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# The emerging structure of Russian urban system: a classification based on Self-Organizing Maps

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## Abstract

*After the collapse of the Soviet regime and the end of centralized policies on urban planning, Russian cities underwent deep transformations. The complex socio-economic, spatial and political trends are leading towards an increasing unevenness among Russian cities.*

*This topic has been poorly investigated by the current urban research. The paper aims to analyze and classify the cities belonging to the Russian urban system on the base of some socio-economic indicators captured at two different temporal thresholds.*

*By means of the Neural Networks Self-Organizing Maps (SOM), the study has investigated and singled out groups of cities with high internal resemblance. Due to SOM implementation it has been possible to identify twenty five groups of cities with similar socio-economic trends, where each group is characterized by an appropriate profile (a codebook). Moreover the empirical results have allowed to identify a new urban ranking, structured in four layers: “urban engine”, “strong cities”; “dynamic cities” and “weak cities”. The outcomes should support the definition of appropriate urban development strategies.*

**Key words:** Self-Organizing Maps, Russia, Urban network, Urban policy

## **1. Introduction**

In recent years, researches on Russian spatial urban network and urban transformation are scarce and highly uneven. The most holistic studies on urban network are done by two Russian urban geographers Treivish (2009) and Lappo (2012). Other scholars are focusing on particular types of cities, including industrial cities, one-company cities, Soviet closed (military) cities and knowledge cities (Turkov, 2012, Engel, 2006, Shevyrev, 2003, Lehmann and Ruble, 1997). Recently some other researchers have proposed different types of urban ranking (Perov and Finogenov, 2011, Andrievskii, 2012, Stolyarov and Serebryakova, 2011).

Nevertheless, Russia experiences a lack of studies taking into account that, in modern globalized world, cities should be considered a powerful machine stimulating the country's development.

Assuming that in Russia the urban policy is no more driven by the State the question is what is happening to the cities left to their spontaneous evolution. What are the existing spatial urban patterns, which urban hierarchy is emerging and which interactions among cities are transforming the whole system? This study could represent a substantial contribution for the formation of an integrated urban policy. The aim of this paper is to investigate the urban dynamics of Russian cities by using Neural Network Self-Organizing Maps (NN SOM). This approach is able to discover the high internal similarity among cities and to build clusters in order to understand the existing urban networks, revealing spatial patterns and interferences of cities at different hierarchical levels.

The paper starts with a brief overview of the urban networks formation during the Soviet period, then explains their transformation after the breakup of the USSR and the consequences of these two processes for the contemporary cities. The second section briefly describes the data used for the analysis. The third part outlines the SOM algorithm. The subsequent section presents the outcomes in terms of spatial urban patterns and geographical characteristics. The conclusions discuss further the nature of those patterns focusing on the possible urban development.

## **2. Russian urban network dynamics**

During the last century Russian urban landscape has changed significantly. In the middle of the 20<sup>th</sup> century, a rapid country's industrialization, engaged by the necessity to exploit natural resources in Far East and Siberian areas, fostered a relevant amount of new cities and

settlements. As a consequence of the industrialization, cities were characterized by a poor housing stock, unattractive urban environment, lack of infrastructure and absence of individuality (Pivovarov, 2001, Lappo, 2002). Nevertheless, during seventy years of Soviet regime, a new spatial urban network has been created; in one century Russia has been transformed from a rural to a highly urbanized country with few big cities along it (Treivish, 2009, Lappo, 2012).

After the USSR collapse, the urban spatial system has significantly degraded. If, during the soviet period, cities were integrated into a hierarchically-ordered national economic space, under the new market conditions cities lost themselves among chaotic strategic initiatives without any spatial or urban agenda (Golubchikov, 2004). Indeed the changes in political and economic regime, giving the local authority independence from the federal government, have not created any instruments for urban development during those first twenty years of new regime. Currently, various spatial initiatives and tools have arisen, but in reality the life and prosperity of the cities depends on the federal investments which are oriented to support national strategies such as the development of economic clusters and the hosting of mega-events.

Factors as the lack of a spatial agenda at federal level, fundamental changes in the institute of the private property and a protracted demographic crisis became sufficient reasons for a rapid change in the settlements geography in the post-soviet-Russia. Likewise, under the new political regime the removal of migration barriers (the limitation of urban growth, the institute of “*propiska*”) generates the new highly uneven spatial landscape in the new Russia. Now a strong and increasing centripetal movement is taking place. Everything rushes to Moscow: investments, tax flows, people flows. Moscow was “distinguished” from all the rest of Russia far before, but after the USSR collapse Moscow is “detached” from Russia completely. Small cities became smaller; the few big cities (mainly regional capitals) became bigger. In a neo-liberal reality the life of a city also became dependent on the attractiveness for business and for people as well, so the competition for resources such as investment, people and knowledge, became more and more evident.

In parallel with the polarization of Russian space, some cities began to decay significantly. The main urban problems which cities are facing are: unsatisfactory housing conditions, intraurban transport collapse and poor transport connections among cities; social disparities and degradation of social services including welfare sectors (health and education). In some

respect this is the result of an absent urban policy at federal and regional level, which neglect cities as centers of human life. Whereas in the developed world “*cities are powerhouses of innovation, socio-economic progress and sustainable transformation*” in the Russian reality it is not true so far (Arribas-Bel Daniel et al., 2012).

It is an intricate task for the existing municipalities to solve all the evidenced problems without a clear urban policy, supported by effective instruments and mechanisms. Many of the municipalities are rather weak, not only because the highly centralized taxation system leaves cities without local resources, but also for a lack of proficiency and capacity to understand the city as a spatial asset where many different sectoral policies should merge; in other words a very low ability to set up an urban policy with a comprehensive approach.

While the formulation of principles for urban policy formation is an arduous problem without a good understanding of the general situation and the main urban trends along the whole country, this research attempts to obtain a classification of existing spatial urban patterns and to identify the urban hierarchy, by the application of a Neural Network Self-Organizing Maps, which is able to single out groups of cities with high internal resemblance. This classification could be used to design scenarios of further spatial development.

### **3. Collecting data on Russian cities**

Making a comprehensive urban network analysis on the base of Russian statistical reality is a complicated task. Practically there is not an extensive and qualitatively sound statistical urban database. The existing data are fairly scarce and scattered, with a lot of missing values.

On one hand, at the city level, the data collected by the official statistical institute “*Rosstat*” and its regional branches are few and insufficient for this study. On the other hand the collected information is represented in an useless way for a further processing, i.e. it is split in several files with no connection among them, nor in a table format. For instance, since 2004 *Rosstat* publishes a special issue “*Russian regions*” with the main socio-economic indicators of Russian cities with more than 100 000 inhabitants, but unfortunately also this resource has an unsuitable data format. Obviously the lack of reliable, complex and geographically comparable data may bring to misleading conclusions on the socio-economic trends.

In this work governmental statistics deriving from a special information resource called “*Multistat*” have been used, as they include a section regarding the economy of Russian cities. The database contains statistics on population, finance and investments, construction, trade,

transport, education and culture for the years 1970, 1975, 1980 and yearly from 1985 to 2010. Unfortunately a lot of data are missing, so the data selection is not the optimal one for this analysis.

For the present analysis 856 cities have been selected and analyzed by means of twenty eight indicators. On these cities the information is almost complete. Urban indicators have been divided into three groups: population dynamic; characteristics of the housing stock; economic aspects. The list of the indicators and their formulae are presented in the *Appendix 1*. The analyzed period is limited at two official Russian censuses taking place in 2002 and 2010, even if few indicators have a larger observing horizon.

The *population dynamic* group contains eight indicators, describing the changes of cities' population based on natural balance and migration flows. Unfortunately those data are limited mainly by historically reason. The role of interurban migration was underestimated in the soviet reality, because everything (including population moving) was supposed to be under control and centrally planned (Mkrtchan, 2008), so there were no reasons to study these processes. This also applies to the commuting: in 1970 it raised the question on the necessity to study this phenomenon, but the pertinent data were not collected even in the 2002 Census (Mkrtchan, 2008).

