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Projecting the urbanization effect on soil organic carbon stocks in polar and steppe areas of European Russia by remote sensing

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A R T I C L E I N F O

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A B S T R A C T

This paper describes the effect of urbanization on soil organic carbon (SOC) stocks by projecting the main urban land cover classes over the initial pre-urban soil maps. Two cities different in climate and soil conditions as well as in availability of SOC data were chosen as the case studies. Rostov-on-Don is the center of Russian South, where croplands and natural steppes have been conventionally thoroughly studied by soil scientists. In contrast, soils of Murmansk located in Russian Arctics have always been overlooked due to low suitability for agriculture. Global, national and regional soil maps and databases were used to estimate pre-urban SOC stocks in the areas. The outcomes based on Harmonized World Soil Database were highly uncertain, underestimating 0-100 cm SOC stocks in the polar region and overestimating them in the steppe region, whereas the results based on Digital Soil Map of Russia and regional maps were comparable. Land cover structures of Rostov-on-Don and Murmansk were mapped based on the stepwise per-pixel and sub-pixel classification algorithms applied to Sentinel-2 and included the following classes: sealed soils, green lawns, trees and shrubs, bare soils and water. Murmansk was dominated by trees and shrubs (58.1%) with the proportion of area 17.5% covered by sealed soils. In Rostov-on-Don, less than 30% of the total area was covered by trees and shrubs which is also comparable with bare soils (19.6%)_and lawns (23.4%), whereas almost one third of the territory was sealed (27.6%). These land cover structures had a different impact on the topsoil SOC stocks: a 30-50% increase in Murmansk compared to the 18% decrease in Rostov-on-Don. An increase of the 0-100 cm SOC stocks was shown for both regions, however in the polar conditions it was two times higher compared to the steppe. In polar conditions, conversion of natural soils into urban non-sealed soils increased SOC stocks from 30% to more than 4 times in 0-10 cm layer and from 47% to almost 3 times in the 0-100 cm layer. The highest increase was reported for the lawns, whereas SOC under trees and shrublands were considerably lower. In Rostov-on-Don , sealed and bare soils stored less SOC compared to the initial natural soils. The conversion of natural areas into urban green infrastructure increased SOC up to 50-70%. Although the absolute SOC values based on the global and national legacy data are highly uncertain, especially for the polar areas, the research outcomes clearly reveal possible patterns in SOC changes induced by different urbanization pathways in contrast climatic conditions and highlight the complexity of the urbanization effect on soils

1. Introduction

Environmental impacts and consequences of urbanization are among the main challenges of the 21st century (Sharma et al., 2016; UN, 2018). Conversion of natural and arable lands into urban coincides with substantial and often irreversible changes in vegetation and soils (Pickett

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et al., 2011). As a result, urban areas are dominated by man-changed and man-made soils, which are very specific in properties, processes, and functions (Lehmann and Stahr, 2007). Carbon (C) sequestration and accumulation is widely recognized as a key soil function (Blum, 2005; Dobrovolskiy and Nikitin, 2012). Soil capacity to accumulate and store C distinguishes provisioning of such ecosystem services as climate mitigation, nutrient supply and biodiversity (Dominati et al., 2014; Vasenev et al., 2018). Although the considerable effect of urbanization on soil organic carbon (SOC) stocks has been previously reported (Lorenz and Lal, 2015, 2009; Vasenev et al., 2018, 2013) the existing estimates of SOC stocks in urban soils vary from negligible to substantial (Raciti et al., 2011; Schulp and Verburg, 2009; Vasenev and Kuzyakov, 2018). In fact, urbanization has a multiple impact on SOC stocks and trigger mechanisms, which can enhance SOC accumulation or results in SOC depletion.

Soil sealing for building construction and infrastructural development results in cutting and translocation of topsoil layer and therefore in a considerable depletion of SOC stocks (Romzaykina et al., 2020; Tao et al., 2015; Villa et al., 2018). Although soil sealing is among the main environmental impacts in cities, the effect of urbanization on soil C stocks in not limited to sealing only. Landscaping and greenery practices have a considerable and versatile effect on soil C stocks. Implementation of C-rich substrates (e.g., composts, organic wastes and sewage) for urban soils' construction can result in fast growth of topsoil SOC stocks. However in longer perspective this effect is questionable due to intensive mineralization rate of the substrates in warm urban climate (Brianskaia et al., 2020; Shchepeleva et al., 2017; Smagin et al., 2018). Development and maintenance of urban green infrastructures, including irrigation, cutting, pruning and fertilization has a long-term positive effect on SOC stocks by stimulation root and aboveground biomass growth with further humification into soil (Selhorst and Lal, 2012; Zirkle et al., 2011).

The variability of SOC between and within cities are affected by regional bioclimatic conditions and land use / land cover structure. For example, a review based on the data analysis from more than 100 cities highlighted the capacity of urban soils at high latitudes to store SOC, explained by slow mineralization hampered by low temperatures (Vasenev and Kuzyakov, 2018). In dryland cities of US, SOC stocks were significantly smaller compared to the humid cities due to a more intensive mineralization and a limited carbon input with biomass (Pouyat et al., 2006). Within cities, land-use zoning is one of the key factors of SOC stocks' spatial distribution (Vasenev et al., 2017; Weissert et al., 2016). Soils of industrial areas and roadsides are often anthropogenically disturbed and store less SOC compared to residential and recreational zones (Ivashchenko et al., 2019; Sarzhanov et al., 2017). Spatial analysis and mapping land-use zoning is needed to project the effect of urbanization on soil SOC stocks in different climate zones. In condition of scarcity and limited access to legacy inventory data on land-use zoning in many cities, remote sensing provides an alternative solution.

In last decades, a considerable progress was achieved in mapping land-use zoning and soil sealing in urban areas based on land use / land cover classification (Weng, 2012). This progress was possible due to substantial improvements in data quality of the satellite images (i.e. spatial, radiometric and spectral resolution) and significantly developed pixel-, subpixel- and object-based classification algorithms. Recently, the data from newly launched Sentinel-2A,B satellites have been successfully tested for mapping urban land-use zoning and land cover categories (Xian et al., 2019; Xu et al., 2018). Per-pixel and sub-pixel algorithms have shown a robust (>80 % accuracy) results in extracting such categories as sealed soils, bare soils and vegetation within the urban landscape (Xu et al., 2018).

This paper aims to project the effect of urbanization on SOC stocks in polar and arid conditions of the European Russia. Based on the two urban case studies contrasting in climate, soils and land-use structure as well as in availability of SOC data we explored the applicability of remote sensing techniques based on utilization of the optical Sentinel-2 MSI data to map land-use zoning and estimate changes in SOC stocks induced by different urbanization pathways.

2. Material and methods

2.1. Research area

The region of European Russia is very diverse in vegetation and soil conditions ranging from tundra on Podzols in the North to steppes on Chernozems in the South. The region is also the most populated and urbanized with 55% of total population settling on 20% of the total territory of Russia. Nine of total thirteen cities with population above 1 million locate in the region. Two cities selected as case studies represent the regional diversity in climate, soils and vegetation and at the same time vividly illustrate different availability of soil data needed for SOC assessments.

Murmansk (68°58′ N 33°05′ E) lies over the polar circle on the Kola Peninsula and with the population above 250 thousand it is the largest polar city in the world. The regional subarctic climate in the city is strongly influenced by the proximity to the Barents Sea. In result, the area is not underlain by permafrost and dominated by Podzols in comparison to the areas to in the northeast of European Russia where Cryosols are widely spread (Table 1, Fig. 1). The area belongs to the forest tundra zone, which stretches in a narrow strip about 50 km wide parallel to the coast of the Barents Sea. Murmansk is a perfect case study to analyze the urbanization effect on SOC in polar climate, considering that the absence of permafrost excludes the cryoturbation mixing of SOC within the soil profile, which is a typical source of uncertainties in SOC estimates in the North (Goryachkin, 2010). Murmansk is a relatively modern city dating back to the beginning of 20th century. City area of 171 km^2 is mainly comprised from residential areas dominated by five-ten floor apartment buildings, wide industrial zones and a large peri-urban (71.7 km^2) uninhabited area. Green areas are limited and are mainly represented by urban parks, community gardens and preserved natural forest-tundra sites in uninhabited area.

