,75	3
Balashiha	0,4368	0,2194	0,7552	0,7552	3
Belgorod	0,4195	0,2822	0,8073	0,8073	3
Dolgoprudnyj	0,4028	0,2226	0,8073	0,8073	3
Kaliningrad	0,4214	0,3189	0,8333	0,8333	3
Kursk	0,382	0,282	0,8464	0,8464	3
Lyubercy	0,4135	0,1535	0,75	0,75	3
Penza	0,4024	0,327	0,8594	0,8594	3
Sarov	0,3583	0,2502	0,8984	0,8984	3
Tver'	0,3865	0,476	0,7083	0,7083	3
Tula	0,4476	0,1808	0,75	0,75	3
Vologda	0,4027	0,225	0,7813	0,7813	3
Zarechnyj	0,3298	0,2417	0,8984	0,8984	3
Irkutsk	0,4852	0,2837	0,75	0,75	3
Joshkar-Ola	0,4182	0,2583	0,8464	0,8464	3
Kaluga	0,3971	0,2857	0,8333	0,8333	3
Kostroma	0,3997	0,2416	0,8203	0,8203	3
Stavropol'	0,4005	0,345	0,8854	0,8854	3
Taganrog	0,3909	0,243	0,8073	0,8073	3
Ulan-Ude	0,3976	0,2522	0,8073	0,8073	3
Cheboksary	0,4146	0,2755	0,8073	0,8073	3
Chistopol'	0,3948	0,2068	0,7943	0,7943	3
Arhangel'sk	0,337	0,2578	0,9375	0,9375	3
Barnaul	0,4429	0,3144	0,8073	0,8073	3
Volgograd	0,4587	0,4248	0,8854	0,8854	3
Gatchina	0,4693	0,1468	0,75	0,75	3
Dubna	0,3662	0,1999	0,9635	0,9635	3
Zhukovskij	0,3992	0,2453	0,8984	0,8984	3
Innopolis	0,4177	0,2331	0,8464	0,8464	3

Klincy	0,4339	0,2212	0,8203	0,8203	3
Korolev	0,4746	0,1917	0,7552	0,7552	3
Magnitogorsk	0,3737	0,2877	0,8594	0,8594	3
Mytishchi	0,3561	0,2684	0,8724	0,8724	3
Naberezhnye Chelny	0,3854	0,3037	0,8594	0,8594	3
Novokuzneck	0,3367	0,239	0,9635	0,9635	3
Petrozavodsk	0,4111	0,2024	0,7552	0,7552	3
Rostov-Na-Donu	0,4043	0,3236	0,8594	0,8594	3
Smolensk	0,4399	0,2932	0,7943	0,7943	3
Surgut	0,3928	0,2671	0,8984	0,8984	3
Habarovsk	0,4109	0,3558	0,8724	0,8724	3
Chernogolovka	0,3815	0,2433	0,8594	0,8594	3
Yuzhno Sahalinsk	0,3549	0,2273	0,9375	0,9375	3
Aleksandrov	0,4002	0,2178	0,8203	0,8203	3
Al'met'evsk	0,3332	0,2525	0,8984	0,8984	3
Bronnicy	0,3376	0,249	0,8724	0,8724	3
Bryansk	0,4233	0,2072	0,75	0,75	3
Bugul'ma	0,3705	0,2199	0,8203	0,8203	3
Velikij Novgorod	0,3745	0,2375	0,8203	0,8203	3
Vladimir	0,4083	0,2497	0,7943	0,7943	3
Volzhskij	0,3192	0,2088	0,9766	0,9766	3
Gelendzhik	0,3906	0,1913	0,7682	0,7682	3
Dzerzhinsk	0,3002	0,2011	0,9766	0,9766	3
Dimitrovgrad	0,2933	0,1916	0,9766	0,9766	3
Zheleznogorsk	0,3101	0,2147	0,9375	0,9375	3
Ivanovo	0,3897	0,2584	0,8203	0,8203	3
Kamensk-Ural'skij	0,3071	0,2045	0,9635	0,9635	3
Kirov	0,3185	0,2324	0,9505	0,9505	3
Kolomna	0,4184	0,1819	0,7552	0,7552	3
Komsomol'sk-Na-Amure	0,2941	0,1683	1	1	3
Kudrovo	0,4144	0,1473	0,75	0,75	3

Lipeck	0,3631	0,2936	0,8984	0,8984	3
Miass	0,3169	0,2118	0,9505	0,9505	3
Murmansk	0,2959	0,2014	1	1	3
Neryungri	0,3005	0,1955	0,9635	0,9635	3
Nizhnevartovsk	0,2843	0,1854	1	1	3
Novomoskovsk	0,3187	0,2326	0,9245	0,9245	3
Novoural'sk	0,2851	0,1803	0,9896	0,9896	3
Novoshahtinsk	0,2618	0,1484	1	1	3
Noril'sk	0,4055	0,1595	0,75	0,75	3
Orenburg	0,4048	0,3508	0,9115	0,9115	3
Pereslavl'-Zalesskij	0,4106	0,2247	0,8333	0,8333	3
Protvino	0,3732	0,2279	0,9115	0,9115	3
Pskov	0,3425	0,2654	0,8854	0,8854	3
Pushkino	0,3426	0,2559	0,8724	0,8724	3
Pushchino	0,3188	0,2267	0,9115	0,9115	3
Pyatigorsk	0,3832	0,2495	0,8203	0,8203	3
Raduzhnyj	0,29	0,1688	1	1	3
Reutov	0,4144	0,0937	0,75	0,75	3
Ruzaevka	0,3274	0,2201	0,9245	0,9245	3
Saransk	0,3037	0,417	0,8646	0,8646	3
Sevastopol'	0,3201	0,2345	0,9896	0,9896	3
Semenov	0,3697	0,2235	0,8333	0,8333	3
Simferopol'	0,3611	0,2874	0,8724	0,8724	3
Fryazino	0,4027	0,1582	0,75	0,75	3
Hanty-Mansijsk	0,3404	0,2502	0,8854	0,8854	3
Chekhov	0,4034	0,1335	0,75	0,75	3
Engel's	0,292	0,1837	1	1	3