The *housing stock characteristics* comprise thirteen indicators on the housing stock conditions, the internal equipment and its dynamics from 2002 to 2010.

The last group of indicators *city's economic profile* describes trends in economic sphere including the level of average salary, the changes in unemployment rate, the volume of capital investment from 1998 up to 2010 and the share of inefficient factories.

#### **4. The self-organizing maps as a clustering toolbox**

Self-Organizing Maps (SOM) is a type of Neural Network (NN) which allows to solve non-linear problems with highly-dimensional fuzzy data by organizing them into clusters on the base of their similarity (Kohonen, 2001). Nowadays the SOM is popular and its competitive and unsupervised learning is primarily used for the visualization of nonlinear relations of multidimensional data and dimensionality reduction (Silva and Marques, 2010).

The SOM algorithm has been created by the Finnish scientist Teuvo Kohonen in the eighties to display similar patterns into adjacent parts of the out flowing space. Generally SOM is “a

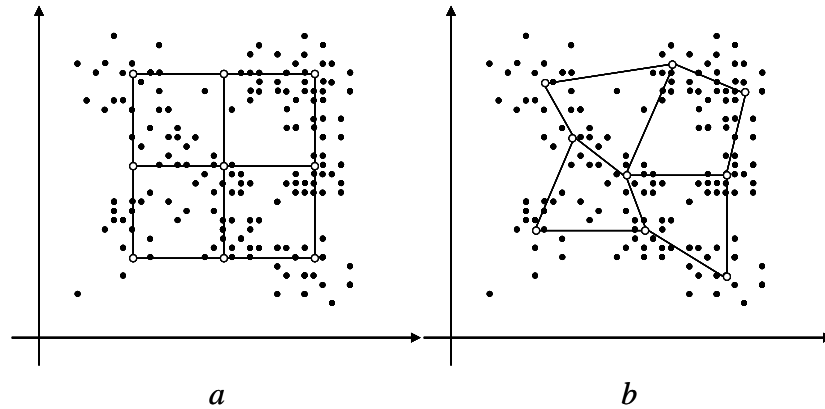
result of a nonparametric regression process that is mainly used to present high-dimensional, nonlinearly related data items in an illustrative, often two-dimensional display and to perform unsupervised classification and clustering” (Kohonen, 2001). From the beginning the SOM algorithm has been proposed as a method of data clusterisation, visualization and generalization (Kohonen, 2001). Currently its application is extending and interest for this analytical tool is growing. Now SOM is applied in a wide range of fields and its use has extended during the last years, but in spite of it, its impact in the social sciences was limited (Arribas-Bel Daniel et al., 2012). As a matter of fact recently more and more urban studies based on SOM implication have appeared such the ones of Arribas-Bel Daniel (Arribas-Bel Daniel et al., 2012) and Lidia Diappi and Paola Bolchi (Diappi et al., 2013).

As any neural network, SOM demands a good data set up but an important advantage is that it is rather “unpretentious” in comparison with other neural models (Kohonen, 2001).

## **5. The implementation of SOM neural network**

As it was said before the SOM is used to classify a set of observed data into groups by identifying similarities and differences among them. Each observation of the sample may be thought of as a point in an  $n$ -dimensional space, where  $n$  is the number of variables acting as coordinates (in our case 856 vectors/points with 28 variables/dimensions). Superimposed on the cloud of points thus obtained is a set of nodes which are connected together in order to form a regular, square or triangular, grid (the so called *Kohonen layer*). Figure 1a shows, necessarily in a two-dimensional space, the points corresponding to the observations and the nodes in their initial positions. During the learning process, the algorithm deforms the grid of nodes in order to approach each node to a cluster of observations (fig. 1b). The observations, described by data vectors, are repeatedly presented to the network, which identifies the nearest node (winner node) and “moves” it closer to observed point. The distance assigned to the node depends on the time step of the process. Initially, the displacements are bigger in order to speed up the learning process; then the spatial configuration stabilizes and progressively refines the fitness of the network to the points. The nodes connected with the winning node move as well, even if their movement is more limited in terms of distance covered. In this way the structural property of the grid is maintained and the connected nodes are placed in the centers of clusters of records presenting similarities. Once the learning process has been accomplished, the records are assigned to the various groups, which are

identified by the nearest node. The final coordinates of the nodes of the grid form a typical profile (*Codebook*) of each group (Diappi et al., 2013).



**Figure 1 Functioning of the SOM NN:** The network is deformed by the learning algorithm to bring the nodes close to the groups of observations (Diappi et al., 2013)

To work correctly the SOM needs normalized data. This has been made, between 0 and 1, outside the used software, prior to feed it the data, since knowing correspondences between raw and normalized data is anyway necessary.

The cities data records were divided into three groups: cities with all data, cities with missing data, and cities with "outlier" data. This last group comprises cities where the value of one or more indicators is largely out of range, and this could produce inaccuracy in the SOM results.

The parameters to be used for the data normalization have been calculated from the data of the first group. This set has been used also to train the SOM, and then to classify the cities into clusters. Experiments have been made changing the size of the Kohonen layer; finally a 5x5 matrix was chosen, being evaluated as a good compromise between number of clusters and clustering quality.

The cities of the second group, not used for the training, were classified ignoring the missing data (i.e. calculating the distance to find the nearest node using only the existing data). For the cities of the third group, data were scaled using the same parameters of the normalization (obviously obtaining also data outside the 0-1 range), and then classified.

## 6. The results: an overview of the city clusters

As said the NN SOM has identified twenty five groups of cities which are located in a 5x5 matrix (fig. 2). Each group has been named C  $i$ - $j$ , where  $i$  is the row and  $j$  is the column in the



matrix. Each cell in the figure 2 shows the group name, the number of cities in the group and the share of urban population belonging to this group. The position of a group inside the matrix has a meaning, because the group's characteristics are similar in the neighbor cells and change gradually moving from one vertex to another.

City size					
City size	C 1-1	C 1-2	C 1-3	C 1-4	C 1-5
	45 0.7%	26 0.5%	34 0.8%	18 0.7%	25 0.7%
	C 2-1	C 2-2	C 2-3	C 2-4	C 2-5
	32 0.7%	29 0.7%	22 0.9%	35 1.8%	24 1.7%
	C 3-1	C 3-2	C 3-3	C 3-4	C 3-5
	39 1.6%	41 1.8%	35 1.9%	42 2.7%	32 1.9%
	C 4-1	C 4-2	C 4-3	C 4-4	C 4-5
	24 1.1%	28 2.2%	48 3.8%	52 6.6%	39 5.3%
	C 5-1	C 5-2	C 5-3	C 5-4	C 5-5
	32 2.3%	27 1.9%	49 2.6%	32 5.7%	46 49.5%
Dilapidated houses					
Housing facilities: water, sewerage, heating, hot water					

