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SPATIAL SURROGATE FOR AIR EMISSIONS FROM SMALL RESIDENTIAL COMBUSTION − ANALYSIS USING SCARCE TOP-DOWN ESTIMATES

15.1 INTRODUCTION

Emission inventories are compiled in different spatial resolutions: from global [13] to regional [8] and local [14] also in various spatial resolutions adjusted to the aim of particular analysis. Emission estimates are determined frequently using top-down methodologies [9, 11] then disaggregated to obtain desirable spatial resolution. The LRTAP emission inventories [8, 14] are good example of studies which are aimed at air pollutants' transport and dispersion modeling.

From the perspective of technical issues and cost-effectiveness is far easier to apply the top-down approach, however that is always charge with bigger uncertainty of determined estimates [2].

Emissions from small, residential combustion sources are also estimated using top-down official statistics provided by the Central Statistical Office of Poland and EUROSTAT [14]. In this paper we would like to present spatial disaggregation of emissions from small, scattered combustion sources, mainly domestic furnaces and cooking stoves, using only two data sets: gridded population density [10] and auxiliary information derived from the Polish bottom-up system of air emission data collection and reporting [24]. The sector took into account is residential combustion due to its significance in national emission budget [14] and substantial health impact [15]. Disaggregation results are performed using the new EMEP grid [3].

15.2 MATERIALS AND METHODS

Using the population density as emission surrogate [22] is widely recommended in official guidance [7] to downscale emission estimates, however applying this approach in the simplest form causes various misinterpretations of spatial emission distributions and then, modeling results.

Number of studies [4, 12, 17] use this approach due to clear relation between population density and anthropogenic air emissions. The problem with the simplifying of that approach is connected with occurrence of heating infrastructure. In the most cases strongly urbanized and more populated regions are equipped with the developed heating networks. However, that cannot change the budget (total emission estimate), but substantially changes the spatial emission distribution. In urbanized areas the share of population which is not supplied with the heat and hot water from the heating network is significantly lower. The assumption on linear relation between the population density and emissions from residential sources is true only for less populated, rural areas. This fact can be concluded from the linear dependency between the population and heat demand occurring in rural communes [21]. Overall dependency between the population density and the emission from residential combustion is presented as follows (Tab. 15.1).

Tab. 15.1 Dependency between residential air emission and population density in various areas

Area	Dependency
Rural	Linear
Urban – less populated	Linear
Urban – highly populated	Quasi-linear

Source: own elaboration

Quasi-linear dependency between the population density and residential emissions is the result of occurrence of strongly developed heating networks. In strongly urbanized regions population density must be decreased using particular parameters to obtain number of people which is not supplied with the heat and hot water. To resolve the problem another parameter can be also introduced (λ), connected with the percentage of population using district heating systems [5, 6]. The parameter values for selected Polish cities are presented in Tab. 15.2.

Tab. 15.2 Percentage of population being supplied from the district heating in selected Polish cities

City	λ [%]	City	λ [%]
Warszawa	80–90	Sopot	35
Gdynia	60	Tarnów	72
Lublin	73	Wejherowo	70
Łódź	60	Wrocław	62
Poznań	47–50	USMA	60 (average)
Rumia	30		

Source: own elaboration

The main aim of presented analysis is to rescale population density [10] in more populated regions to obtain representative grid for residential emission disaggregation. The locations to rescale population density are determined using probability density functions. Population density derived from [10] and aggregated in the new EMEP grid [3] is shown in Fig. 15.1. Method used in this paper is based on analysis of the probability density function taking into account values of aggregated population density (Fig. 15.1 b). This approach makes that information of locations is lost, however the main assumption considers occurrence of developed heating infrastructure only if the population density exceeds particular threshold value. This can be presented as below (Eq. 15.1):

$$E \sim \kappa \cdot P \tag{15.1}$$

where: E - emission from residential sector (mass of released pollutant per year),
$\kappa \in [0;1]$ - correction factor (dimensionless),
P - population density,
$\sim$ - the linear dependency is denoted as the tilde.

