Sergiy V. Kostrikov[1], **Kateryna Yu. Sehida**[2]

GIS-MODELLING OF REGIONAL COMMUTING (A CASE STUDY OF KHARKIV REGION)

This paper introduces an original theoretical approach, empirical data, and a simulation model for research on commuting within a regional workforce market. This research involves the use of GIS software for spatial modelling, analysis and visualization. The regional geodatabase has been updated with the data relevant to spatial distribution of commuting. The elaborated empirical/analytical GIS-model of regional commuting has become the key component of econometric analysis completed consequently for two research levels: for a single administrative district ("rayon") => for the whole Kharkiv administrative unit ("oblast").

Keywords: *commuting; geoinformation system (GIS); geodatabase (GDB); regional workforce market; spatial distribution.*
JEL classification: C69; J20; J61.
Peer-reviewed, approved and placed: *11.04.2016.*

Сергій В. Костріков, Катерина Ю. Сегіда

ГІС-МОДЕЛЮВАННЯ МАЯТНИКОВОЇ ТРУДОВОЇ МІГРАЦІЇ В РЕГІОНІ (НА ПРИКЛАДІ ХАРКІВСЬКОЇ ОБЛАСТІ)

У статті представлено авторський теоретичний підхід, емпіричні дані та імітаційну модель маятникової трудової міграції на регіональному ринку праці. Дослідження виконано як просторове моделювання, аналіз і візуалізацію проведено через програмне забезпечення геоінформаційної системи (ГІС). Регіональну базу геоданих модифіковано через емпіричні дані, на підставі яких можна описувати просторовий розподіл маятникової трудової міграції. Розроблена емпірико-теоретична ГІС-модель відіграла роль ключової складової економетричного аналізу, який послідовно впроваджувався на двох дослідницьких рівнях: для адміністративного району => для всієї Харківської області.

Ключові слова: *маятникова трудова міграція; геоінформаційна система; база геоданих; регіональний ринок праці; просторовий розподіл.*
Форм. 4. Рис. 4. Літ. 24.

Сергей В. Костриков, Екатерина Ю. Сегида

ГИС-МОДЕЛИРОВАНИЕ МАЯТНИКОВОЙ ТРУДОВОЙ МИГРАЦИИ В РЕГИОНЕ (НА ПРИМЕРЕ ХАРЬКОВСКОЙ ОБЛАСТИ)

В статье представлены авторский теоретический подход, эмпирические данные и имитационная модель маятниковой трудовой миграции на региональном рынке труда. Исследование выполнено посредством пространственного моделирования, анализа и визуализации с использованием программного обеспечения геоинформационной системы. Региональная база геоданных была модифицирована посредством данных, на основе которых описано пространственное распределение маятниковой трудовой миграции. Разработанная эмпирико-теоретическая ГИС-модель стала ключевой составляющей эконометрического анализа, который последовательно выполнялся на двух исследовательских уровнях: для административного района => для всей Харьковской области.

Ключевые слова: *маятниковая трудовая миграция; геоинформационная система; база геоданных; региональный рынок труда; пространственое распределение.*

[1] V.N. Karazin Kharkiv National University, Ukraine.
[2] V.N. Karazin Kharkiv National University, Ukraine.

Problem statement. Labor migration and commuting are the two key issues in the study of any workforce market at its *national* level. If we attempt to understand its lower, *regional* level, we have to choose just *commuting* as its dominant trend. As far as Ukrainian workforce market is concerned, such a choice becomes even more evident, taking into account mass unemployment in some geographic regions, while others lack workforce. Both empirical data and theoretical developments studies allow stating: the only socioeconomic phenomenon contributing to the solution of the existing social and economic problems at the national level is the *interregional labor migration*, while at the regional level it would be *intraregional commuting*.

Neither relevant interregional trends at the Ukrainian workforce market, nor intraregional ones have been research topics of thorough quantitative simulation or analysis yet. The authors here attempt to fill this gap by employing a geographical information system (GIS) to study commuting at the intraregional level: at the level of the biggest administrative unit in Ukraine — oblast. Such a study necessarily implies a downshift to the lowester research level (below national and regional ones) — to the local level of the workforce market, which is the level of an administrative district ("rayon" in *Ukrainian*).

A GIS has provided applications for almost 40 years in a wide range of subject areas — from natural sciences to humanities and social science, including human geography, social geography and economics.

Brief overview of earlier publications on the issue. The contemporary modelling study of commuting started with a seminal paper of M. Renkow and D. Hoover (2000), American social scientists, who examined two competing explanations due to labor migration, commuting and population dynamics in urban and rural areas of North America. They developed the series of empirical tests, which indicated, if commuting and migration were positively or negatively related with other social and economic factors (Renkow and Hoover, 2000). Many studies used empirical data to verify theoretical quantitative models of commuting and labor migration (Huffman and Feridhanusetyawan, 2007; Deding et al., 2009; Shuai, 2012). Search models were also applied to define complex relation between commuting and migration as between different processes (Rouwendall, 2004). Quite a few recent publications made progress in the description of migration/commuting dynamics at regional workforce markets and found evidences decentralization trends at regional labor markets of North America and Europe (Partridge et al, 2010; Ali et al., 2011; Moretti, 2011), while some other works neglected one or another degree of the commuting variable in formalizing regional workforce models (Allen and Arkolakis, 2014). All recent papers, while studying the commuting phenomenon, referred to GIS, but normally not more, than as to a routine mapping tool. Only few researches employed it also for advanced functional modelling of commuting spatial regularities (Hincks and Wong, 2010; Wong et al., 2015).