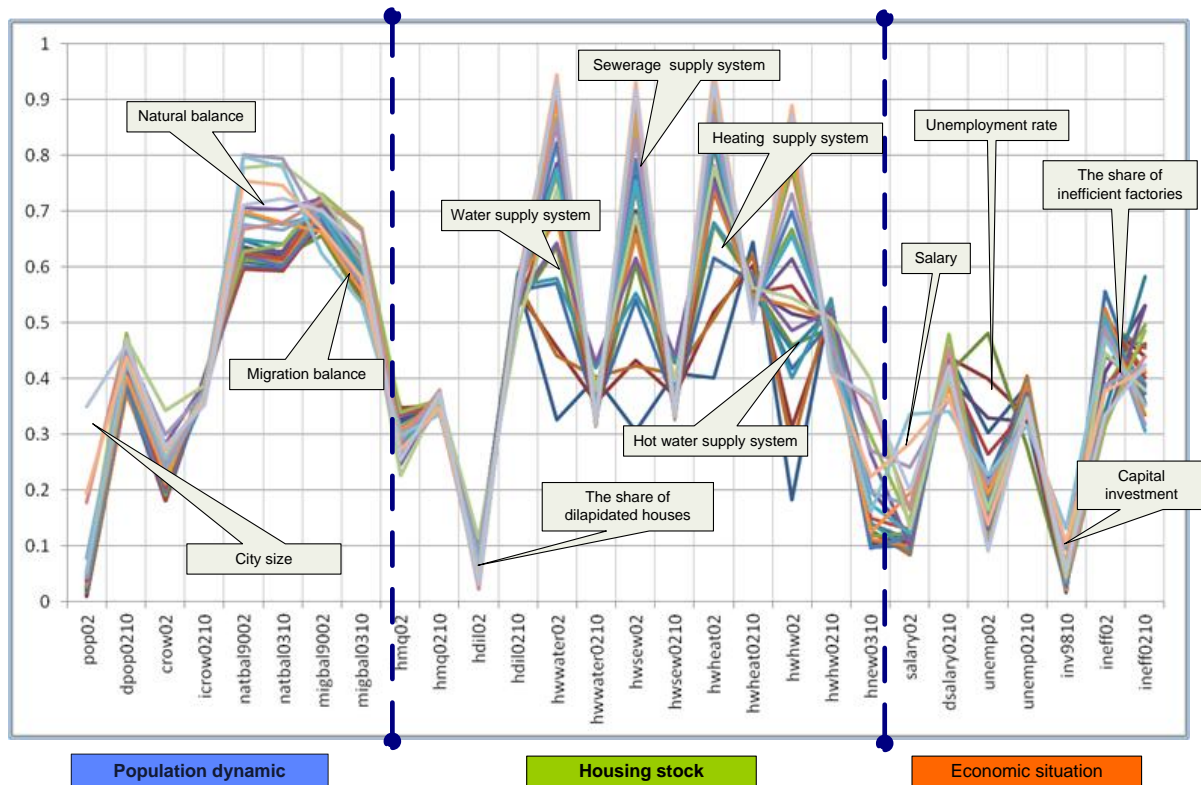
**Figure 2. Some variables distribution into groups in the 5x5 matrix**

Each cluster of cities is characterized by a Codebook, which synthesizes the information of the group. All twenty five codebooks are represented in the figure 3 and provide a general description and comparison of the clusters.

The cities size, in terms of population, is growing moving from left to right and from top to bottom simultaneously. The share of dilapidated houses considerably decreases with the increasing city's size and it is decreasing going from left to right, while the housing equipment including heating, water supply and sewerage are improving from left to right. Then the analysis has revealed a correlation between city's size and housing equipment: big cities perform better than the small ones. Moving top-down the majority of economic characteristics is improving, but not evenly along the columns. Not all the variables follow a linear and monotone trend, as it is possible to see in the one-parameter matrix in *the Appendix 2*.

As shown in the figure 2, while the number of cities in the groups is quite equal, on the contrary, the population is highly concentrated. The most populated cities are concentrated at the right-bottom zone. Around sixty seven percent of analyzed population lives in the cities

belonging to four groups (C4-4; C 4-5; C 5-4; C 5-5), which include twenty percent of the analyzed cities. The group C 5-5 comprises almost half of the analyzed urban population (49.5%), which is distributed in forty six cities only. Unlike the previous group, in the other corner top-left clusters (C 1-1; C1-2; C1-3; C-1-4; C1-5; C 2-1; C 2-2; C 2-3) only 5.7% of urban population lives in 231 cities.

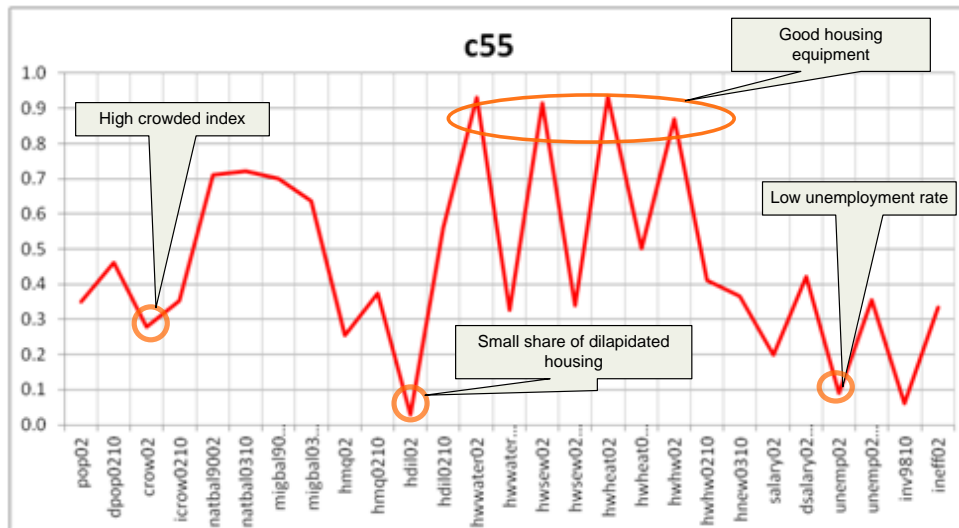


**Figure 3. Codebooks of the twenty five clusters**

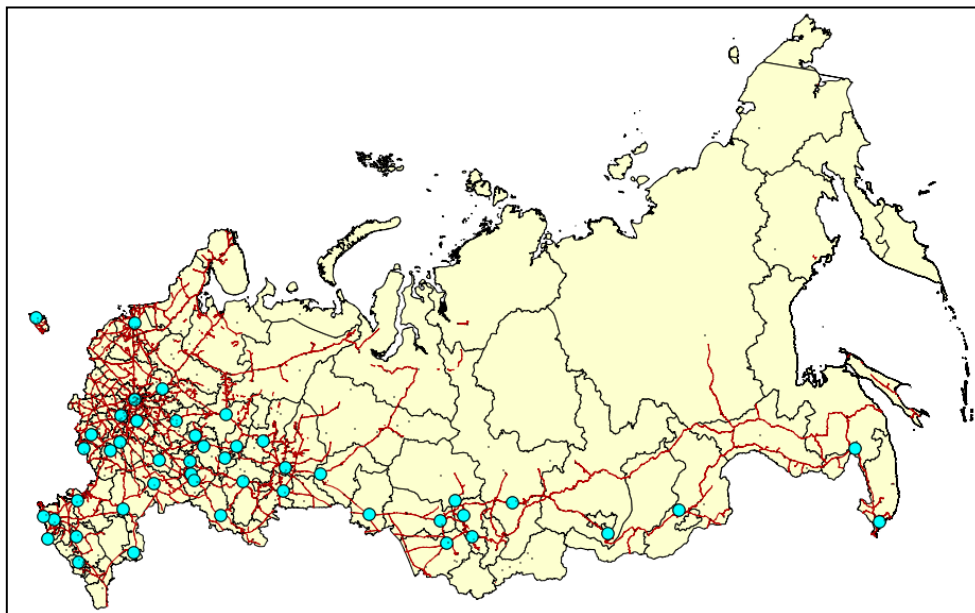
### 6.1 A description of the vertex groups

The four vertices of matrix present the most divergent urban profiles. Below, a description of C 5-5 group is provided in detail, as it is the most relevant in terms of population, whereas for all the other groups only the essential details for a comparison are provided.

**Group C 5-5** embraces forty-six cities, including twelve cities with more than one million inhabitants. The cities of this group are a fairly similar for all variables, except for the population size. The ninety percent of them are regional capitals, including Moscow and Saint Petersburg.



**Figure 4. The codebook of the group C 5-5**



**Figure 5. Geographical location of the cities belonging to the group C 5-5**

All these cities could be classified as multifunctional systems with a highly developed industrial and service base. Even Togliatti and Naberejnie Chelni, that are officially recognized as company towns, could be identified as multifunctional ones in terms diversified economy which includes well developed chemical, food, building, processing industries, and others. Most of them have grown in the period 2002 - 2010 mainly for a significant migration inflow. The housing stock of this group is significantly better in comparison with others. Here we observe one of the lowest share of dilapidated houses in Russia and one of the best situations of housing equipment, including water supply, sewerage, and heating. Also this

group has a significant volume of new housing construction. From the economic point of view this group performs quite well. In 2002 the lowest unemployment rate was here.