Rostov-on-Don (47°14′ N, 39°42′ E) is located 3000 km to the South from Murmansk along the Don river. The area has an arid climate, and the natural areas are dominated by dry steppe vegetation on Chernozems (Table 1, Fig. 1). Historically, the territory was actively involved in agriculture and croplands occupied up to 80% of the region. The settlement foundation dates back to the middle 18th century, when an industrial and commercial town was developed in an area historically dominated by agricultural land-use. During 20th century, Rostov experienced continuous urbanization, which mainly occurred on the former croplands. In result, the Rostov agglomeration, including the Rostov-on-Don and several satellite towns, with the total area of 356 km^2 and population over 1.1 million is one of the largest cities of the Russian South. Today, Rostov-on-Don is a multifunctional city with vast residential, industrial, and public zones, unevenly distributed between city districts. Green zones are spacious and include an artificial protective

Table 1
Environmental characteristics of studied cities.

	Murmansk	Rostov-on-Don
Climate (updated Köppen-Geiger classes), (Beck et al., 2018)	Subarctic, Dfc (Cold, no dry season, cold summer)	Arid, Dfa (Cold, no dry season, hot summer)
Topography	Hilly terrain, elevation ranges from 0 to 420 n a.s.l.	Flat terrain, highly dissected, elevation up to 120 m a.s.l.
Parent materials	Moraine deposits on massive-crystallic granites and gneisses	Loess lime loams
Vegetation zone	Forest tundra	Steppe
Dominating soil type	Podzols	Chernozems
Main type of land use	Industry, marine port	Agriculture, croplands

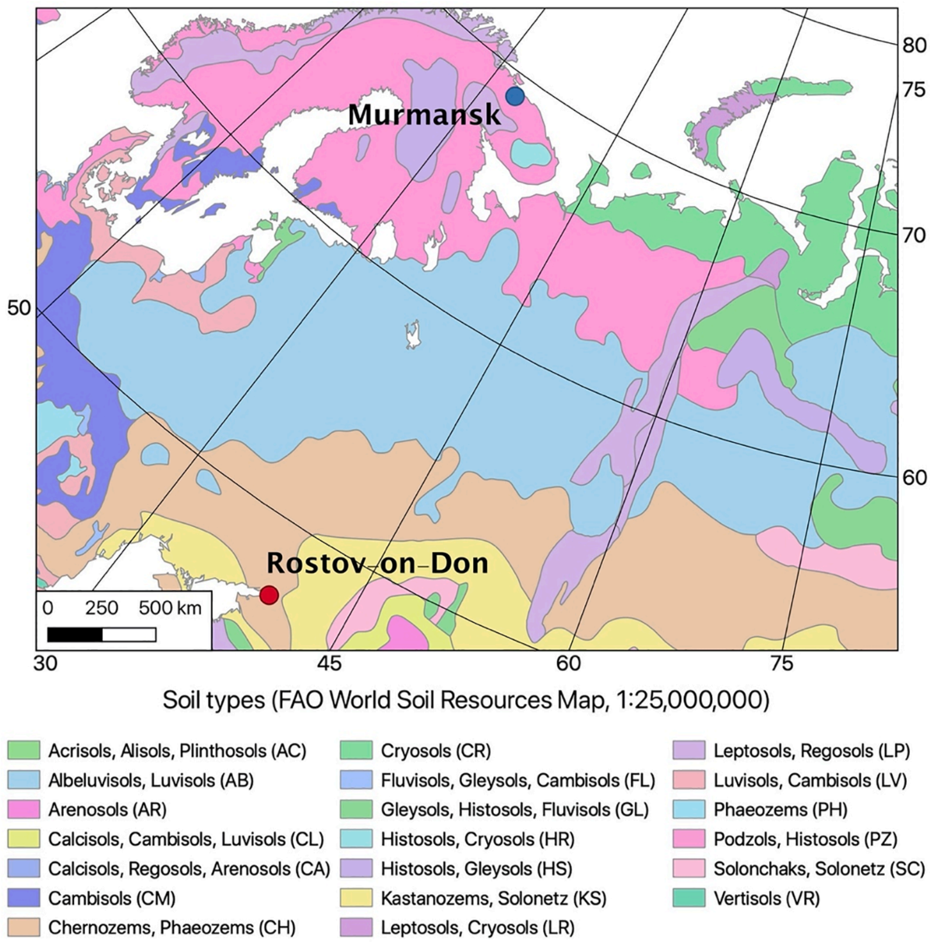

Fig. 1. Location of studied cities placed over the World Soil Resources Map.

"forest belt" located in the East of the city, as well as urban and district parks, botanic and community gardens, sport grounds and stadiums.

2.2. Soil data

The aim of the research was to project the effect of urbanization on SOC stocks in polar and steppe conditions. To estimate the initial (pre-urban) SOC stocks, severalopen source maps and databases were utilized due to the scarcity of the field data, especially with the accuracy needed for spatial analysis and mapping in a very heterogeneous urban environment (Vasenev et al., 2014). Data from several global and regional sources were used: i) Harmonized World Soil Database v 1.2 (Fischer et al., 2008) and WISE soil property database (Batjes, 2016); ii) Digital Soil Map of Russia (Shoba, 2011) and iii) soil maps of Rostov and Murmansk regions. Harmonized World Soil Database (HWSD) is an open-source global facility developed by FAO in collaboration with different international and national institutions. The HSWD v 1.2 is a 30 arc-second raster database with the information corresponding to 1:5,000,000 FAO-UNESCO soil map. WISE database (v. 1.1, 30 arc-second) comprises data collected from about 21,000 soil profiles globally. Digital Soil Map of Russia (DSMR) is an open-source feature class, based on the 1:2,500,000 soil map, which comprises the outcomes of several decades of soil survey campaigns and soil mapping efforts (Dobrovolsky and Urussevskaya, 2004; Fridland, 1988; Rozov, 1960; Shoba, 2011). Unfortunately, the collected materials are not fully digitized and data just on 800 of soil profiles are available, whereas the mapping units were based on a much bigger amount of soil data. The regional soil maps were developed based on the regional soil surveys and illustrate the bias existing in soil data for different regions. The soil map for the Rostov region was digitized by the Dokuchaev Soil Science Institute based on the 1:300,000 map developed by Southern state design Institute for land management of the USSR in 1985. The map and corresponding database comprised field data collected at 1045 farms by the soil agricultural service in 1960s-1990s. The legend of the map contains 51 classification units at the level of soil type and subtype, according to the soil classification of the USSR (1977). The database includes information on soil texture, topsoil organic matter content, depth of the organic layer and stoniness. Information on profile distribution of organic matter and bulk density for each subtype was derived from the independent soil survey (Gorbov and Bezuglova, 2019). The soil map of the Murmansk region was digitized from the regional soil map 1:1,000,000 developed by Kola research center (1955), which was the only soil map available for the region. The legend includes 15 soil types and subtypes. The dataset for the map was not available and therefore an alternative dataset was developed based on the few available literature sources (Goryachkin, 2010; Korneykova et al., 2020; Nikonov and Pereverzev, 1989; Pereverzev, 2011, 2007, 1987; Pereverzev et al., 2000). The dataset comprises field data from 40-50 soil pits described in tundra and forest-tundra areas of Murmansk region and includes thickness of horizon, organic matter content, bulk density and stoniness.

The regional soil maps were considered to illustrate the pre-urban SOC stocks at the areas currently occupied by Rostov-on-Don and Murmansk. For these areas, soil C stocks (kg m^{-2}) in the 0-10 cm and 0-100 cm layers were estimated and mapped by extrapolation of the average SOC stocks per soil unit (i.e., soil type or subtype) to the corresponding polygons on the soil maps. The following equation was used to estimate and map SOC stocks based on the previous studies (Minasny et al., 2013; Poeplau et al., 2017; Wang and Dalal, 2006):

$$SOC = SOC_{conc} \times BD \times H \times (1 - RF)$$

where SOC – SOC stock (kg m^{-2}), SOC_{conc} – SOC concentration in fine soil (%), BD – bulk density of the fine soil (g cm^{-3}), H – soil layer depth (cm), RF – rock fragment fraction (%).