Even fewer papers and books analyzing labor migration and commuting have been published in Ukraine in recent years, e.g. (Rohozhyn, 2004; Libanova et al., 2010; Prybytkova, 2011). Only a few publications provided quantitative labor migration and commuting study, for instance, for different regions of Ukraine (Kupets, 2012) and defined ratios between external and internal labor migration for our whole country (Balakirieva and Shestakovskyi, 2012). As far as Kharkiv region is concerned, it is reasonable to mention the regional study of migration and populations dynamics covered a period of more, than 40 years, and exclusively completed by the census data (Rachkov, 2011). There is an advanced example of commuting study for Moscow region in Russia (Shitov and Shitova, 2008). The latter was later transformed into an interesting GIS-analysis of the regional commuting (Shitov and Shitova, 2015). The authors of this paper once outlined a wide row of possible GIS-applications in human, social and economic geography (Kostrikov and Segida, 2013). Unfortunately, up to now we could hardly mention a couple of efficient examples, which concern workforce market study in Ukraine with application of GIS-tools.

The main research goal of this paper is to introduce an example of community quantitative study with GIS at two research levels (local and intraregional) within the boundaries of Kharkiv oblast.

Key research findings.

Initial empirical data and geodatabase update. The lack of commuting data at the workforce market in Ukraine up to its complete unavailability was already referred above. We can state there is no cross-regional commuting data for any administrative region of Ukraine. Governmental institutions, which must have been concerned, do not accumulate relevant data, and there is neither labor migration, nor commuting data in Ukrainian population census (UPS) of 2012 (Naselennia, kh.ukrstat.gov.ua, 2016). Recent closure of several statistics offices in Kharkiv region evidently made the whole situation even worse. Nonetheless, supplementary data sources issued by the regional office of statistics provide some unique information about enterprises, firms and services in all districts of the region (Mista ta raiony..., HUS, 2014). The data is updated by the field survey completed by the authors of this paper for all city centers of district in Kharkiv region and for almost 100 enterprises, firms, services and institutions in Kharkiv city during 2012–2014.

Our original geodatabase (GDB) as a structured set joined and linked MapInfo tables of Kharkiv region generated for GIS "*MapInfo Professional 12.02*" with vector and raster layers of spatial referencing for all cities, district boundaries, railways, roads and places of employment (related to urban areas of Kharkiv, Izyum, Pervomjskiy, Kupyansk, Lozova, Lyubotin, Chuguiv and to rural areas of 27 rayons) is applied for this study (visualizations presented in Figures 1, 2, 4). Rural areas and their city centers were numbered as 1–27 GDB ID entities; 7 urban areas – as 28–34 GDB ID entities.

There are *3 levels of update* for the GDB mentioned above according to the standardized procedure of a geodatabase update (Kostrikov, 2014). We entered these levels into the GDB proceeding from the referred source of regional statistics (Mista ta raiony..., HUS, 2014) and from the performed field survey.

The *first update* entered detailed demographic data from UPS of 2012 for all administrative districts, cities, townships and villages of the Kharkiv oblast (two examples of the first level fields in the GDB are: *pop_urban_2012* – aggregated population for urban areas; *pop_rural_2012* – for rural areas). This data was obtained from open sources (Mista ta raiony..., HUS, 2014; Naselennia, kh.ukrstat.gov.ua, 2016).

The *second level of update* bound by ID of an Employer (*ER*) and by "conventional ID of an Employee" (*EE*) (which does not correspond to an actual ID of a person, and thus does not allow tracing personal data) the database records related to: 1) *ER*: business (economic) activity characteristics – *BA*; form of property – *FP*; personnel (number of workers) – *P*; capital – *C*; and to 2) *EE*: monthly salary – *MS*; resident or non-resident in this area of a work – *R_or_NR*, that record follows from two records: place of residence – *PR*, place of work – *PW*; age – *AG*; if non-resident, then commuting cost (estimated) – CC. It includes both transportation cost to a place of employment and other supplementary expenses. The second updated level of GDB consists of almost *300 ths records*, approximately varying from 1 ths to 25 ths records, which correspond to a single GDB segment – an administrative district or a city center. These records were compared with the first updated level (demographic) level for conditional verification according to the geodatabase building rules. The template record of the second level looks like the follows:

$$ER(BA \times FP \times P \times C) \Leftrightarrow EE\{MS \times [PR \times PW(R\_or\_NR)] \times AG \times CC(if\_NR)\} \Rightarrow CMT, \tag{1}$$

where *CMT* – a probable number of *daily/weekly* commuters (according to the second level of updated GDB content).