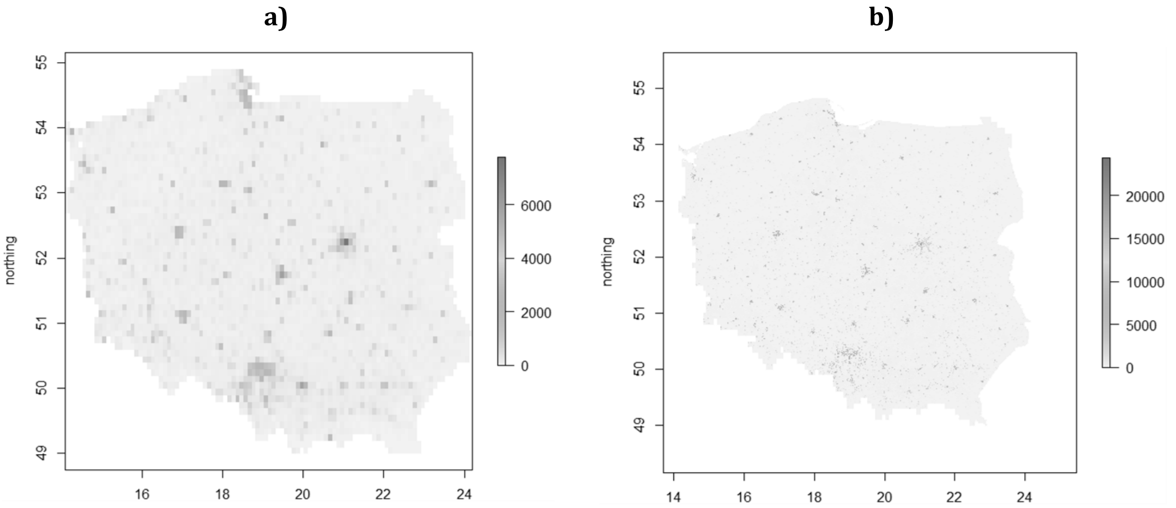

Fig. 15.1 Population density in Poland [people • km-2]
a) Raw data, 100m×100m grid b) Aggregated, 0.1°×0.1° grid

Source: own elaboration based on: [3, 10]

Proposed factor (κ) represents the influence of residential sector in highly populated areas on emissions. When the population density grows, the value of the factor decreases due to increasing probability of occurrence of the district heating system supplying dwellers with the heat and hot water. In the simplest case, values of the parameter κ achieve nearly the $1 - \lambda$, however in real conditions it should also take into consideration (spatial) randomness of the public utility plants (the sector providing the heat and the hot water). Because the part of information is lost, it could not be possible to take into consideration the error connected with the spatial variability. The Fig. 15.2 presents empirical probability density function of aggregated population density (Fig. 15.1 b).

Using aggregated population density set we determined peak values [20]. Peak values, according to the Eq. 15.1, are chosen to determine population densities connected with the κ values. Assuming than the percentage of population using district heating grows every 10% with the particular quartile of the peak values' set, the model for κ was determined as below (Tab. 15.3). Using modeled κ values the initial population density grid was rescaled.