The resulting maps were used to estimate total soil C stocks (Tg) in the areas and were considered as the basis for projecting the urbanization effects.

2.3. Remote sensing data processing

We used cloud-free Sentinel-2A MSI (level 2A) optical satellite images availably at ESA Copernicus Scientific Data Hub () for the territories of the two cities to assess the areas covered by sealed soils and to divide the urban green area into landcover classes. Two acquisitions were used for Murmansk and one – for Rostov-on-Don (Table 2). The image pre-processing included resampling to 10-m spatial resolution of 10 bands with initial 10 and 20 m spatial resolution and mosaicking (Fig. 2).

We have applied stepwise sub-pixel and per-pixel classification procedure in order to divide the entire surface of the city areas into six land cover classes (endmembers): sealed surface, water, bare soil, urban forests and green stands, shrublands and lawns. The procedure consisted from several consecutive steps (Fig. 2). Initially, water pixels were extracted by applying Linear Spectral Mixture Analysis (LSMA) (Keshava and Mustard, 2002), where water, urban (high and low albedo surfaces), bare soil, urban forest, shrublands and lawns were used as endmembers. For each endmember, four to six regions of interest were delineated for which spectral signatures were extracted by averaging surface reflectance values of each spectral band. Water was further masked by extracting the water fractions more than 80% threshold. After masking the water, pixels corresponding to sealed surface were extracted as having specific surface reflectance values including i) low (< 0.28) values of Soil-Adjusted Vegetation Index (SAVI); ii) $< 20\%$ reflectance in short-wavelength infrared (SWIR) band (B11); iii) $> 10\%$ reflectance in the blue band (B2) and iv) reflectance of the near-infrared (NIR) band (B8) greater than reflectance of B11. We calculated SAVI by applying the following equation:

$$(1 + L)^{*}(B8 - B4)/(B8 + B4 + L)$$

where $L = 0.428$ is the soil brightness correction factor for Sentinel-2, B4 and B8 – surface reflectance in the red and NIR bands respectively. The SAVI threshold of 0.28 has been established empirically. The other proposed surface reflectance limits of several spectral bands (B2, B8, B11) mostly aimed to exclude areas covered by bare anthropogenically-transformed soils (agricultural fields, areas under construction etc) classified as sealed by the SAVI threshold due to its similar spectral signatures as sealed surface (Weng, 2012). At the last step, fractional maps of remaining four classes were obtained for all "green" pixels (not belonging neither to sealed pixels nor to water pixels) by applying the LSMA using existing spectral signatures of bare soils, urban forest and green stands, shrublands and lawns. The resulting land cover maps for Rostov-on-Don and Murmansk reflected the spatial distribution of water bodies (binary), sealed surfaces (binary), and green areas (urban forests and green stands, shrubs, green lawns and bare soils as fractional maps). The processing of satellite data was performed within ESA SNAP 6.0 software.

For the quality assessment, we compared the extracted sealed surface with manually mapped sealed surfaces of several small regions scattered within cities: 21 for Rostov-on-Don and 25 for Murmansk. These regions were extracted from OpenStreetMap as areas with different land use (commercial, residential, industrial and military). Within these regions with area varying from 0.018 km^2 to 1.63 km^2 sealed surfaces were manually mapped from very high-resolution imagery available through Google tiled imagery XYZ in QGIS 3.12.1 and were considered as true sealed area. The percentages of sealed surfaces within these regions derived from two different sources were statistically compared (Wilcoxon test) and the root mean square errors (RMSE) calculated within R environment (R Core Team, 2017) software. Preliminary, these two data arrays were tested for the normality of distribution (Shapiro-Wilk normality test) and for homogeneity of variances (Bartlett test). Further, linear regression between "true" and Sentinel-2 based proportions of sealed surface was produced in order to assess the percentage of explained variability by Sentinel-2 data. The complete dataset obtained for test areas of Rostov-on-Don and Murmansk ($n=46$) was analyzed for the random effects of land use types on the Sentinel-2 based assessment using *'lmer'* function available within *'lme4' package* (Bates et al., 2015) in R environment.

Table 2
Sentinel-2 data acquisitions used in the analysis.

Acquisition ID	City	Date
S2A_MSIL2A_20190829T081601_N0213_ _R121_T37TEN_20190829T110625	Rostov-on-Don	August 29, 2019
S2A_MSIL2A_20190724T094041_N0213_ _R036_T36WVB_20190724T101017	Murmansk	July 24, 2019
S2A_MSIL2A_20190724T094041_N0213_ _R036_T36WWB_20190724T101017		

2.4. Mapping soil organic carbon stocks

The vector maps representing initial SOC stocks in the current areas of Murmansk and Rostov-on-Don prior to urbanization were converted to the raster format and resampled to the 10-m spatial resolution which corresponds to the Sentinel-2 based data and were further overlaid with the developed land cover maps, representing current land cover of the urban areas as one of the five classes: sealed areas, urban forests and green stands, shrubs, green lawns and bare soils. Water bodies were excluded from the analysis and zero SOC stocks were considered for these areas. Each of the remaining land cover classes evidences conversion of initial natural areas into one of the urban land-use types with a corresponding effect on SOC stocks. Possible effects of urbanization pathways on SOC stocks in 10 cm and 100 cm layer were determined by correction coefficients, estimated based on the independent soil surveys. For Rostov-on-Don, field soil data was derived from (Bezuglova et al., 2018; Gorbov, 2018; Gorbov et al., 2017; Tagiverdiev et al., 2020). For Murmansk, soil properties and descriptions were derived from (Polyakov et al., 2018). For the cases, where the legacy data for the research areas were not available, the literature data describing similar land conversion pathways were used instead. For example, no data on SOC stocks in the sealed soils were found for Murmansk and the coefficients were estimated based on the reviews of soil sealing effect on SOC stocks in different climates (Richter et al., 2020; Szatmári et al., 2019; Vasenev and Kuzyakov, 2018). To quantify the post-urbanization SOC stocks, the initial SOC stocks were re-calculated using the obtained correction coefficients in QGIS 3.12.

3. Results

3.1. Initial C stock in soils of Rostov-on-Don and Murmansk territories

Estimates of SOC stocks in the research areas prior to urbanization based on global, Russian and regional soil maps showed a significant difference of the initial SOC stocks between the research areas and between the considered soil maps. On the HSWD map, the total Murmansk area corresponded to one soil unit – Albic / Entic Podzols. The average SOC stocks for the unit recalculated to 0-10 and 0-100 cm were correspondingly 2.73 and 14.11 kg C m^{-2}. The major part (311 km^2) of the

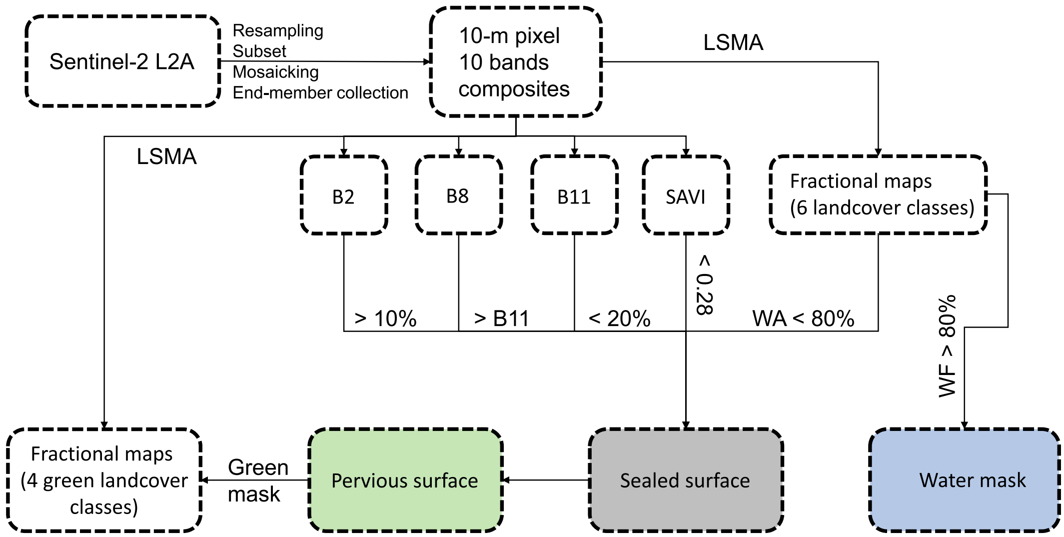

Fig. 2. Workflow for Sentinel-2 data processing. LSMA – linear spectral mixture analysis; B2, B8, B11 – reflectance at blue, NIR and SWIR bands, SAVI - Soil-Adjusted Vegetation Index, WF – water fraction.