Totally opposite to the group C-5-5 is the **group C 1-1**. It comprises 45 small cities, from Gorbatov in Nizhny Novgorod with a population of less than 3 000 people to Kurganinsk, the biggest city of this group, with 46 600 inhabitants. These cities belong to 29 regions and are distributed along the country. They have experienced significant depopulation in 2002-2010 caused by a negative natural balance since 1990 together with a high migration outflow. Even though this group is characterized by the minimum crowding index in the country (e.g. in Okulovka there was only 1.27 people per flat in 2002) the conditions of the housing stock are the worst, both in terms of sanitary equipment and share of dilapidated houses, and it is considerably worse in respect of all the other clusters. The economic profile of this group is quite weak and has a negative trend. It is characterized by the low salary and high unemployment rate. The level of investment into the cities since 1991 up to 2010 is the lowest among all other clusters.

The analysis of the other groups has shown an intermediate situation between the above mentioned two poles. For example **group C 1-5** shows a significant economic decline in 2002-2010. During this period the cities faced a remarkable growth of inefficiency in their companies as well as increasing unemployment rate. These processes could partly explain their fast shrinking since 2002. Moreover all cities of this group have a negative natural balance 1991-2010. Considering the geographical position, these cities are concentrated in two opposite parts of Russia. Most of them are situated in the European part of country spreading to Volga and Ural regions, while four of them are situated in the Far East, including three cities on the Sakhalin Island.

Turning to the last vertex of the matrix, cities in **group C 5-1** are mainly concentrated in the South Federal District (FD) and in the Volga FD, but also three Northern cities are placed here. The group includes four regional capitals: Kizil, Mahachkala, Elista and Cherkessk, and also the sub-capitals of the richest autonomous okrugs<sup>1</sup>: Hanti-Mansiisk, Salehard and Narjan-Mar. These two polar types of cities are contained in one group due to their high population growth during 2002-2010. In fact the cluster is characterized by a positive natural balance since 1990, as well as by the highest migration inflow in 1990 - 2002. Due to the positive population trend, this group has the highest (dwelling) crowding index in the country, but the

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<sup>1</sup> Autonomous Okrug (AO) is one of the six types of Federal Subject of Russia

situation has taken a turn for the better since the group has also the highest rate of housing construction 2003-2010. The economic situation is slightly worse than the country average, but it does not concern Hanti-Mansiisk, Salehard and Narjan-Mar. The presence of these three rich sub-regional capitals significantly improves the general economic base of this group.

The analysis of the twenty five clusters has outlined the different processes prevailing in each group, making it possible to divide cities into strong and weak ones, depending on their position in the matrix: the strong cities bottom-right, the weak ones top-left.

## 6.2. The resulting urban classification

Based on the obtained results the following urban classification can be proposed: “urban engines”, “strong cities”, “dynamic cities” and “weak cities”. Their position is represented in the figure 6, while table 1 provides a definition of criteria and characteristics underlying such classification. The list of city clusters 1-3 is provided in *the Appendix 3*, being weak cities all the others.

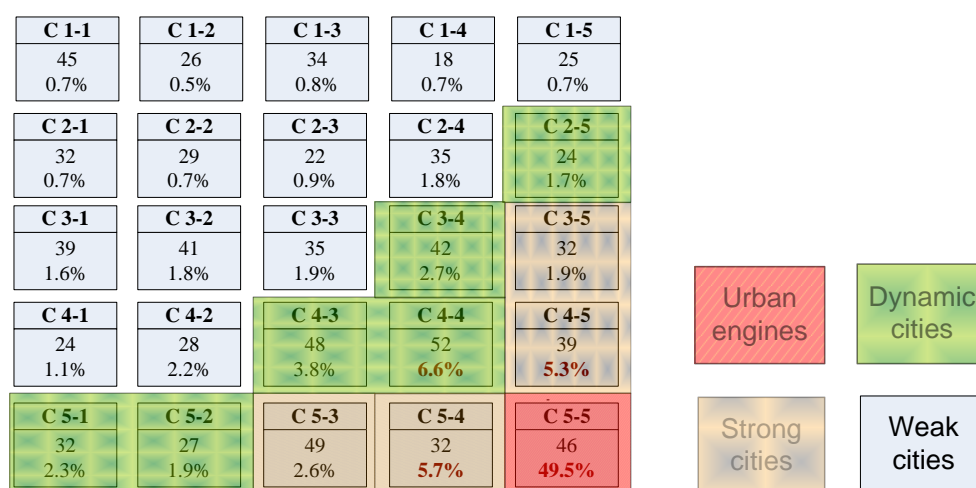


Figure 6. Classification of Russian cities

Table 1. Characteristics of Russian urban network

	Cluster	Population dynamic	Housing stock	Socio-Economic profile	Geographical location
Urban Engine	C 5-5	Urban population growth: considerable immigration; natural population loss. High crowding index.	Good housing equipment. Small share of dilapidated houses. High level of new housing construction.	High wages. The lowest unemployment rate.	Cities form the country's settlement framework.
Strong cities	C 5-3	Urban population loss: Natural population increase; emigration. High crowding index.	Good housing equipment. Large share of dilapidated houses. Low level of new housing construction.	The highest wages. High unemployment rate. High capital investments	Northern oil-gas cities. The cities of national importance.

	C 5-4	Urban population growth: immigration; natural population loss. High crowding index.	Good housing equipment. Small share of dilapidated houses. High level of new housing construction.	High wages. Low unemployment rate. High capital investments	Almetievsk agglomer.; Nizhnekamsk agglomer.; Sterlitamak agglomer..
	C 3-5	Urban population growth: considerable immigration; high natural population loss. Average crowding index.	Good housing equipment. Small share of dilapidated houses. High level of new housing construction.	Average wages. Low unemployment rate. Average capital investments.	Moscow region.
	C 4-5	Urban population growth: Considerable immigration; natural population loss. High crowding index	Good housing equipment; Small share of dilapidated houses. High level of new housing construction.	Average wages. Low unemployment rate. Average capital investments	Six regional capitals. Moscow region.
Dynamic cities	C 2-5	Urban population growth: Considerable immigration; natural population loss. Average crowding index.	Good housing equipment. Small share of dilapidated houses. Average level of new housing construction.	Low wages. Low unemployment rate. Low capital investments. Small share of inefficient factories.	Cities of Krasnodar krai Transport nodal points
	C 3-4	Urban population loss: natural population loss; immigration. Average crowding index.	Good housing equipment. Small share of dilapidated houses. Low level of new housing construction.	Low wages. Low unemployment rate. Average capital investments.	Cities of central European part, Tula region, Moscow region, Vladimir region
	C 4-3	Urban population loss: Natural population loss; Emigration. Average crowding index.	Good housing equipment; Small share of dilapidated houses. Low level of new housing construction.	High wages. Average unemployment rate. Average capital investments	16 cities form the official list of one-company cities. Second tier agglomerated cities: Bugulma
	C 4-4	Urban population loss: natural population increase; immigration. Average crowding index.	Good housing equipment; Small share of dilapidated houses. Average level of new housing construction.	Low unemployment rate. Average capital investments.	Five regional capitals. 15 cities from the official list of one-company cities. Cities are situated in the Western part.
	C 5-1	Urban population growth: immigration; natural population increase. The highest crowding index.	Good housing equipment but with big variation among cities. Large share of dilapidated houses. High level of new housing construction.	Average wages. Average capital investments. Average share of inefficient factories	The North Caucasus agglomeration. Naryan-Mar; Hanti-Manissik; Salehard, Kizil.
	C 5-2	Urban population growth: immigration; natural population increase. High crowding index.	Good housing equipment; Large share of dilapidated houses. High level of new housing construction.	High wages. High capital investments. Low unemployment rate.	Two regional capitals. Second level agglomerated cities: Elabuga; Zainsk
Weak cities	all other groups	Shrinking cities: considerable emigration; natural population loss. Low crowding index	Considerable share of dilapidated houses. Bad housing equipment. Low level of new housing construction.	High unemployment rate. High share of inefficient factories. Low wages. Low level of capital investment.	Spread along the country. Some cities are without transport connection.