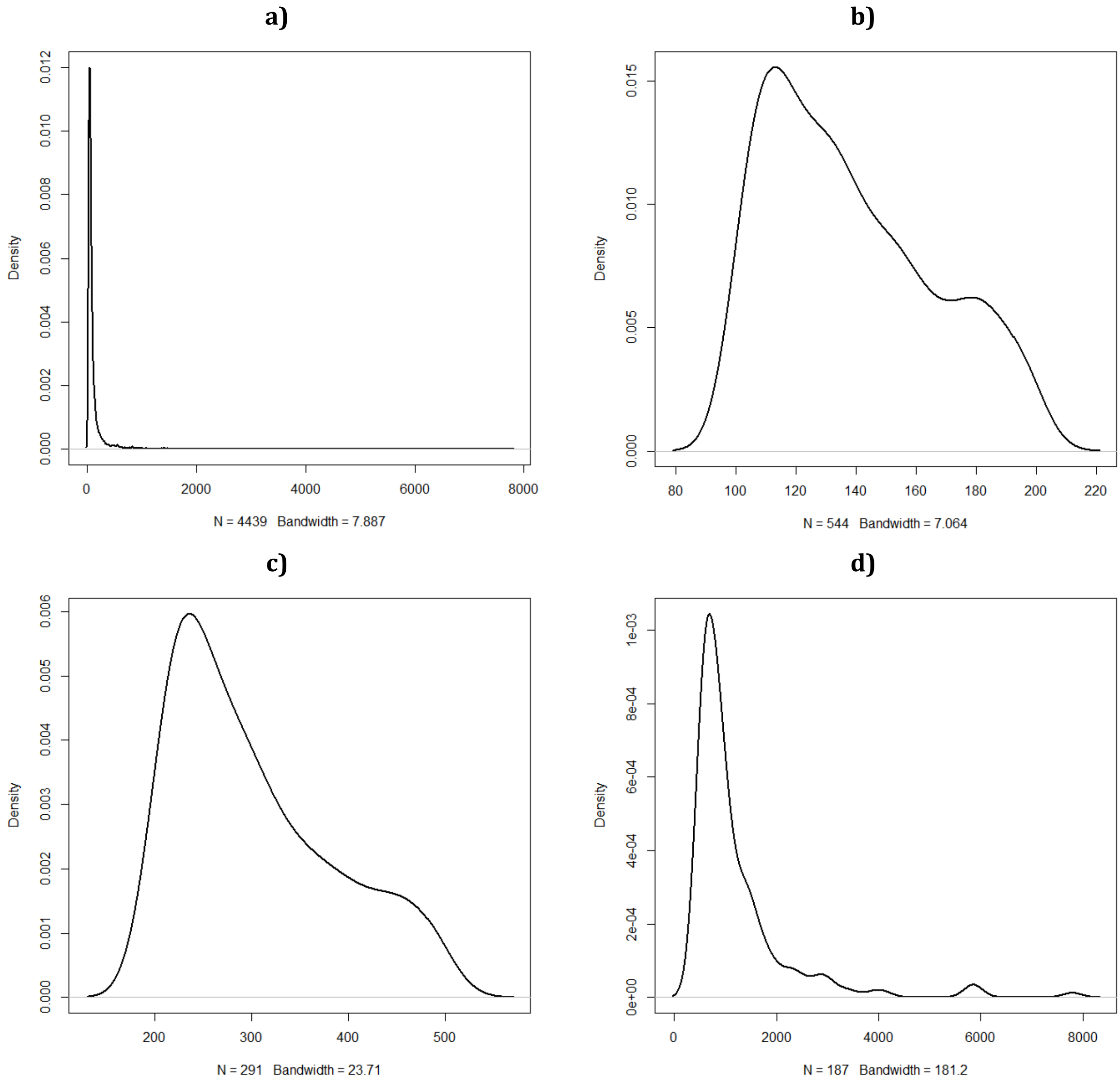

Fig. 15.2 Empirical probability density functions of aggregated population density (Pop)
a) All data b) 100 < Pop < 200
c) 200 < Pop < 500 d) 500 < Pop

Source: own elaboration

Tab. 15.3 Model for κ values

Quantile [%]	Population density*	Pop (corrected)*	κ [dimensionless]
0.28	102.13	100	1
0.50	164.84	150	0.9
0.75	236.10	250	0.75
2	407.90	400	0.65
5	617.70	600	0.5
7.5	802.76	800	0.4
20	1,582.43	1,500	0.2
25	1,880.51	1,800	0

* [people • km^{-2}]
Source: own elaboration

15.3 RESULTS AND DISCUSSION

Rescaled population is shown in the Fig. 15.3a). For comparison added initial grid with population densities exceeding 1,800 converted to zeros – Fig. 15.3b).