terrestrial territory currently occupied by Rostov-on-Don was covered by Eutric Fluvisols, whereas Haplic Chernozems covered 32 km^2 in the northern part. The average SOC stocks in 0-10 and 0-100 cm layers of Chernozems were 2.88 and 19.99 kg C m^{-2} that was two times higher than in Eutric Fluvisols (1.17 and 7.11 kg C m^{-2}). DSMR provided more details on soil complexity. Murmansk area was mostly comprised from combinations of Albic Podzols (~82%) and Dystric Histosols (~18%). SOC stocks for Albic Podzols were estimated to 2.29 and 11.25 kg C m^{-2} for 0-10 and 0-100 cm layers correspondingly. Dystric Histosols stored 4.00 kg C m^{-2} in 0-10 cm and 20.00 kg C m^{-2} in 0-100 cm. Zero SOC stocks were considered in rock outcrops (Leptosols and soloids) which are often exposed in the peri-urban area of Murmansk. Soil of the territory currently occupied by Rostov-on-Don was comprised from different subtypes of Calcic Chernozems (~59%), Eutric Fluvisols (~29%) and Pellic Vertisols (~0.3%). The highest SOC stocks were estimated in Pellic Vertisol – 4.75 and 32.82 kg C m^{-2} in 0-10 and 0-100 cm layers correspondingly. SOC stocks in Calcic Chernozems and Eutric Fluvisols were in average 25 and 35% less for both layers. Rock outcrops (Leptosols and soloids) not covered by soils accounting 10% of the territory and zero SOC stocks were considered for these areas. According to the 1:1,000,000 soil map of Murmansk region, the territory of Murmansk city was dominated by different subtypes of Albic Podzols. However, Dystric Histosols were not included, that resulted in smaller SOC stocks compared to estimates based on DSMR. The regional soil map of Rostov-on-Don showed the area currently occupied by the city as a combination of Haplic Chernozems (~65%), Eutric Calcaric Fluvisols (Humic) (~34%) and Calcaric Cambisols (Colluvic, Humic) (~1%). The average SOC stocks in 0-10 and 0-100 cm layers of Haplic Chernozems were 3.26 and 16.0 kg C m^{-2}, which was comparable to the global and Russian databases. Calcic Gleysols stored in average 3.03 and 13.28 kg C m^{-2} in 0-10 and 0-100 cm, which was comparable to Haplic Chernozems, whereas SOC stocks in Calcaric Cambisols (Colluvic, Humic) were almost 70% higher. The total pre-urban SOC stocks (Tg) estimates are summarized in Table 3.

3.2. Changes in SOC stocks for different urbanization pathways

Conversion of natural areas into sealed surfaces, urban forests and green stands, shrubs, green lawns or into bare soils were the urbanization pathways changing SOC stocks. Comparative analysis of urban and natural soils based on the independent soil surveys and literature data allowed estimating changes in SOC for each pathway by correction coefficients, which differed between the urban land use / land cover categories and between the regions. In Murmansk, conversion of natural soils into urban non-sealed soils increased SOC stocks from 30% to more than 4 times in 0-10 cm layer and from 47% to almost 3 times in the 0-100 cm layer. The highest increase was reported for the lawns, whereas the increase of SOC in urban soils under trees and shrubs was the lowest compared to the natural soils. We didn't find any legacy data on SOC in sealed soils of Murmansk or other towns located in similar climate. Existing publications for various climatic zones report a decrease from 50% to several times, mainly caused by translocation of the topsoil layer. The depth of the translocated layer depends on the type of the built infrastructure and climatic conditions. Building construction results in removal of the whole soil profile, therefore SOC stocks under build-up areas are considered zero. Construction of the federal roads affects in average top 80-100 cm that also means a complete removal of the Podzol profile. However, construction of the regional and local roads and walking paths results in translocation of in average top 40 cm. Therefore, topsoil SOC stocks are lost and SOC stocks in 0-100 cm are reduced almost 10 times compared to the initial natural soils (Fig. 3). In Rostov-on-Don, the conversion of natural areas into urban green

Table 3
SOC stocks (Tg) at the research areas prior urbanization estimated based on the global, Russian and regional soil maps.

Soil map	Murmansk			Rostov-on-Don		
	Soil units	SOC (0–10)	SOC (0–100)	Soil units	SOC (0–10)	SOC (0–100)
HSWD	Albic / Entic Podzols	0.40	2.07	Haplic Chernozems, Eutric Fluvisols	0.46	2.85
DSMR	Albic Podzols, Dystric Histosols	0.42	2.05	Haplic Chernozems, Eutric Fluvisols, Pellic Vertisol	1.08	7.15
Regional maps	Albic Podzols	0.41	1.13	Haplic Chernozems, Eutric Calcaric Fluvisols (Humic), Calcaric Cambisols (Colluvic, Humic)	1.12	5.24

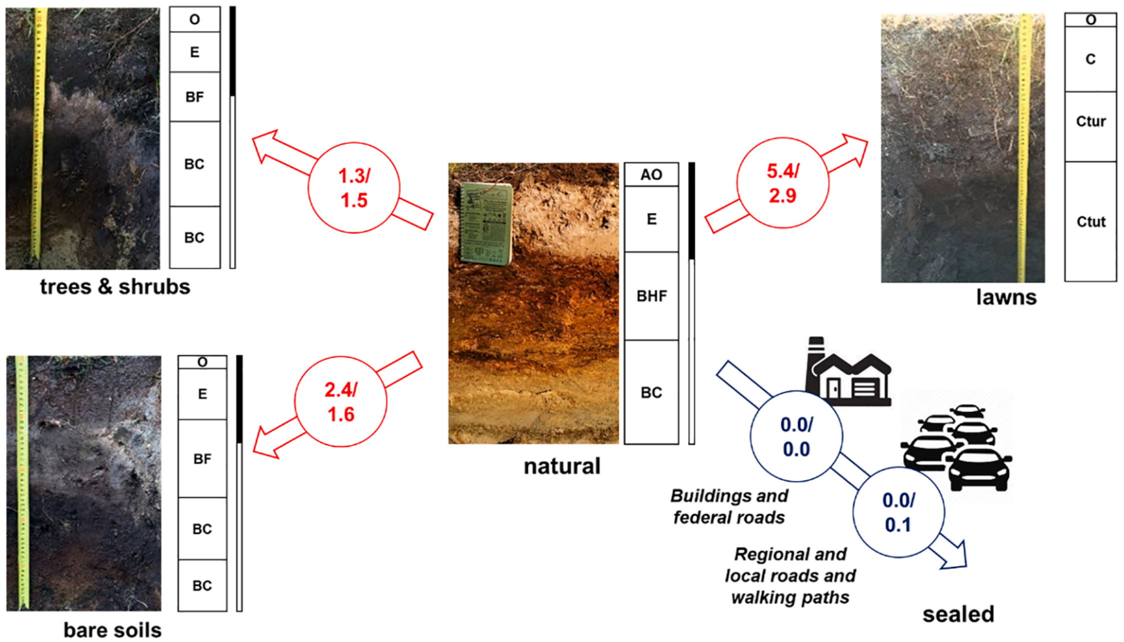

Fig. 3. Correction coefficients estimating the urbanization effect on SOC stocks in Murmansk (0–10 cm/ 0–100 cm) (derived from (Korochkin and Kostsov, 2018; Pereverzev, 1987; Pereverzev et al., 2000; Polyakov et al., 2018); black line refers to 0–20 cm layer).

infrastructure also resulted in considerable changes in SOC with the maximal 50-70% increase reported for the soils under trees and shrubs. In contrast, SOC stocks in 0-10 cm of bare soils were only half from those in natural soils. Similarly to Murmansk, soil sealing resulted in complete loss of SOC stocks under buildings and federal roads. Construction of regional and local roads and walking paths also affected top 40 cm of soil profile and decreased the SOC stocks in 0-100 cm by 30% (Fig. 4).