The *third level of update* implies binding spatially the transport network (*TN*) – roads and railways – from the initial GDB with its content updated according to (1):

$$ER \times EE(CC) \Leftrightarrow TN_i(TN_1, TN_2, \ldots\ldots TN_n) \Rightarrow ROUTE_{CMT}, \tag{2}$$

where TN_i – transport network segments, which put together different commuting routes $ROUTE_{CMT}$ within a giving administrative district. All routes were reconstructed and mapped by GIS tools. This way (2) we obtain the final GDB update with a template record as:

$$ER \times EE(CC) \times ROUTE_{CMT} \Rightarrow CMT[ER \times EE(CC) \times CD \times CT], \tag{3}$$

where *CD* – commuting distance; *CT* – commuting time for a $ROUTE_{CMT}$ selected within a certain rayon of Kharkiv oblast.

Due to lack of data not all the second level update records could be bound with the regional transport network by (2), thus the efficiency of GIS-reconstruction to (3) can be estimated as no more than 70% of the GDB content. It means that the whole number of records was decreased to 210 thu. This can be accepted as a representative indicator for our regional workforce market, therefore we have to choose and develop further if necessary some analytical frameworks, so that to extrapolate GDB data to rural/urban areas, where this data is unavailable as an empirical value.

Modelling outlines. Regional commuting is a complicated phenomenon impacted by a number of social and economic variables. We accept a regional closed economy model with two basic locational variables: *place of residence – PR,* as *rural areas; place of work – PW,* as *urban areas.* Each model variables fits the corresponding field in the GDB of the second updated level (1). Commuting direction is accepted as from rural to urban areas, not opposite. Our aim is to model rural-urban commuting (from a village or a township to a city) only at the local level and ignore this process within only urban or only rural areas of districts. Consequent commuting regularities examined as spatially distributed and classified among different administrative districts of Kharkiv oblast implies the regional level of the study or a intraregional commuting research.

While choosing modelling outlines for further regional data update and implementation in the GIS environment, we select from two alternatives: it could be either Fujita's core-periphery model formalized by a condensed system of 8 equations that can be applied for each commuting separately (Fujita et al., 2001: 65); or Renkow's empirical model of aggregated commuting (Renkow and Hoover, 2000: 274).

Members of the system of equations in Fujita's model consist of 4 equations for each commuting area and 8 ones in total. These authors recognized the actual complexity: "does not look particularly tractable: eight simultaneous nonlinear equations!" (Fujita et al., 2001: 65), but it would not be a reason for this model rejection, because GIS software does not face any computing limits. We did not accept this first alternative, but preferred Renkow's model, because this model variables correspond to the structure of our GDB fields (1)–(3), than Fujita's model variables. The latter model is precisely oriented on income/salary rates and price indices, but there was lack of such information in our geodatabase.

The common expression of Renkow's empirical model used for econometric analysis (Renkow and Hoover, 2000: 274) was rewritten according to the updated GDB structure (see (1)–(3) and the previous paper section) and with an intent of further GIS-implementation, which produces an average aggregated number of *daily/weekly commuting in the period of 2012–2014.* It not only allows extrapolating GDB empirical content to those areas, where GDB records are absent, but also complete empirical data with analytical ones for the whole region:

$$CMT_{i,jNET} = f(\Delta MS_{i,j}, \Delta CC_{i,j}, CD_{i,j}, CT_{i,j}, EM_{AD}), \tag{4}$$

where $CMT_{i,jNET}$ – net number of commuters in an administrative district, moving from rural area locations, i.e., places of residence PR_i to PW_j – a place of work in a city center of this district – an urban location; $\Delta MS_{i,j}$ – a difference in a monthly salary rates in a rural area place of residence i and an urban area work place j; $\Delta CC_{i,j}$ – difference in commuting costs (taking into account transport availability and supplementary commuting expenses, but not distance and time of commuting) between various commuting routes started to the same urban work location j from different places of residence i in rural areas; $CD_{i,j}$, $CT_{i,j}$ – commuting distance and commuting time across different routes available between a rural place of residence i and an urban work location j; EM_{AD} – average yearly net labor migration into this administrative district (both to city center and to rural areas) normalized by population (average value for recent years). The value of average yearly migration into district can be only approximately estimated on the basis of demographic characteristics of the first regional GDB update.

Despite model variables in (4) differs from variables of Renkow's model, we can assume the similarity of the first derivative expected signs for the key individual variables of both models: *a positive difference* of salary variable is the main reason for commuting; *a negative difference* of commuting cost from a pair of various residences in a rural area determines the movement from starting residing points, which provide low commuting cost, not from those ones of high cost; the expected signs of distance and time first derivatives are obviously negative; the sign of estimated net labor migration is positive, if migration trend coincides with commuting one, and it is negative, if these trends do not agree.

GIS-visualization of regional commuting and other results. The empirical-analytical GIS-model has been implemented on the basis of formalization introduced in the previous section (4). The model elaboration, as one of "*MapInfo Professional*" plug-ins, was completed by "*MapBasic*" programing language.

We have already mentioned that we restricted this econometric analysis subject to a number of pairs "a city-center of district – a village or a township in a rural area of this ADA, from where people may commute to a city center". We did not consider commuting between districts, the only exception was made for Kharkiv agglomeration. Rural area as a source of commuting to Kharkiv was not limited to fixed boundaries of its administrative region, but was flexibly extended to those parts of 4 neighboring districts (with city centers in Zmiiv, Chuguiv, Dergachi, Nova Vodolaga), from which it would be more preferable to commute to Kharkiv, rather than to local city centers. The only gauge for such commuting spatial limit extension over district boundaries is *CC* parameter (1)–(4), since we do not have relevant reliable data for Kharkiv employment market preferences in comparison with those 4 district. These commuting bounds are made flexible by modelling iterations for lower commuting cost definition – either to Kharkiv, or to a local city center.