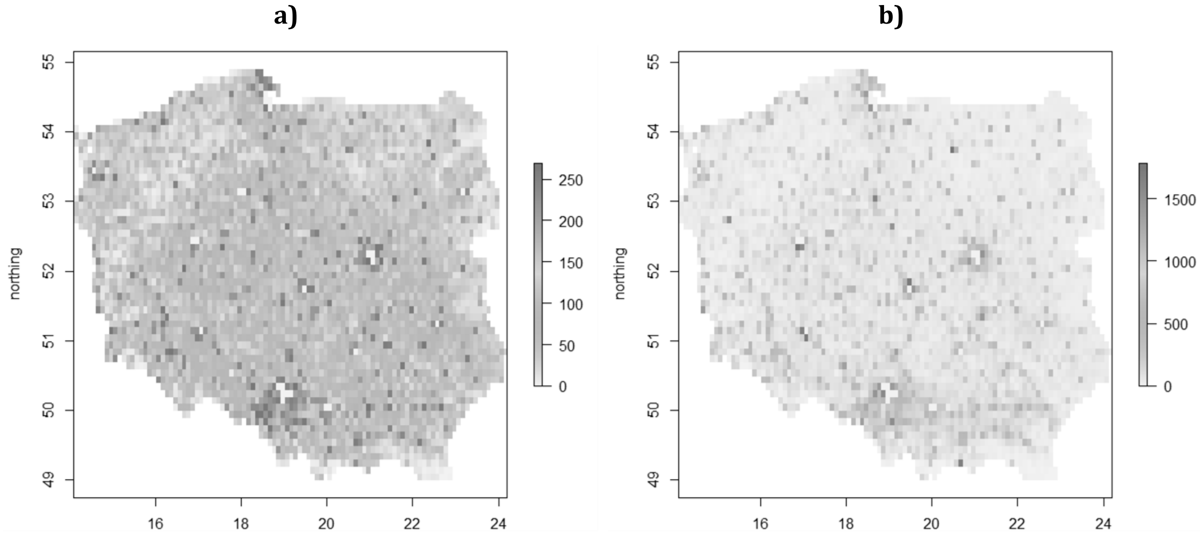

Fig. 15.3 Result of the population density rescaling
a) Rescaled data (with model for κ values) **b) Initial grid with converted densities exceeding 1,800**

Source: own elaboration

In comparison to the earlier works connected with spatial disaggregation [19, 22] this approach took into account the spatial variability of population. In presented case, the difference between statistics on number of inhabitants and those calculated from population density is negligible due to equal areas of the grid. It is worth to remember, that very frequently the population density is only available statistical information about considered region. To decrease the influence of extreme values the final grid was normalized. The final result is pictured in the Fig. 15.4.

For initial verification of the calculations, the normalized grid was compared with the initial (raw) values. Additionally for comparison there was an added location of public utility plants: power plants (PP) also combined heat and power (CHPs).

Initial comparison of obtained results suggests that the most populated areas such as USMA (the south of Poland), Warsaw (the center-east) and the Tricity (northern part of Poland) should be treated separately. The density of public utility plants located in the USMA indicates possibility of overestimation. This fact is caused by the loss of geographical information during statistical analysis. The further works on spatial distributions of air pollutants emissions should be devoted to analysis of the spatial variability in more populated regions, using geostatistical methodologies [23] such as simulations. From the other hand presented methodology can be effectively aimed to determine outlying regions that should be treated (analyzed) separately.

In comparison to another studies on spatial distributions of air pollutants' emissions [1, 4, 18, 19] presented analysis cannot be treated as simple GIS methodology for air emission disaggregation. In authors' opinion, the spatial surrogates [1, 4, 7, 17, 18, 19] based on the unconverted ('raw') data derived from official statistics are reliable only if the considered area is (quasi) homogenous due to its population density or other parameters selected as emission surrogates. When considering bigger areas (up to regional scales) there imore appropriate to use more advanced data integration methods including expert knowledge [16].