3.3. *Spatial structure of land cover in Murmansk and Rostov-on-Don*

The distinguished changes in SOC caused by different urbanization pathways were extrapolated to the areas of Murmansk and Rostov-on-Don based on the land cover structure obtained from remote sensing data analysis. According to Sentinel-2A data, 17.5% of the entire Murmansk area was sealed with the highest percentage of the sealed areas reported for the see port, city center and industrial parcels in the North and South. Only one fifth of the total sealed areas was built-up or

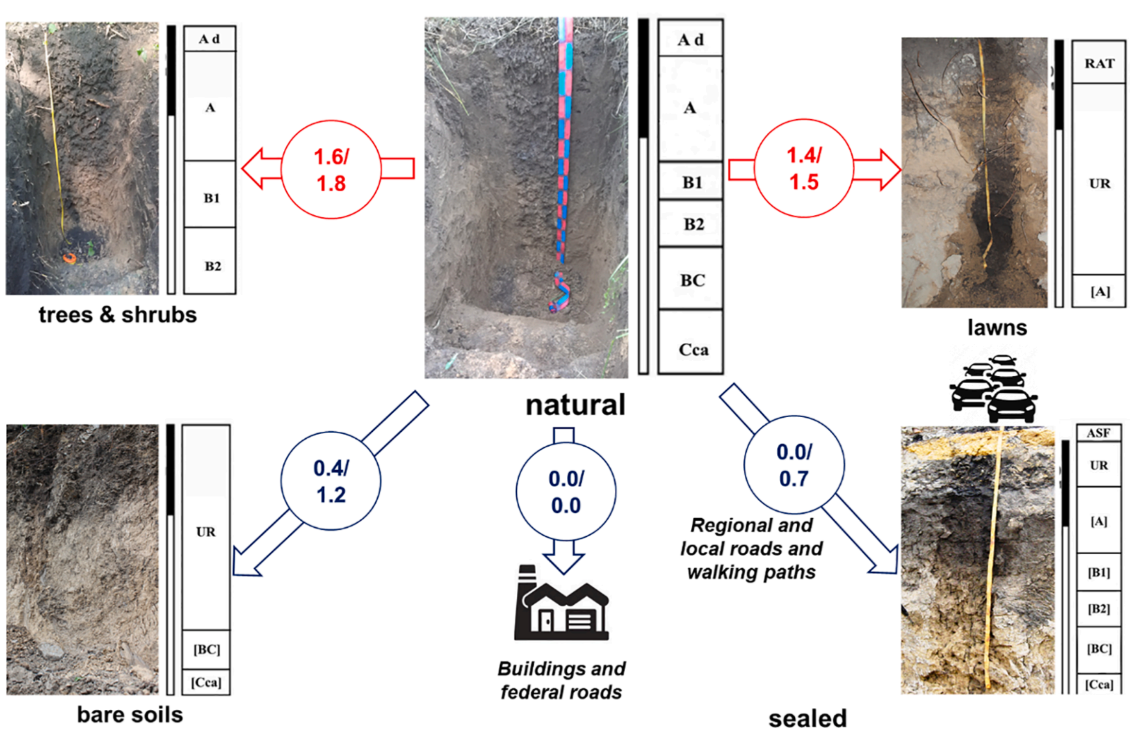

Fig. 4. Correction coefficients estimating the urbanization effect on SOC stocks in Rostov-on-Don (0–10 cm/ 0–100 cm) (derived from (Bezuglova et al., 2018; Gorbov, 2018; Gorbov et al., 2017; Tagiverdiev et al., 2020) black line refers to 0–40 cm layer).

occupied by federal / main roads with zero SOC stocks underneath. Murmansk had a low percentage of bare soils (less than 3%) which were evenly distributed within the city. Lawns covered around 8% of the city area, however this value could be overestimated due to overlapping with open tundra plots abundant to the East of Murmansk. The mixture of trees and shrubs was the largest land cover class covering more than 58% of the area. These patches were concentrated in green zones within the city as well as in the peri-urban areas in the West and East (Fig. 5).

In Rostov-on-Don, almost one-third (27.6%) of the city area was sealed with the largest percentage of the sealed areas close to the river port. Only 25% of the sealed area belonged to built-up areas and federal / main roads. The sealing fraction ranged from 48% in the central part to less than 13% in the suburbs. In contrast to Murmansk, the percentage of bare soils was almost 20%, which could be considered a typical feature for an urban area in arid climate. Lawns covered more than 23% of the total area and were the most spread land cover class. The combination of bare soils and lawns was very typical for a major part of the city. Urban forests and green stands covered 15% of the area and were mostly concentrated in parks, court yards and along the roadsides. Around 10% of Rostov-on-Don were covered by shrublands randomly distributed within the area with the highest density within the floodplain of the Don river (Fig. 6).

3.4. Quality assurance of the remote sensing results

Soil sealing fraction of test polygons identified by remote sensing in both cities was considered for the validation and quality assurance of the analysis. In Murmansk, true sealed fraction within test areas of industrial, commercial, residential and military land use (n=25) varied between 19.6% and 90.8%. The normal distribution was confirmed by Shapiro-Wilk normality test ($p = 0.75$, Table 4). For these test sites, sealed fraction extracted from Sentinel-2 processed image varied between 10.7% and 91.0% having the normal distribution, too ($p = 0.75$). Sentinel-2 based algorithm has also explained more than 80% of the true values ($R^2 = 0.84$) with the homogeneous variances (*Bartlett test, p = 0.9*). No statistically significant differences between two datasets were found (*Wilcoxon rank sum test with continuity correction, p = 0.76*).

In Rostov-on-Don, true sealed fraction within test areas of commercial, industrial and residential functional purposes (n=21) varied between 16.9% and 92.3% with the normal distribution shown by Shapiro-Wilk normality test ($p = 0.12$, Table 4). For these test sites, sealed fraction extracted from Sentinel-2 processed image varied between 25.1% and 89.5% having the normal distribution, too ($p = 0.23$). In general, Sentinel-2 based algorithm explained more than 80% of the true values ($R^2 = 0.81$) with the homogeneous variances (*Bartlett test, p = 0.47*). No statistically significant differences between two datasets were found (*Wilcoxon rank sum test with continuity correction, p = 1*). The linear regression model with Sentinel-2 based sealing assessment as predictor for the complete dataset explained 82% of the variance of the real sealed fractions within 46 test polygons. The one-way ANOVA test didn't show significant statistical differences between linear (variation that is explained by Sentinel-2 based sealed fraction only) and linear mixed (variation that is explained by Sentinel-2 based sealed fraction with random effects of land use type) models, which may indicate no