The **group C 5-5** creates a **cluster of “urban engines”**. It contains the cities most attractive for people and for business. High migration inflow, high wages, low unemployment rate, and good housing equipment characterize these cities. They could be considered as locomotives of the country’s economic growth because all of them are growing multifunctional systems, with an high developed industrial, service and educational base. Actually the cities of this cluster are distributed quite evenly along the country (fig. 7). They form the skeleton of Russian

urban system. Most of them are the core of large agglomerations: Moscow, St. Petersburg, Samara-Tolyatti, Rostov, Yekaterinburg.



**Figure 7. Location of Russian urban engines**

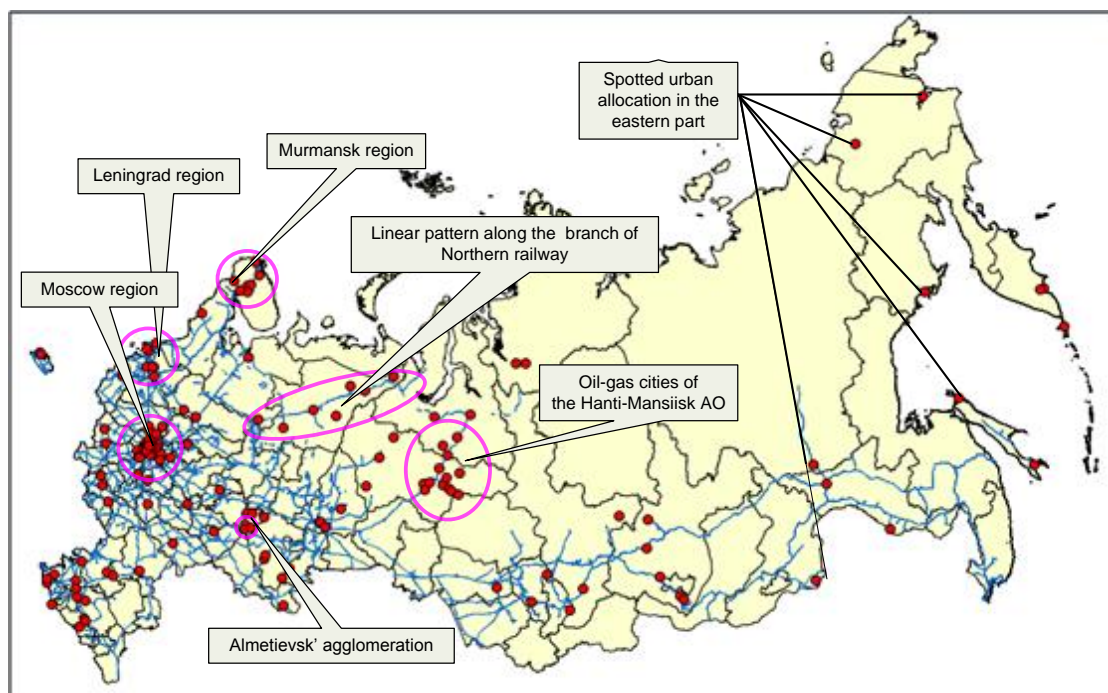
The second urban level is a cluster of “strong cities”, it includes four groups: C 4-5; C 3-5; C 5-4 and C 5-3 for an amount of 152 cities. Generally, they could be divided into three types. Forty (out to 64) of them belong to Moscow region. Others are Northern industrial cities and cities of strategic importance, such as Krasnokamensk, Bilibino, Polyarnie zori. The last type is composed by cities belonging to urban agglomerations, for instance, Almetievsk – Aznakaevo - Leninogorsk; or Nijnekamsk – Naberejnie Chelni.

Most of them are growing due to a considerable immigration, with the exception of the shrinking cities in group C 5-3 (Dudinka, Norilsk, Tinda), where the migration outflow exceeds the positive natural balance. The strong cities have good housing equipment. The economic profile is characterized by high wages and considerable investments, especially in Northern cities, low unemployment rate and a limited share of inefficient companies.

The geographical location of strong cities is represented in the figure 8. Their spatial distribution reveals several patterns. The first one is formed by the 40 cities belonging to the Moscow region. The second spatial pattern is around Saint-Petersburg and contains six cities of Leningrad region. In the Northern part of Russia three distinguished urban patterns stand out: the first one is formed by cities of the Murmansk region; the second one includes the



‘rich cities’ of Hanti-Manssiisk Autonomous Okrug, among them are Surgut, Nefteyugansk, Nignevartovsk, Radugnii, Langepas, etc.; the last one is a line of cities along the branch of the Northern railway including Koryagma (Archangelsk region), Syktyvkar, Uhta, Usinsk, Inta, Vorkuta (Komi republic). The strong cities in the eastern part of Russia, such as Magadan, Blagoveshensk, are isolated cities.



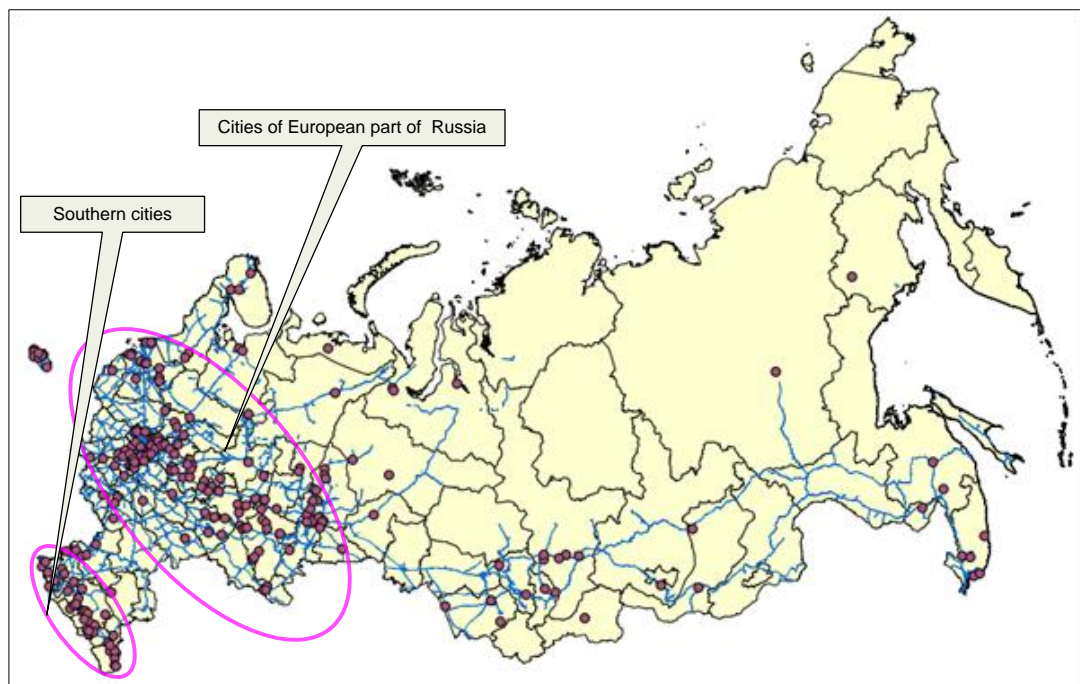
**Figure 8. The strong cities**

The next **urban cluster identifies the “dynamic cities”** (figure 9). This cluster is ambiguous. It comprises six groups: C 5-1; C 5-2; C 4-3; C 4-4; C 3-5; C 2-5 and contains 225 cities in which lives almost twenty percent of the Russian urban population. The cities are distributed along the country and form two distinguished spatial patterns. The first one stretches from the North-West with compaction around Moscow region, Volga and Ural districts. The second pattern extends on the Southern border of the country. The cities in eastern part of the country have a spotted distribution.