We use GIS capability of creating buffer zones around sources of commuting. Concentric buffers with different quantitative classes of potential numbers of commuters was put around each source – village or township, so that to deal with areal features upon spatial modelling, not with point ones. Outer concentric rings were prescribed a fewer commuting number, inner ones – a larger number. If rings of different sources intersected, this area was prescribed the maximum commuting value from two or more intersecting rings. Such approach seems to us to be grounded enough, because of relatively high settlement density. In this way the *local level* of commuting study is implemented as *the first modelling step*.

The results of our empirical/analytical GIS-model implementation are visualized in "MapInfo" interface. The derivative modelled field "*Commuting*" (in ths of people) is added to GDB and compared with all city centers' population numbers from the initial GDB demographic content. It is depicted in the "*Browser*" "MapInfo" window (Figure 1). Commuting modelled values are also compared with populations of district city centers by pie-charts drawn in logarithmic scale. The dark sector in the chart indicates a population value of a relevant city center (pointed to by the black line from the *Legend window*, see Figures 1–2), the light sector – a commuting value in this district.

The substitution of point objects by areal objects as commuting sources allows performing TIN (Triangular Irregular Network) modelling embedded into basic functionality of GIS "*MapInfo Professional*". TIN is a surface model, representing the surface to be covered connected, continuous triangles, presenting planar edges of the landscape (Kostrikov, 2014). This approach generates *the spatially distributed surface of commuting values,* thus we enter *the second modelling step – the intraregional level* of commuting. The modelled TIN-surface overlays the raster spatially referenced layer of Kharkiv region and the vector layers of districts' boundaries and their city centers. The pie-chart thematic layer is bound to the latter. General regularities of TIN modelling results are as follows: the darker the triangle and polygon surface segment, the lower spatially distributed commuting values they represent. Spatial definition of the

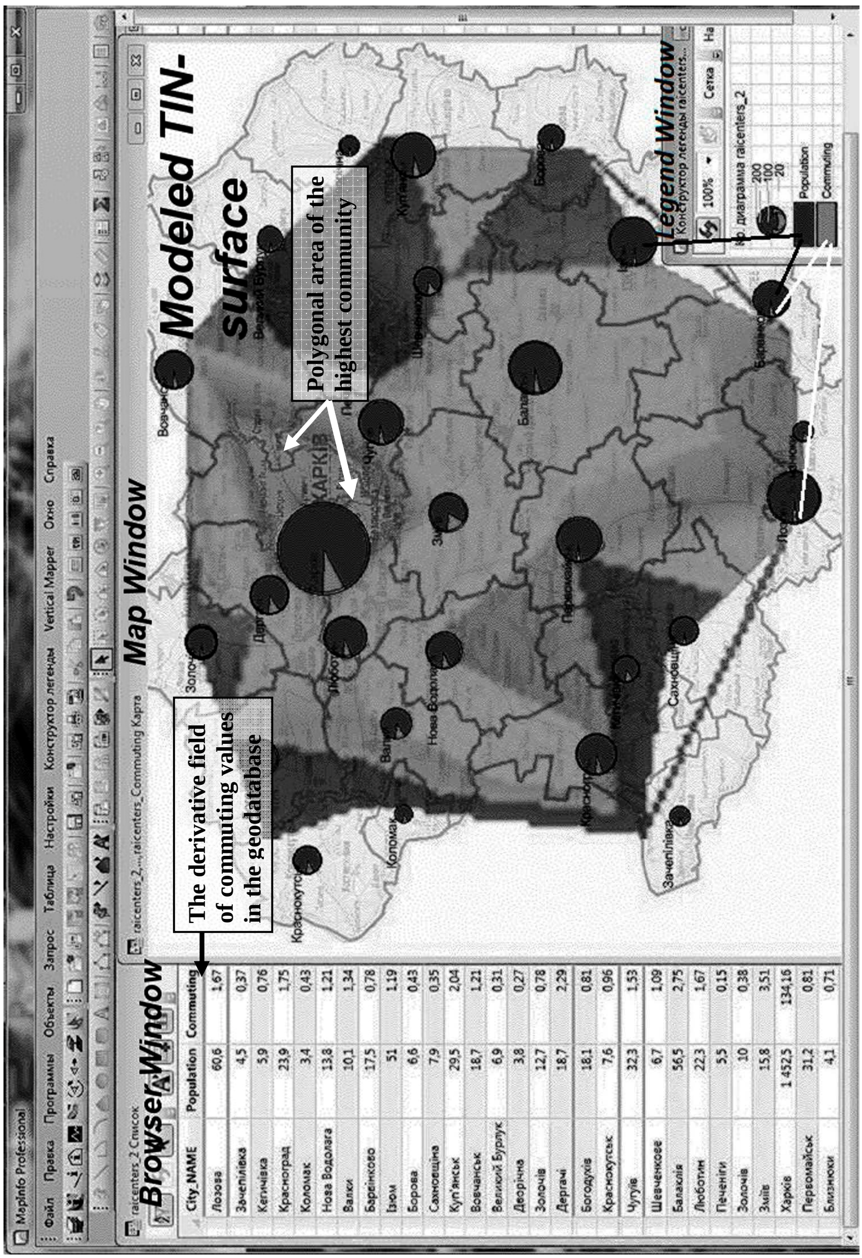

Figure 1. **Visualization of commuting modeling at the local level, 1st illustration,** *authors'*

highest intraregional community, which may occur in the polygonal area extended to the northeast (more) and to the southeast (less) from Kharkiv agglomeration (Figure 1) — is one of the key research development at the intraregional level of commuting. TIN surface does not cover most of the peripheral areas in the Kharkiv region not only due to data lack, but also since modelling technique must fit regional boundaries as much as possible.