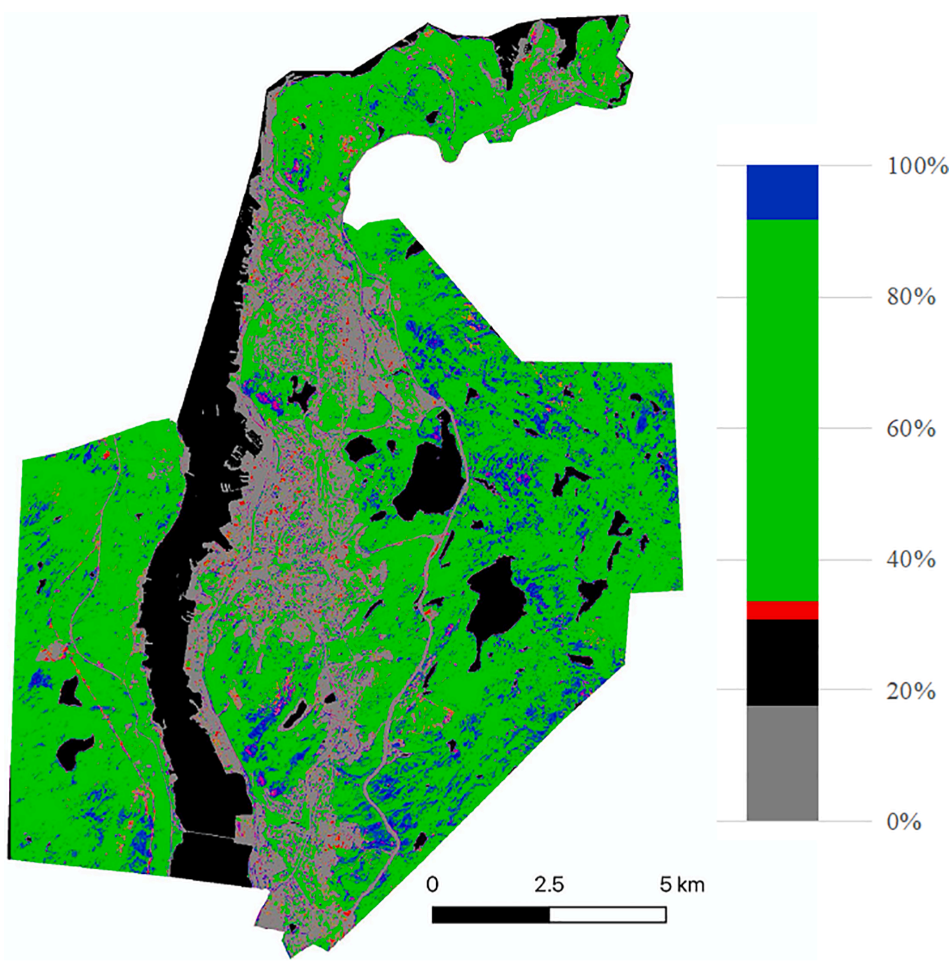

Fig. 5. Land-cover classification of Murmansk: grey – sealed surface, black – water, Red – Green – Blue – color coded bare soils, urban forest / shrublands and green lawns. Cumulative bar chart indicates the proportion of areas occupied by each land-cover class. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

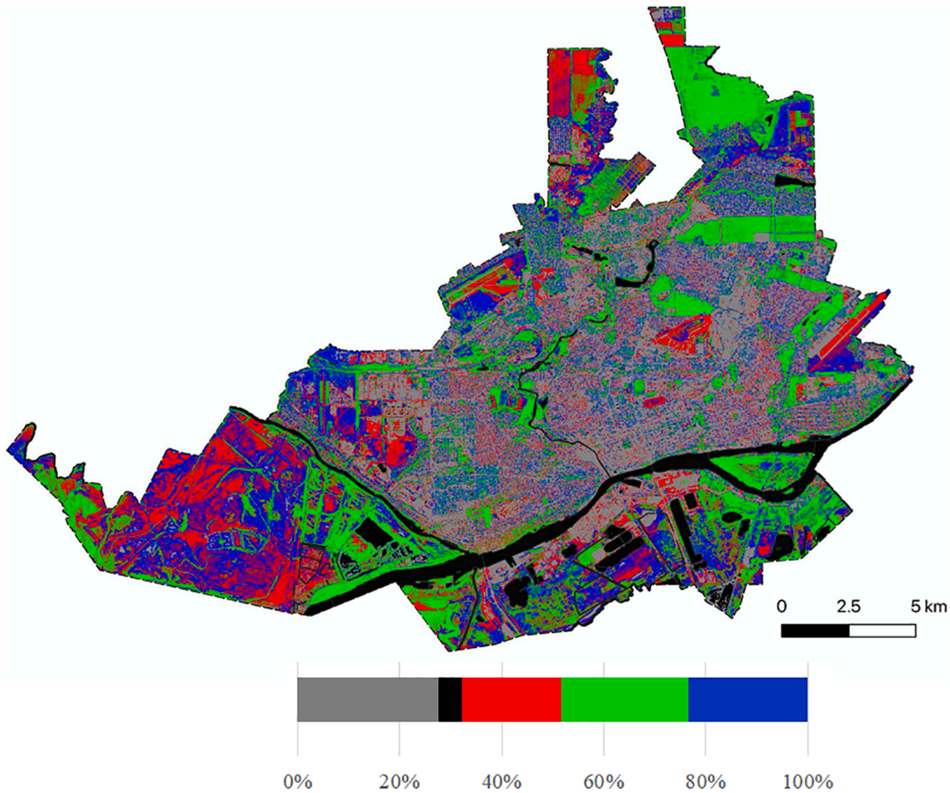

Fig. 6. Land-cover classification of Rostov-on-Don: grey – sealed surface, black – water, Red – Green – Blue – color coded bare soils, urban forest / shrublands and green lawns. Cumulative bar chart indicates the proportion of areas occupied by each land-cover class. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 4
Validation of the soil sealing assessment (real and Sentinel-2 based estimations).

	Rostov-on-Don		Murmansk	
N	21	21	25	25
Method	Manual delineation	Sentinel-2	Manual delineation	Sentinel-2
p-value (Shapiro-Wilk normality test)	0.12	0.23	0.75	0.75
p-value (Bartlett test)	0.47		0.9	
Mean value	59.2	60.2	55.8	57.5
p-value (Mann–Whitney *U* test)	1		0.76	
R-squared	0.81		0.84	

influence of the nature of urban development on the accuracy of Sentinel-2 based sealing assessment. The total RMSE of Sentinel-2 estimations was 9%.

3.5. Urbanization effect on SOC stocks in polar and steppe conditions

The effect of urbanization on SOC stocks was driven by the land use / land cover structure within the city and was distinctively different between polar and steppe zones. Moreover, the final estimates and some spatial patterns depended on the initial soil maps. The estimated SOC stocks in Murmansk ranged from 0.56 to 0.62 Tg in 0-10 cm and from 1.54 to 2.8 Tg in 0-100 cm. Related to the initial SOC stocks, urbanization in polar conditions increased SOC stocks on 34-38 % in 0-100 cm layer and 46-50% in topsoils. The lowest SOC stocks were shown for the area near the sea port, where soil sealing was the highest. Higher SOC stocks were projected in the East part of the city and on the left bank of the Kola gulf with hotspots in residential zones and district parks. The distribution of SOC stocks in 0-100 cm layer had similar patterns but was more homogeneous (Fig. 7 A and B).

In steppe conditions, urbanization decreased topsoil SOC stocks 13 by 18% but increased the stocks in 0-100 cm layer on 21-16% in comparison to the initial soils. The average topsoil SOC stocks in Rostov-on-Don were 2.6 kg C m^{-2} which was 40% less than in Murmansk. The highest topsoil SOC stocks were shown in the North part, where low level of soil sealing coincided with the areas initially covered by Calcic Chernozems. Several hotspots in the south-western part corresponded to green stands and district parks. The average SOC stocks in 0-100 cm layer were 22.1 kg C m^{-2}, which was 40% higher than in Murmansk. The distribution was rather heterogeneous with the highest values in the suburbs and several residential and recreational areas within the city (Fig. 7 C and D).

In polar condition, topsoil SOC stocks increased on 0.18-0.2 Tg as a result of urbanization in Murmansk area. The outcomes were very similar for HSWD and regional map, whereas the results based on DSMR were 20% higher. In contrast, urbanization of the Rostov-on-Don area decreased topsoil SOC stocks on 0.17-0.20 Tg based on the DSMR and regional soil maps. The decrease of topsoil SOC stocks on 0.06 Tg based on HSWD was likely an underestimation since the map underestimated the initial area covered by Chernozems more than 5 times compared to DSMR and the regional soil map. An increase of SOC stocks in 0-100 cm was reported for both polar and steppe conditions. In steppe condition, the highest increase on 1.64 Tg was estimated based on the DSMR, whereas the estimates based on HSWD and regional map were respectively 50 and 30% lower. In polar conditions, an increase in SOC stocks was 0.71 Tg predicted based on HSWD, whereas DSMR and the regional map showed 0.75 and 0.41Tg increase correspondingly (Fig. 8).