The cities inside the cluster are various and have different sets of characteristics (table 1). Actually, the cities belonging to this cluster could be estimated as “average” cities with a mix of advantages and disadvantages. For instance, northern cities have a good economic profile but weak housing equipment; southern cities historically have a positive demographic trend but a very bad housing stock and a weak economic basis. Actually, the common aspect of this cities is that the most part of them have a good potential for a further development, which



could take off with a strong government support, as for cities of Northern Caucasus, or by a good strategic location and industrial base as many cities in European part; or by the access and exploitation of natural resources as the Northern cities. A good example exploitation of the existing potential could be Kaluga, that during the last few years became a pioneer in attracting foreign investments to the region, having created a technological clusters and appropriate institutions and infrastructure.



**Figure 9. Location of dynamic cities**

The last hierarchical level is a cluster of “weak cities”. Including 433 cities and around 16 percent of the Russian urban population this group is the most multiform. It is mainly composed by small Russian cities in all regions, but also few big cities are included in this cluster, for example Novoshahtinsk, Maikop, Prokopievsk. Almost all of them are shrinking, with poor housing equipment and a very weak economic base, including low wages, high unemployment rate, high share of ineffective factories and low level of capital investments.

## 7. Conclusion

The SOM algorithm revealed itself as a helpful tool to explore the huge and multiform urbanized space of Russia and, moreover, to build and organize the knowledge on such complex system. Based on the SOM implementation our analysis has revealed a set of urban profiles and the emerging structure of the contemporary Russian cities.

During last twenty years the unevenness of the urban development has been amplified along Russia and now a huge socio-economical disproportion exists among urbanized areas. Russian “urban engines” are the most prosperous and remarkably are more and more pulling ahead of the other ones in terms of population dynamics, quality of housing stock and robust urban economics. The national policy aggravates and stimulates this situation. For instance at the 2011 Moscow Urban Forum, the Minister for Economic Development declared that the twenty largest Russian cities produce half of the country's GDP and therefore they deserve worthwhile public investments, while the support of the "ineffective" small cities "might" cost to the country 2-3% of GDP growth (Nabiullina, 2012). In addition to this statement now Russia has adopted an urban policy of revitalization based on hosting mega-events, such as 2011 Summit APEC, 2014 Sochi Olympics, 2018 FIFA, which stimulate and give an unprecedented investments flow to a few pointed cities from a list of "urban engines", while "weak" cities are left without any governmental support and are doomed to a further degradation.

Another aspect is the development of the physical infrastructural network by rail, road and air among different levels of urban hierarchy. Again, we observe that the government supports the development of transport infrastructure (e.g. air hubs, or high-speed railways) mostly in "urban" engines, while the other cities and the "weak" cities particularly, suffer from poor connection or isolation and no re-equilibrium strategies are provided. The housing policy also assumes a pronounced uneven character; the new constructions and rehabilitations are concentrated in cities belonging to the highest ranks of the urban hierarchy (urban engines, strong and dynamic cities), while in the "weak" cities very few investments on housing are provided.

The cluster of "dynamic" cities assumes an intermediate position where two situations are prevailing. Most dynamic cities are receiving a government support (such as the cities of Northern Caucasus) which stimulates their development. Some others, such as Kaluga, demonstrate that the development could arise from local initiatives integrated with local resources exploitations.

The knowledge contribution of this paper is an exposure of urban classification, which has proved scientifically that the national space policies are applied in favor of "urban engines" and stimulate uneven development. We argue, that due to the Russian territorial extension, polycentrism could be a practicable decision towards an even spatial development. The

proposed urban classification could create the base to design tools to support different types of cities and to promote a direction to a balanced development. It could be a triple level polycentric model in order to avoid a strong polarization effect (EESC, 2009). The first level facilitates the emergence of urban engines along the country, their purpose is to create hubs for economic growth and jobs. The second level aims to create the links and synergies between main urban cores, enforcing agglomerations. The third level of dynamic and weak cities consolidates the links between cities inside the region and across borders.

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## Appendix 1

Indicator	Short name	Description
<b>Population dynamic</b>		
Population 2002	pop02	
Pop. 02-10	dpop0210	(pop 2010 - pop 2002)/pop 2002
Pop per flat 2002	crow02	pop2002/numb. of dwellings 2002
Pop per flat 10-02	icrow0210	(pop2010/numb. of dwellings 2010)-( pop2002/numb. of dwellings 2002)
% natural balance 1990-2002	natbal9002	( $\Sigma$ natural balance 1990-2002) / pop 2002
% natural balance 2003-2010	natbal0310	( $\Sigma$ natural balance 2003-2010) / pop 2010
% migratory balance 1990-2002	migbal9002	( $\Sigma$ migratory balance 1990-2002) / pop 2002
% migratory balance 2003-2010	migbal0310	( $\Sigma$ migratory balance 2003-2010) / pop 2010
<b>Housing conditions</b>		
mq/pers 2002	hmq02	houses tot surf. 2002 / pop 2002
mq/pers 2002	hmq0210	(houses tot surf. 2010 / pop 2010)- (houses tot surf. 2002/ pop 2002)
% dilapidated housing 2002	hdil02	dilap. houses tot surf. 2002/ houses tot surf. 2002
% dilapidated housing 2010-02	hdil0210	(dilap. houses tot surf. 2010/ houses tot surf. 2010) - (dilap. houses tot surf. 2002/ houses tot surf. 2002)
% housing with water 2002	hwwater02	houses with water tot surf. 2002/ houses tot surf. 2002
% housing with water 2010-02	hwwater0210	(houses with water tot surf. 2010/ houses tot surf. 2010)- (houses with water tot surf. 2002/ houses tot surf. 2002)
% housing with sewerage 2002	hwsew02	houses with sewerage tot surf. 2002/ houses tot surf. 2002
% housing with sewerage 2010-02	hwsew0210	(houses with sewerage tot surf. 2010/ houses tot surf. 2010)- (houses with sewerage tot surf. 2002/ houses tot surf. 2002)
% housing with heating 2002	hwheat02	houses with heating tot surf. 2002/ houses tot surf. 2002
% housing with heating 2010-02	hwheat0210	(houses with heating tot surf. 2010/ houses tot surf. 2010)- (houses with heating tot surf. 2002/ houses tot surf. 2002)
% housing with hot water 2002	hwhw02	houses with hw tot surf. 2002/ houses tot surf. 2002
% housing with hot-water 2010-02	hwhw0210	(houses with hw tot surf. 2010/ houses tot surf. 2010)- (houses with hw tot surf. 2002/ houses tot surf. 2002)
new construction/ tot.surf. 2003-2010	hnew0310	( $\Sigma$ new houses surf. 2003-2010) / houses tot surf. 2010
<b>Economic profile</b>		
average salary 2002	salary02	average salary 2002 * inflation index
average salary delta 2002-10	dsalary0210	(average salary 2010 - average salary 2002 * inflation ind.) / average salary 2002 * inflation ind.
% unemployment 2002	unemp02	unemployed 2002 / population 2002
% unemployment 2010-2002	unemp0210	(unemployed 2010 / population 2010) - (unemployed 2002 / population 2002)
investments 98-10	inv9810	( $\Sigma$ inv 1998-2010) / pop 2010
% ineff. factories	ineff02	rate of inefficient factories 2002
ineff. factories 2010-2002	ineff0210	rate of inefficient factories 20010 - rate of inefficient factories 2002