Hence, not to overload the illustration above and to compare easily different values we add to the "MapInfo Map" window another thematic bar-chart layer, the rural population throughout all districts, and place it as another map (Figure 2). There is also the same pie-chart thematic layer of "city center population — commuting" on this map. Thus we get an opportunity to compare spatially two key modelling values (city center population, rural population) with two modelled ones (discrete commuting values and TIN surface).

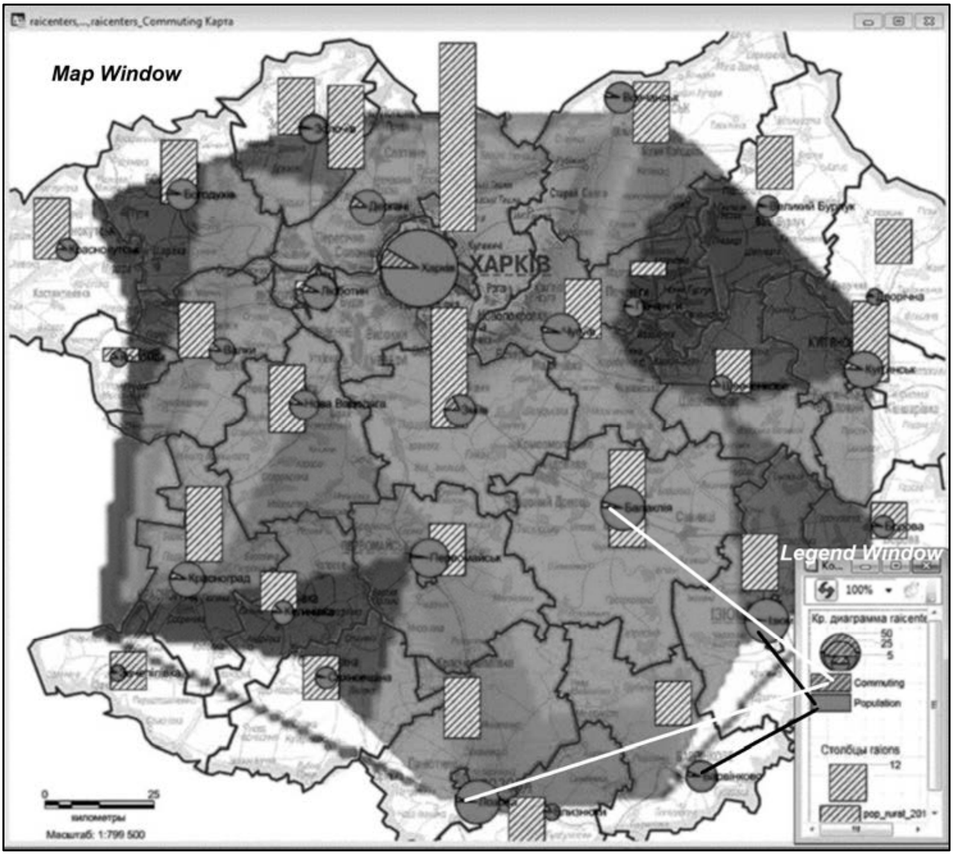

Figure 2. **Visualization of commuting modelling at the local level,** *ths districts*, **2nd illustration,** *authors'*

Finally we introduce the concluding step of our research level by entering the definition of "*commuting density*" — the value of commuting bound to an administrative district and normalized by its area. With further spatial classification of these results we obtain the answer whether commuting in spatial extent of the regional workforce market are uniform, or it is skewed to Kharkiv agglomeration, or to some districts. The complete calculating record is in the "*Expression*" dialog of "*Building Thematic Map*" "MapInfo" menu (Figure 3). A multiplier of 1000 is entered into the record, because once commuting values were counted in thousands of people, but we are calculating commuters now in integers per square kilometer.