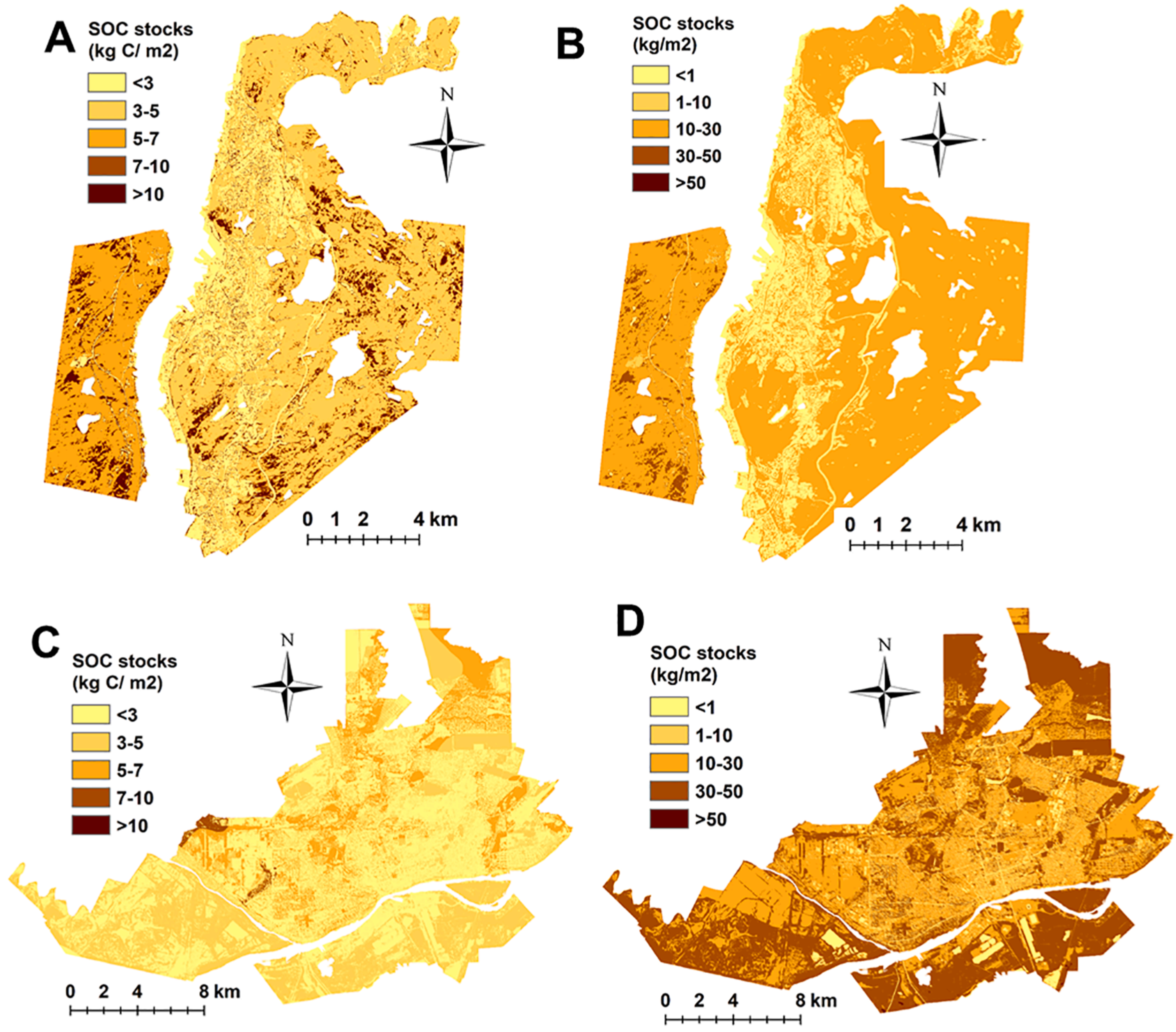

Fig. 7. SOC stocks in Murmansk (0–10 cm -A; 0–100 cm – B) and in Rostov-on-Don (0–10 cm -C; 0–100 cm –D) projected based on the regional soil maps.

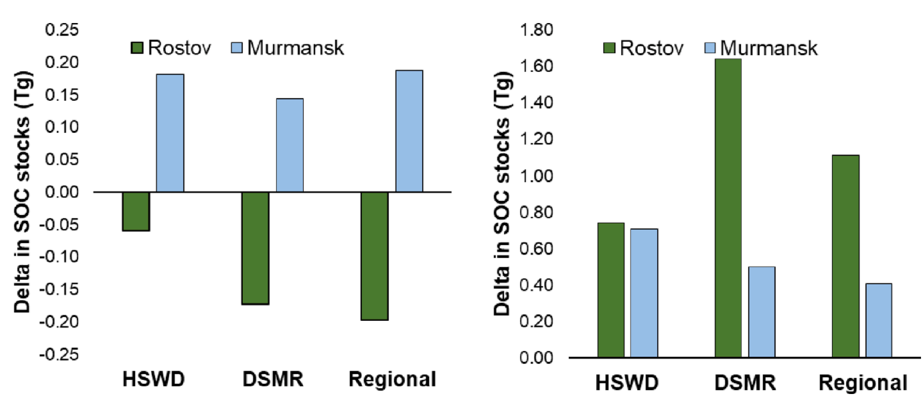

Fig. 8. Delta in SOC stocks (difference between SOC stocks after and before urbanization) in steppe (Rostov-on-Don) and tundra (Murmansk) bioclimatic zones estimated for 0–10 cm (left) and for 0–100 cm (right).

4. Discussion

4.1. Urban spatial structure analyzed by remote sensing: estimates, algorithms and uncertainties

The information on sealed area in Russian cities is extremely sparse. Data for Moscow, Volgograd and Rostov-on Don exist as revealed from the literature, wherein the sealing fractions is usually calculated for functional areas (i.e., residential, recreational, industrial etc). As a rule, the highest sealing fraction is reported for the industrial areas (more than 75% in Moscow (Ermakova and Martynenko, 2011; Haibrakhmanov et al., 2017), 80 - 90% in Volgograd (Gordienko et al., 2019; Kosheleva, 2019), 75 - 90% in Rostov-on-Don (Gorbov and Bezuglova, 2019), whereas recreational areas are the least sealed. Soil sealing fraction in the residential areas varies in a wide range, especially in smaller regional towns where the low-story buildings and private houses prevail in most of the parts in the city (Gordienko et al., 2019; Kosheleva, 2019).

Assessment of soil sealing with remote sensing data is a common issue in land use / land cover mapping (Weng, 2012). In the urban landscape, sealed surface is one of the main land cover classes within the V-I-S concept: vegetation – impervious surface – soil (Ridd, 1995). And optical remote sensing data is considered as most powerful tool in the assessment of sealed soils. Studies have also shown, that the spatial resolution of optical remote sensing data of 10-20 meters can be considered as optimal (Xian et al., 2019) given the numerous uncertainties in extraction impervious surface area (e.g. shadows from buildings) that are still persistent on data with higher spatial resolution (QuickBird, Worldview-2,3) and high costs of data itself.

Regression / decision trees, artificial neural networks and LSMA (Li, 2020 and references therein) are among the most often used techniques applied for such assessments. In this research we applied an algorithm, that considers specific spectral properties of urban surface, commonly used spectral index (SAVI) and LSMA to divide the urban area of two different cities into six main classes: sealed surface, water, bare soil, urban forest, shrublands and lawns. To achieve this, different spectral indices including Normalized Difference Vegetation Index (NDVI), Normalized Built-Up Index (NDBI) (Zha et al., 2003), index-based built-up index (Xu, 2008) and LSMA with built-up endmembers were tested at the preliminary stages of the study and considered for developing the final algorithm with the best performance for the research areas (Fig. 2). The Sentinel-2 based overall accuracy of the presented algorithm applied to Rostov-on-Don and Murmansk was comparable with other studies that used Sentinel-2 or similar sensors for assessments of sealed surface areas or sealed surface fraction in other regions and, by applying different algorithms (Table 5).