## Appendix 2

pop02					
	1	2	3	4	5
1	0.01	0.01	0.02	0.02	0.03
2	0.02	0.02	0.03	0.03	0.04
3	0.03	0.03	0.04	0.047	0.051
4	0.04	0.04	0.053	0.08	0.18
5	0.046	0.044	0.054	0.20	0.35

hdil02					
	1	2	3	4	5
1	0.08	0.09	0.11	0.08	0.07
2	0.07	0.09	0.09	0.07	0.04
3	0.05	0.06	0.06	0.04	0.03
4	0.06	0.05	0.05	0.03	0.02
5	0.11	0.09	0.07	0.04	0.03

unemp02					
	1	2	3	4	5
1	0.30	0.40	0.48	0.33	0.21
2	0.19	0.22	0.27	0.17	0.13
3	0.12	0.14	0.17	0.14	0.12
4	0.13	0.16	0.194	0.14	0.10
5	0.17	0.21	0.23	0.14	0.09

dpop0210					
	1	2	3	4	5
1	0.38	0.38	0.38	0.38	0.39
2	0.38	0.38	0.39	0.41	0.445
3	0.38	0.37	0.39	0.42	0.4804
4	0.42	0.40	0.41	0.429	0.47
5	0.47	0.45	0.431	0.438	0.46

hdil0210					
	1	2	3	4	5
1	0.575	0.556	0.527	0.5687	0.59
2	0.572	0.558	0.535	0.555	0.5668
3	0.5661	0.5673	0.55	0.562	0.5672
4	0.541	0.558	0.56	0.5661	0.573
5	0.49	0.53	0.55	0.560	0.5605

unemp0210					
	1	2	3	4	5
1	0.39	0.33	0.28	0.32	0.38
2	0.40	0.38	0.35	0.36	0.37
3	0.40	0.39	0.37	0.37	0.36
4	0.37	0.37	0.34	0.36	0.35
5	0.36	0.34	0.32	0.34	0.36

crow02					
	1	2	3	4	5
1	0.19	0.18	0.19	0.20	0.21
2	0.20	0.18	0.18	0.191	0.203
3	0.23	0.21	0.20	0.20	0.21
4	0.28	0.24	0.23	0.24	0.25
5	0.34	0.30	0.26	0.27	0.28

hwwater02					
	1	2	3	4	5
1	0.33	0.46	0.64	0.72	0.77
2	0.44	0.57	0.71	0.77	0.79
3	0.58	0.69	0.82	0.86	0.87
4	0.64	0.78	0.90	0.92	0.92
5	0.74	0.86	0.93	0.95	0.93

inv9810					
	1	2	3	4	5
1	0.02	0.02	0.03	0.03	0.0305
2	0.02	0.02	0.02	0.03	0.03
3	0.02	0.02	0.03	0.04	0.04
4	0.03	0.03	0.07	0.05	0.04
5	0.04	0.09	0.13	0.10	0.06

icrow0210					
	1	2	3	4	5
1	0.39	0.39	0.39	0.38	0.37
2	0.39	0.39	0.40	0.40	0.406
3	0.38	0.37	0.38	0.39	0.40
4	0.39	0.38	0.37	0.36	0.36
5	0.39	0.38	0.37	0.36	0.35

hwwater0210					
	1	2	3	4	5
1	0.40	0.36	0.34	0.34	0.35
2	0.40	0.34	0.33	0.33	0.33
3	0.42	0.36	0.322	0.3188	0.3203
4	0.43	0.36	0.317	0.3146	0.3160
5	0.38	0.34	0.3153	0.3187	0.33

ineff02					
	1	2	3	4	5
1	0.47	0.50	0.50	0.41	0.34
2	0.51	0.56	0.51	0.38	0.32
3	0.48	0.53	0.50	0.39	0.31
4	0.44	0.51	0.49	0.39	0.33
5	0.45	0.49	0.47	0.38	0.33

natbal9002					
	1	2	3	4	5
1	0.61	0.61	0.63	0.64	0.65
2	0.62	0.60	0.60	0.61	0.63
3	0.65	0.62	0.62	0.62	0.63
4	0.71	0.70	0.70	0.68	0.67
5	0.78	0.801	0.798	0.75	0.71

hwsew02					
	1	2	3	4	5
1	0.31	0.43	0.61	0.70	0.74
2	0.42	0.54	0.68	0.75	0.77
3	0.55	0.66	0.79	0.84	0.85
4	0.62	0.75	0.88	0.91	0.91
5	0.69	0.83	0.92	0.93	0.92

ineff0210					
	1	2	3	4	5
1	0.46	0.44	0.45	0.53	0.58
2	0.41	0.36	0.40	0.50	0.53
3	0.39	0.33	0.37	0.46	0.49
4	0.39	0.31	0.35	0.43	0.44
5	0.38	0.32	0.35	0.42	0.42

natbal0310					
	1	2	3	4	5
1	0.60	0.61	0.62	0.62	0.62
2	0.62	0.60	0.59	0.61	0.63
3	0.64	0.61	0.60	0.61	0.64
4	0.70	0.68	0.68	0.67	0.68
5	0.7844	0.794	0.7796	0.75	0.72

hwsew0210					
	1	2	3	4	5
1	0.41	0.37	0.35	0.35	0.36
2	0.41	0.36	0.34	0.34	0.35
3	0.43	0.37	0.3343	0.3292	0.3337
4	0.44	0.37	0.3303	0.3260	0.3295
5	0.40	0.35	0.3313	0.3336	0.34

hwhw02					
	1	2	3	4	5
1	0.18	0.31	0.46	0.52	0.45
2	0.28	0.42	0.57	0.67	0.61
3	0.40	0.53	0.70	0.78	0.79
4	0.49	0.66	0.82	0.87	0.86
5	0.54	0.73	0.87	0.89	0.87

migbal9002					
	1	2	3	4	5
1	0.69	0.67	0.657	0.68	0.69
2	0.71	0.68	0.68	0.72	0.73
3	0.71	0.69	0.69	0.72	0.73
4	0.72	0.69	0.663	0.70	0.72
5	0.73	0.67	0.63	0.67	0.70

hwheat20					
	1	2	3	4	5
1	0.40	0.52	0.68	0.76	0.78
2	0.51	0.62	0.74	0.82	0.82
3	0.68	0.74	0.85	0.89	0.90
4	0.75	0.84	0.91	0.94	0.93
5	0.78	0.87	0.94	0.95	0.93

hwhw0210					
	1	2	3	4	5
1	0.54	0.51	0.49	0.50	0.52
2	0.54	0.50	0.48	0.474	0.48
3	0.54	0.50	0.475	0.4627	0.44
4	0.52	0.48	0.45	0.44	0.43
5	0.51	0.4675	0.43	0.41	0.41

migbal0310					
	1	2	3	4	5
1	0.57	0.55	0.54	0.56	0.57
2	0.581	0.56	0.57	0.60	0.62
3	0.59	0.577	0.578	0.62	0.67
4	0.61	0.576	0.56	0.61	0.67
5	0.62	0.571	0.53	0.581	0.64

hwheat0210					
	1	2	3	4	5
1	0.64	0.60	0.57	0.56	0.55
2	0.62	0.57	0.55	0.54	0.53
3	0.58	0.55	0.53	0.5220	0.51
4	0.58	0.53	0.516	0.51	0.51
5	0.56	0.522	0.50	0.50	0.50

hnew0310					
	1	2	3	4	5
1	0.13	0.11	0.10	0.10	0.14
2	0.13	0.10	0.10	0.12	0.20
3	0.14	0.11	0.10	0.15	0.30
4	0.26	0.17	0.12	0.20	0.35
5	0.40	0.27	0.16	0.22	0.37

hmq02					
	1	2	3	4	5
1	0.32	0.34	0.34	0.33	0.31
2	0.30	0.33	0.35	0.34	0.33
3	0.27	0.31	0.33	0.34	0.34
4	0.25	0.29	0.31	0.30	0.29
5	0.23	0.27	0.30	0.27	0.25

salary02					
	1	2	3	4	5
1	0.08	0.11	0.13	0.13	0.11
2	0.09	0.10	0.11	0.12	0.12
3	0.09	0.10	0.12	0.13	0.1436
4	0.10	0.12	0.19	0.17	0.16
5	0.13	0.24	0.34	0.28	0.20

hmq0210					
	1	2	3	4	5
1	0.36	0.36	0.36	0.36	0.36
2	0.36	0.36	0.35	0.34	0.34
3	0.36	0.37	0.36	0.354	0.36
4	0.37	0.36	0.35	0.36	0.38
5	0.37	0.3468	0.34	0.3474	0.37

dsalary0210					
	1	2	3	4	5
1	0.44	0.44	0.41	0.40	0.43
2	0.44	0.44	0.41	0.41	0.45
3	0.42	0.43	0.41	0.42	0.48
4	0.42	0.41	0.39	0.41	0.45
5	0.40	0.37	0.34	0.37	0.42