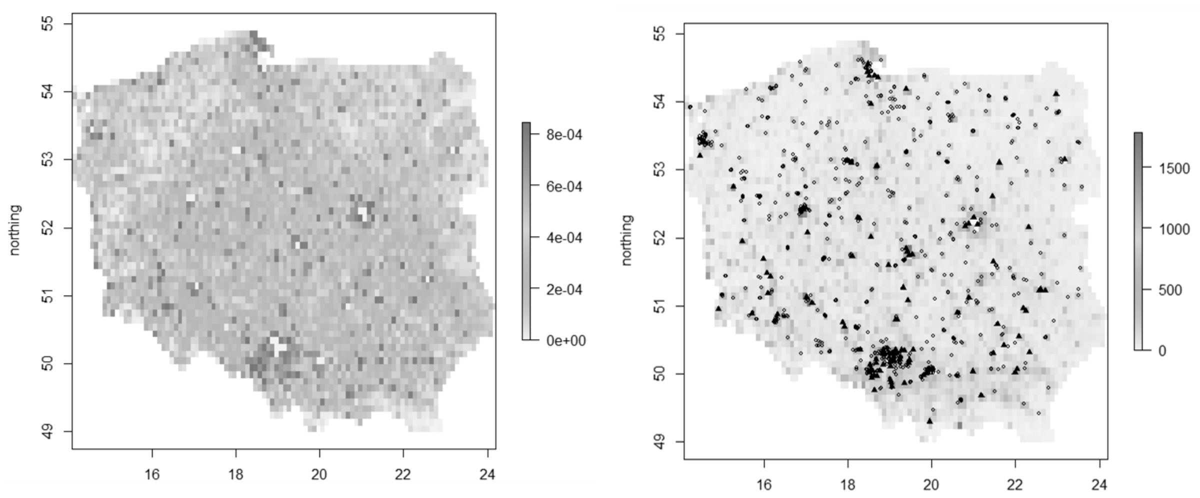

Fig. 15.4. Result of the population density rescaling
a) Normalized data (with model for κ values)
b) Initial grid with converted densities exceeding 1,800, added public utility plants locations: triangles, PP; circles, CHPs

Source: own elaboration

CONCLUSIONS

Analysis presented in this paper refers to and significantly develops earlier proposed approaches concerning spatial disaggregation of emissions from small, scattered combustion sources. Our improved methodology is better suited for determination of potential spatial outliers, which is of vital importance, in strongly urbanized and densely populated regions. In comparison to other spatial analysis and downscaling methodologies the approach elaborated in the paper does not take into account statistical data directly, but converts it to more precise model using spatial dependency between the population density and residential emissions in strongly urbanized areas.

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Abstract: *This paper presents methodology for obtaining 'first step' spatial surrogate for disaggregation of air pollutants' emissions determined using top-down approach. Considered sector was small residential combustion due to its importance in emission budget, also potential health threatening. However our analysis is not flawless due to partial loss of information connected with locations, can be effectively used as specific method for determining of spatial outliers. Simplified approach shown in this paper uses values derived from gridded population density as downs calling factor for air pollutants' emissions. We determined three potential regions that should be treated separately to obtain independent – 'regional" emission surrogates.*

Key words: *air emission, spatial distribution, residential*

SUROGAT EMISJI DO POWIETRZA ZE SPALANIA PALIW W GOSPODARSTWACH DOMOWYCH – ANALIZA Z UŻYCIEM PODEJŚCIA TOP-DOWN

Streszczenie: *Celem przedstawionej analizy było otrzymanie wstępnego surogatu emisji zanieczyszczeń do powietrza ze spalania paliw w źródłach komunalno-bytowych (gospodarstwa domowe). Opisana w artykule metoda, nie jest pozbawiona wad (częściowa utrata informacji nt. lokalizacji), ale może służyć do otrzymywania wstępnych informacji nt. zmienności przestrzennej gęstości zaludnienia, co pociąga za sobą również zmiany w rozkładzie przestrzennym emisji. Przedstawiona metoda może służyć również do pośredniej detekcji przestrzennych wartości odstających.*

Słowa kluczowe: *zanieczyszczenia powietrza, rozkład przestrzenny, gospodarstwa domowe*

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