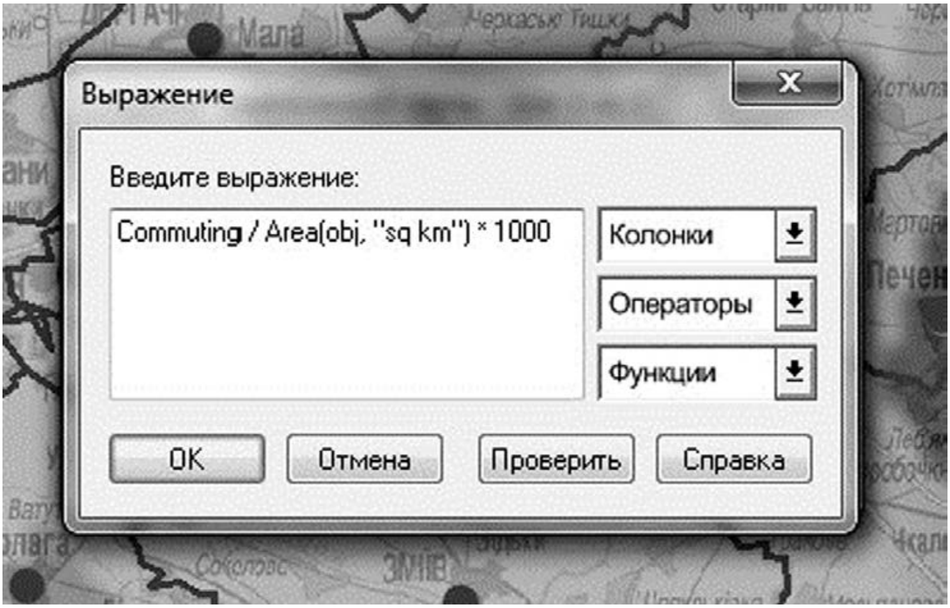

Figure 3. **"MapInfo" dialog "Expression" used for commuting density calculations**

The map of commuting density spatial classification of the Kharkiv region finalizes our research (Figure 4). The illustration represents both "*Browser*" window with discrete commuting values already reported above (Figure 1) next to urban and rural population values throughout all districts, and "*Map*" window with *4 spatial classes.*

The first class reports 20-491 commuters per square kilometer in "*Legend*" window, and evidently the excess of the class threshold value (491) has been caused by extreme demographic characteristics of Kharkiv agglomeration. 8 administrative units – GDB entities are reported to be classified, but there are actually only 7 of them, because we have to place in the GDB a supplementary entity – some "transitional district" made by flexible boundaries of the area – source of commuting to Kharkiv. Besides Kharkiv administrative district there are few areas around the city centers within the third and the fourth class territories, which actually belong to the first class of commuting density (Figure 4).

The second class shows 2–3 commuters per sq km with 2 only GDB entities reported, both are contiguous with Kharkiv agglomeration to the North and South. *The third class of 1–2 commuters per area unit (km)* includes 9 entities, and *the fourth class (0–1 commuters)* – the largest number, 16. In total, all 34 geodatabase entities have been prescribed to a certain class and reported in "*Legend*" window (Figure 4).