## Appendix 3

### Russian urban engines

Astrahan; Penza; Barnaul; Rostov-on the Done; Belgorod; Ryazan; Vladivostok; Samara; Volgograd; Saratov; Voronej; Sochi; Yekaterinburg; Stavropol; Irkutsk; Tolyatti; Kazan; Tomsk; Kaliningrad; Tula; Kemerovo; Uljanovsk; Kirov; Ufa; Krasnodar; Cheboksari; Krasnojarsk; Celyabinsk; Lipetsk; Chita; Nabarajnie Chelni; Yaroslavl; Nalchick; Igevs; Nijnii Novgorod; Kursk; Novokuznetsk; Moscow; Novorosiisk; Saint-Petersburg; Novosibirsk; Tumen; Omsk; Habarovsk; Orenburg; Perm'.

### Strong cities

Azov; Anadir; Aprelevka; Beloyarskii; Berezovskii (Sverdlovsk region); Vorkuta; Bronnici; Vuktil; Vidnoe; Dudinka; Vsevolgsk; Elizovo; Dedovsk; Zapolyarnii; Domodedovo; Inta; Essentuki; Kogalim; Zvenigorod; Koryagma; Kirovsk (Leningrad region); Langepas; Korolev; Leninogorsk; Krasnoarmeisk; Magadan; Kropotkin; Megion; Lobnja; Monchegorsk; Michailovsk (Stavropol krai); Muravlenko; Pokrov; Nadim; Pyatigorsk; Nerjungri; Ramenskoe; Novodvinsk; Sergiev Posad; Noyabrsk; Serpuhov; Nyagan; Sibai; Petropavlovsk-Kamchatskii; Slavyansk na Kubani; Pokachi; Solnechnogorsk; Polyarnie zori.; Sredneuralsk; Primorsk; Tihoretsk; Pit - yah; Shatura; Radugnii (Tumen region); Shlisselburg; Svetogorsk; Electrougli; Severo-Kurilsk; Istra; Stregevoi; Svetlogorsk; Tinda; Yubileinii; Tirniauz; Armavir; Usinsk; Balashiha; Ust-Ilimsk; Berdsk; Sharipovo; Verhnyaya Pishma; Agidel; Vladimir; Bilibino; Vologda; Kirovsk (Murmansk region); Gelendjik; Kovdor; Dzerjinskii; Kodinsk; Dolgoprudnii; Kostomuksha; Dubna; Novii Urengoi; Geleznodorojni; Norilsk; Gukovskii; Olenegorsk; Zelenogradsk; Oha; Ivanteenka; Sayanogorsk; Krasnogorsk (Moscow region); Sayansk; Litkarino; Shelehov; Mitishi; Yasnii; Odincovo; Aznakaevo; Orel; Almetievsk; Podolsk; Angarsk; Pushkino; Blagoveshensk; Reutovo; Volgskii; Sertalovo; Gubkinskii; Smolensk; Magnitogorsk; Tambov; Murmansk; Troitsk (Moscow region); Nefteyugansk; Fryazino; Nignevartovsk; Shelkovo; Salavat; Sherbinka; Saransk; Engels; Sosnovii bor; Dmitrov; Starii oskol; Geleznogorsk; Sterlitamak; Communar; Surgut; Luberci; Siktivkar; Protvino; Urai; Stroitel; Uxta; Tver; Yugno-Sahalinsk; Chimki; Balabanovo; Chernogolovka; Bratsk; Volgodonsk; Volgorechensk; Desnogorsk; Zarechnii; Kirishi; Krasnokamensk; Nignekamsk; Novomichurinsk; Novocheboksarsk; Cherepovets.

### Dynamic cities

Aleksin; Apatiti; Birobidgan; Arsenev; Boksitogorsk; Archangelsk; Venev; Asbest; Verhnyaya Salda; Achinsk; Volokolamsk; Bogdanovich; Voskresensk; Borodino; Viksa; Bugulma; Georgievsk; Volgsk; Gryazovets; Gai; Divnogorsk; Dalnegorsk; Efremov; Kamennogorsk; Geleznovodsk; Kanadalaksha; Gigulevsk; Karachev; Zaisk; Kachkanar; Ivangorod; Kimovsk; Ivanovo; Kingisepp; Kolchugino; Kireevsk; Kondopoga; Kirov-Chepetsk; Krasnozovodsk; Kola; Kulebaki; Kotovsk; Likino-Dulevo; Kumertau; Mineral vodi; Kurgan; Murom; Megdurechensk; Novoulyanovsk; Nazarovo; Noginsk; Nahodka; Pavlovsk (Voronej region); Nignyaya Tura; Revda; Novotroitsk; Ruza; Orsk; Serov; Perevoz; Sosenskii; Pechora; Suvorov; Polevskoi; Syastroi; Solikamsk; Tutaev; Susuman; Uzlovaja; Suhoi log; Usolie-Sibirskoe; Tihvin; Shekino; Trubchevsk; Yasnogorsk; Fokino; Egorevsk; Chaikovskii; Izobilnii; Yurga; Kamensk-Shaxtin; Bolohovo; Klin; Gvardeisk; Agriz; Glazov; Anapa; Komsomolsk na Amure; Aramil; Nesterov; Bataisk; Sorsk; Belebei; Spassk-Dalnii; Borsk; Yarovoe; Goryachii kluch; Arzamas; Gurievsk (Kaliningrad region); Balakovo; Derbent; Baltiisk; Eysk; Berezniki; Izberbash; Great Novgorod; Kizlyar; Vladikavkaz; Kizil; Viborg; Mamadish; Gubkin; Mahachkala; Dzerzhinsk; Sisert'; Dimitrovgrad; Hanti-Mansiisk; Yoshkar-Ola; Hasavjurt; Ishimbai; Elista; Kamensk-Ural; Yadrin; Kashira; Abinsk; Klimovsk; Blagoveshensk; Kovrov; Buynaksk; Kolomna; Dagestanski ogni; Kostroma; Kanash; Krasnoturinsk; Karabulak; Kstovo; Ladushkin; Mendeleevsk; Nazran; Mozdok; Naryan-Mar; Mtcensk; Salehard; Naro-Fominsk; Tsivilsk; Nevinnomissk; Cherkessk; Nignii Tagil; Bavli; Novokuibishevsk; Bagrationovsk; Novomoskovsk; Baksan; Obninsk; Belokuriha; Oktyabrskii; Berezovskii (Kemerovo region); Orekhovo-Zuevo; Beslan; Otradnii; Djurtjuli; Pervouralsk; Elabuga; Petrozavodsk; Zainsk; Pikalevo; Kaspiisk; Prohladnii; Kiziljurt; Ribinsk; Labitnangi; Svetlii; Meleuz; Severouralsk; Neftekamsk; Electrostal; Nurlat; Ardon; Tobolsk; Zavolgie; Tyimazi; Zelenodolsk; Ulan-Ude; Karachaevevsk; Uchali; Lermontov; Chernushka; Neftekumsk; Yugorsk; Novovoroneg; Yakutsk; Peresvet; Abakan; Pskov; Kirovograd; Severodvinsk; Severobaikalsk; Stupino; Sosnovoborsk; Tuapse; Ust-Djeguta.