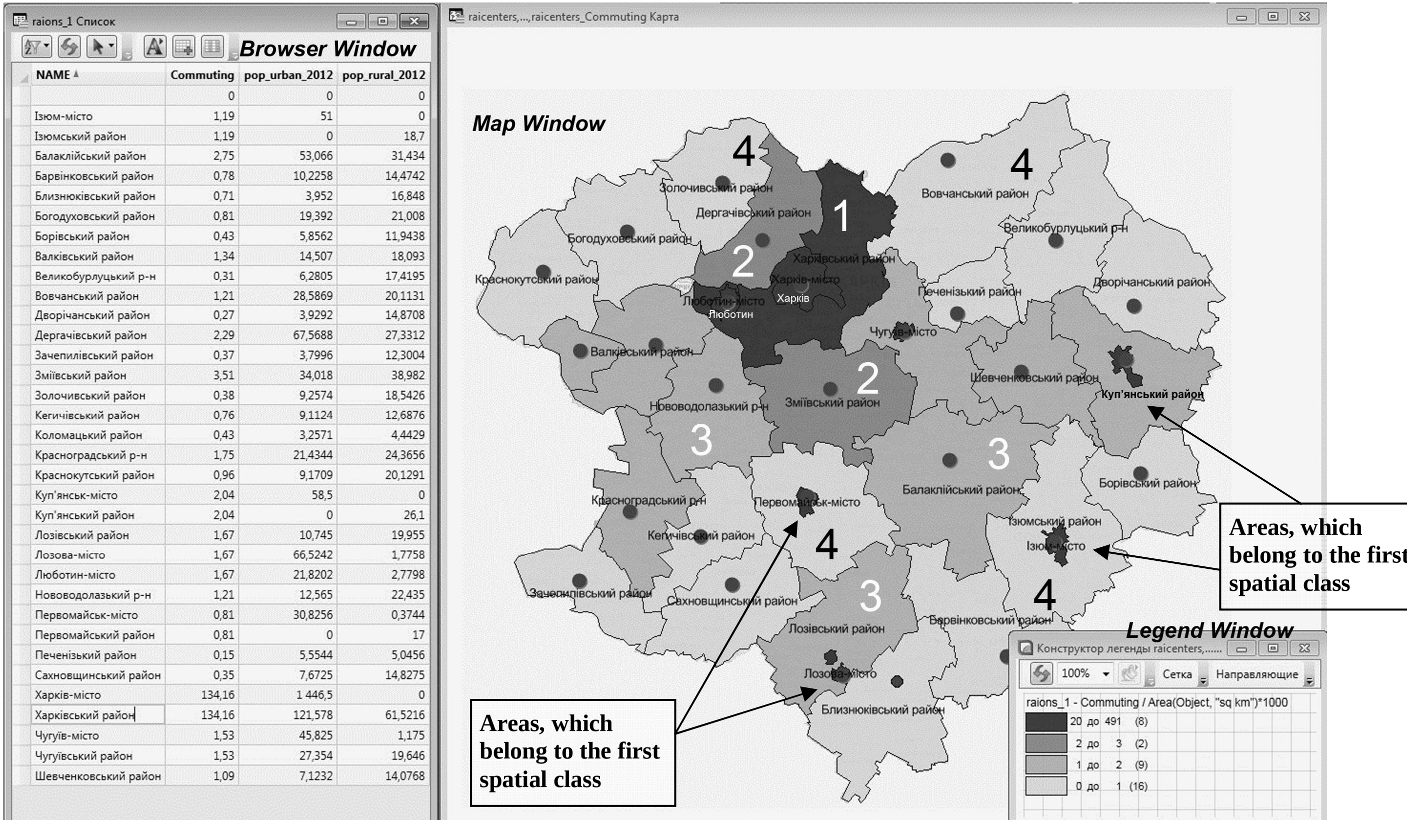

Figure 4. **Study results at the intraregional level (for the whole region): 1–4 – spatial classes of commuting density,** *authors'*

Conclusions and further research prospects. With a focus on two levels of daily/weekly commuting study in 2012-2014 – local and intraregional – spatial distribution and classification have been provided using GIS for modelling and analysis. 4 spatial classes of commuting quantitatively defined strongly agree with the level of socioeconomic development of the relevant territories (Figure 4): 1st and 2nd classes – *highly developed districts*; 3rd class – *moderately developed ones*; 4th class – *depressive areas*. With all its notable deficiencies and disputable issues this study can hardly be undervalued, at least because there is no governmental regional statistics in Ukraine that would describe commuting as such.

As far as discrete modelled values are concerned, our econometric calculations state that the number of regular daily/weekly commuters within Kharkiv agglomeration (around 134 ths) does not contradict drastically the average number of commuters in the last Soviet decade (around 200 ths, reported as an estimated value according various sources) and to the number of regional commuters in the first years of Ukraine's independence (around 150 ths). Continuous modelled values indicate that commuting changes in the spatial extent of the regional workforce market skewed to the regional center and demonstrate extremes around few local townships.

Further commuting research needs to extend the empirical/analytical model presented with much broader number of cross-regional commuting determinants, firstly with those ones caused by the war going on the East of our country – the area neighboring to Kharkiv region. Besides further update of the 3 existing levels of GDB, the authors have to make the fourth level of an update – to complete it with public survey data on commuting. We failed to do this in the reported study, attempting throughout the most of cities in the region to get an answer from employers: "How many of your workers commute from rural areas?". The number of replies we received is not statistically reliable, while this individual-level data may assist in balancing the results of our analytical prediction with the initial database contents. Finally it may give an opportunity to provide the statistical significance testing as a routine modelling procedure.

References:

Балакірєва О.М., Шестаковський О. Масштаби трудової міграції українців: досвід кількісної оцінки // Вісник Харківського національного університету імені В.Н. Каразіна.– 2012.– №993. – С. 102–106.

Balakirieva O.M., Shestakovskyi O. Masshtaby trudovoi mihratsii ukraintsiv: dosvid kilkisnoi otsinky // Visnyk Kharkivskoho natsionalnoho universytetu imeni V.N. Karazina.– 2012.– №993. – S. 102–106.

Костріков С.В. Геоінформаційне моделювання природно-антропогенного довкілля: Наук. монографія. – Харків: ХНУ, 2014. – 484 с.

Kostrikov S.V. Heoinformatsiine modeliuvannia pryrodno-antropohennoho dovkillia: Nauk. monohrafiia. – Kharkiv: KhNU, 2014. – 484 s.

Купець О.В. Статистичний аналіз маятникової трудової міграції в Україні // Формування ринкової економіки: Збірник наук. праць Київського нац. екон. ун-т ім. Вадима Гетьмана / Відп. ред. О.О. Бєляєв. – Спец. вип.: Праця в XXI столітті: новітні тенденції, соціальний вимір, інноваційний розвиток: У 2 т. – К., 2012. – Т. 1. – С. 649–660.

Kupets O.V. Statystychnyi analiz maiatnykovoi trudovoi mihratsii v Ukraini // Formuvannia rynkovoi ekonomiky: Zbirnyk nauk. prats Kyivskoho nats. ekon. un-t im. Vadyma Hetmana / Vidp. red. O.O. Bieliaiev. – Spets. vyp.: Pratsia v KhKhI stolitti: novitni tendentsii, sotsialnyi vymir, innovatsiinyi rozvytok: U 2 t. – K., 2012. – T. 1. – S. 649–660.

Людський розвиток в Україні: мінімізація соціальних ризиків: Колек. монографія / За ред. Е.М. Лібанової. – К.: Ін-т демографії та соціальних досліджень ім. М.В.Птухи НАН України, Держкомстат України, 2010. – 496 с.

Liudskyi rozvytok v Ukraini: minimizatsiia sotsialnykh ryzykiv: Kolek. monohrafiia / Za red. E.M. Libanovoi. – K.: In-t demohrafii ta sotsialnykh doslidzhen im. M.V.Ptukhy NAN Ukrainy, Derzhkomstat Ukrainy, 2010. – 496 s.

Міста та райони Харківської області в 2014 році. – Харків: ГУС, 2014. – 378 с.

Mista ta raiony Kharkivskoi oblasti v 2014 rotsi. – Kharkiv: HUS, 2014. – 378 c.

Населення // Головне управління статистики у Харківській області, 2016 // kh.ukrstat.gov.ua.

Naselennia // Holovne upravlinnia statystyky u Kharkivskii oblasti, 2016 // kh.ukrstat.gov.ua.

Прибиткова І. Зміни в поселенській структурі населення України та тенденції міграції // Українське суспільство. Двадцять років незалежності. Соціологічний моніторинг: У 2-х т. – К.: ІС НАНУ, 2011. – Т. 1. – С. 102–114.

Prybytkova I. Zminy v poselenskii strukturi naselennia Ukrainy ta tendentsii mihratsii // Ukrainske suspilstvo. Dvadtsiat rokiv nezalezhnosti. Sotsiolohichnyi monitorynh: U 2-kh t. – K.: IS NANU, 2011. – T. 1. – S. 102–114.

Рачков Є. Вплив міграційних процесів на зміни чисельності населення Харківської області у другій половині ХХ – на початку ХХІ ст. (за даними заг. переписів населення 1959–2001 рр.) // Актуальні проблеми всесвітньої та вітчизняної історії: Збірник наук. праць Харк. нац. ун-т ім. В.Н. Каразіна. – Вип. 14. – Х., 2011. – С. 209–218.

Rachkov Ye. Vplyv mihratsiinykh protsesiv na zminy chyselnosti naselennia Kharkivskoi oblasti u druhii polovyni KhKh – na pochatku KhKhI st. (za danymy zah. perepysiv naselennia 1959–2001 rr.) // Aktualni problemy vsesvitnoi ta vitchyznianoi istorii: Zbirnyk nauk. prats Khark. nats. un-t im. V.N. Karazina. – Vyp. 14. – Kh., 2011. – S. 209–218.

Рогожин О.Г. Демографічні перспективи українського села: історичні передумови, регіональний аналіз і моделювання. – К.: Ін-т проблем нац. безпеки, 2004. – 296 с.

Rohozhyn O.H. Demohrafichni perspektyvy ukrainskoho sela: istorychni peredumovy, rehionalnyi analiz i modeliuvannia. – K.: In-t problem nats. bezpeky, 2004. – 296 s.

Шитова Ю.Ю., Шитов Ю.А. ГИС-мониторинг маятниковой трудовой миграции как задача регионального управления, 2015 // sovman.ru.

Shitova Iu.Iu., Shitov Iu.A. GIS-monitoring maiatnikovoi trudovoi migratcii kak zadacha regionalnogo upravleniia, 2015 // sovman.ru.

Шитова Ю.Ю., Шитов Ю.А. Микроанализ маятниковой трудовой миграции в Московской области // Регион: экономика и соціологія.– 2008.– 4. – С. 119–137.

Shitova Iu.Iu., Shitov Iu.A. Mikroanaliz maiatnikovoi trudovoi migratcii v Moskovskoi oblasti // Region: ekonomika i sotciologiia.– 2008.– 4. – S. 119–137.

Ali, K., Olfert, M.R., Partridge, M.D. (2011). Urban footprints in rural Canada: Employment spillover by city size. Regional Studies, 45(2): 239–260.

Allen, T., Arkolakis, C. (2014). Trade and the Topography of the Spatial Economy. Quarterly Journal of Economics, 129(3): 1085–1140.

Deding, M, Filges, T., Omerren, J.V. (2009). Spatial mobility and commuting: the case of two-earner households. Journal of Regional Science, 49(1): 261–287.

Fujita, M., Krugman, P., Venables, A. (2001). The Spatial Economy: Cities, Regions, and International Trade. Cambridge, Massachussettes: The MIT Press. 381 p.

Hincks, S., Wong, C. (2010). The Spatial Interaction of Housing and Labour Markets: Commuting Flow Analysis of North West England. Urban Studies, 47(3): 620–649.

Huffman, W.E., Feridhanusetyawan, T. (2007). Migration, fixed costs, and location-specific amenities: A hazard analysis for a panel of males. American Journal of Agricultural Economics, 89(2): 368–382.

Kostrikov, S., Segida, K. (2013). Human geography with geographical information systems. Часопис соціально-економічної географії, 15(2): 39–47.

Moretti, E. (2011). Local Labor Markets. In: Handbook of Labor Economics. Ed. D. Card, O. Ashenfelter. Vol. 4b (pp. 1238–1303). Amsterdam: Elsevier North Holland.

Partridge, M.D., Ali, K., Olfert, M.R. (2010). Rural-to-urban commuting: Three degrees of integration. Growth and Change, 41(2): 303–335.

Renkow, M., Hoover, D. (2000). Commuting, migration, and rural-urban population dynamics. Journal of Regional Science, 40(2): 261–287.

Rouwendal, J. (2004). Search theory and commuting behavior. Growth and Change, 35(3): 391–418.

Shuai, X. (2012). Does Commuting Lead to Migration. Journal of Regional Analysis and Policy, 42(3): 237–250.

Wong, C., Baker, M., Webb, B., Hincks, S., Schulze-Baing, A. (2015). Mapping policies and programmes: The use of GIS to communicate spatial relationships in England. Environment and Planning B: Planning & Design, 42(6): 1020–1039.