The obtained total RMSE in this study of 9% and R^2 of 0.82 can be considered as sufficient. Although the pixel-based algorithms seem not to perform well at resolutions more than 30 m, the spatial resolution of Sentinel-2 (10 m) still allows the pixel-based assessments of imperviousness (Xian et al., 2019). Herewith, some uncertainties may appear in case if built-up objects are small enough even for 10-m resolution. In our case, garages within industrial zones of Murmansk have shown the largest residuals in Sentinel-2 assessments. However, the area of this land use type doesn't exceed 2% as revealed from the OpenStreetMap, and therefore cannot largely contribute to the overall uncertainty of Sentinel-2 based estimations. For better assessments of areas containing such objects, sub-pixel classifications are preferable as many mixed pixels may potentially appear. Another issue in mapping soil sealing is the similar spectral properties with anthropogenically-transformed open soils (e.g. agricultural fields, burned areas etc) (Weng, 2012). To address these issues, we empirically established additional thresholds for blue and SWIR bands (B2, B11) for pixels that are included into the sealed class. These thresholds were first established for Rostov-on-Don and used in case of Murmansk without any empirical tests. However, we cannot exclude that some pixels related to open soil might be misclassified as sealed. Finally, distinguishing between natural and artificial areas with similar spectral characteristics is always challenging. For example, vast areas on the left bank of Don river in Rostov-on-Don were classified as green lawns, whereas a considerable part of the area are covered by natural meadows. Similarly, it was difficult to distinguish between urban trees, shrubs and natural forest-tundra vegetation in the peri-urban areas of Murmansk due to similar spectral signatures of these land cover classes. However, classes urban forest and shrublands were later combined as having similar effect on SOC stocks due to urbanization.

4.2. Urban SOC stocks in polar and steppe conditions

Although C sequestration is widely considered a key soil function, urban SOC stocks and the patterns of their spatial distribution within cities remain overlooked. Recent research estimated and mapped SOC stocks in Moscow (Vasenev et al., 2019), Berlin (Richter et al., 2020), Paris and New York (Cambou et al., 2018). The estimates were based on abundant legacy data (environmental monitoring services, soil archives, citizen science) and extensive soil surveys including 100 to 400 samples per city collected in different times and by different method (e.g., sampling depth ranged from 30 cm in Paris to 150 cm in Moscow). This approach can be applicable for megacities where soil data from different sources are available, but it can be hardly recommended for the smaller regional cities where such data are scarce. Moreover, the estimates obtained for the megacities were still quite uncertain (with variance coefficients above 100% and validation R^2 below 30%) due to limitation in sampling design and very high short-distance variability. In this regard, an approach used in our study, projecting urban SOC stocks from pre-urban soil maps based on the combination of medium resolution images' analysis and correction coefficients for different urbanization pathways seems relevant for the areas where the legacy data is limited, including cities in polar and steppe zones of Russia.

The comparison between the case studies clearly revealed the bioclimatic aspect of the urbanization effect on SOC stocks but it also highlighted the scarcity and bias of the digital soil data available for the Russian regions. The estimates based on the HWSD were highly uncertain, SOC stocks in polar region and overestimated those in steppe conditions. It is not a surprise considering that HWSD was mainly developed for the global implementations. It illustrates the general zonal patterns in SOC stocks but has clear limitations in analyzing the land management and especially the urbanization effect. The reliability of the DSMR is also questionable due to a dataset limitation. Although over 70% of the total 800 profiles locate in European Russia, they are still not enough to give an accurate estimate of the SOC stocks. The reliability of the regional maps differed between the case studies. In steppe zone, the regional map was much more detailed in scale (1:300,000), number of polygons and attribute information in comparison to DSMR, whereas in polar region the regional map didn't improve the DSMR outcomes. It can be explained by different land use dominating in the regions and correspondingly different demand in high-quality soil data. The Rostov region is one of the agricultural centers in the Russian South, therefore soil data support is critical for the regional economy, whereas in the Murmansk region, where agriculture is limited by severe climatic conditions, detailed soil surveys were never made. Scarcity of soil data is a key limitation for environmental surveys and assessment in Russian

Table 5

Algorithms applied to Sentinel-2 and other sensors for assessment of sealed soils. * - as it is described in the source, ** - for comparison, we included Sentinel-2 data from studies only, *** - included are only those close to RMSE for comparison. LULC – land-use and land-cover, MAE – mean absolute error.

Parameter assessed*	Method	Satellite data**	Resolution, m	Accuracy***:method / value	Reference
Impervious surface fraction	Modified LSMA	Sentinel-2A	10	RMSE, R2/ 14%, 0.86	(Xu et al., 2018)
Impervious surface area	Regression tree	Sentinel-2	10	RMSE / 9.05–15.66%	(Xian et al., 2019)
			20	RMSE / 10.59 – 15.18%	
			30	RMSE / 13.34 – 20.10%	
LULC incl. built-up	Support vector machine	Sentinel-2A	10	Overall (built-up) / 77.19)	(Cavur et al., 2019)
Impervious surface	NDVI, NDBI	Sentinel-2A	10	–	(Kuc and Chormański, 2019)
Impervious surface fraction	LSMA with spectral indices as input	Landsat-TM	30	MAE / −10.13 – 12.48%	(Li, 2020)
Sealed area	Reflectance thresholds, SAVI, LSMA	Sentinel-2A	10	RMSE / 9%	This study

North (Goryachkin, 2010).

The comparison of urban SOC stocks in Rostov-on-Don and Murmansk revealed mechanisms of C accumulation and mineralization in the cities under different climate conditions. Urbanization coincides with soil transformation, patrial translocation of organic layers and their substitution by artificial substrates (e.g., peat, composts and soil mixtures) (Brianskaia et al., 2020; Vasenev et al., 2017). In the Murmansk region, peat and soil-peat mixtures are the most widely used materials for urban soil construction (Vikhman et al., 2008). Compared to the natural soils with relatively low SOC contents, especially in subsoils, any urbanization pathway (excluding soil sealing) increases SOC stocks. Moreover, due to cold climatic conditions hampering mineralization, SOC stocks in polar cities are more stable compared to temperate and arid climates (Karelin et al., 2020; Slukovskaya et al., 2020). In Rostov-on-Don, in contrast, urban soils are formed from topsoils translocated from croplands or fallow lands and placed on the technogenic sediments or buried horizons of natural soils (Gorbov and Bezuglova, 2014; Isaev and Zelenskii, 1973; Kazeev et al., 2018). The resulting urban SOC stocks can be less compared to Chernozems dominating areas being recognized among the most fertile world soils. The mineralization rate of urban SOC in Chernozemic region is very high, especially in bare soils, where CO_2 emissions are not compensated by C uptake (Sarzhanov et al., 2017). Therefore, a negative urbanization effect on topsoil SOC stocks is expected in the steppe conditions. Urban subsoils are less exposed to mineralization and contain C-rich materials and artifacts (e.g., buried soil horizon, wood remains and cultural layers) (Vasenev et al., 2017), that explains an increase of SOC stocks in 0-100 cm by urbanization.

The average topsoil SOC stocks in Rostov-on-Don were close to Paris and New York (2.7, 3.3 and 3.8 kg C m^{-2} correspondingly) and less than in Murmansk, Berlin and Moscow (4.1, 5.5 and 6.0 kg C m^{-2} correspondingly), which confirms the regional trend with higher SOC stocks in colder climates (Pouyat et al., 2006; Vasenev and Kuzyakov, 2018). The opposite was shown for the subsoils, where the lowest values were reported in Murmansk. It can be explained by a younger age of the city (104 years compared to 213 years for Rostov-on-Don or over 800 years for Berlin and Moscow) and C-poor natural subsoils, partly inherited in urban soil horizon. The overall SOC estimates for Rostov-on-Don and Murmansk are comparable to the values obtained for natural biomes in Russia (Mikhailova and Post, 2006; Nilsson et al., 2000; Romanovskaya and Karaban, 2008) and are clearly higher than urban SOC stocks estimated by global models (Khaledian et al., 2017; Schulp and Verburg, 2009). One of the reasons is a deeper insight into the urban spatial structure and, first of all, into the distribution of the sealed soils obtained from the medium-resolution imagery and OpenStreetMap data. Many global and regional assessments consider urban areas sealed to at least 50% (Schaldach and Alcamo, 2007) and assign zero SOC stocks to the sealed areas. In our study, it was shown that the actual percentage of the sealed areas was much less. Moreover, only one fourth or even less of the sealed areas were comprised by buildings and federal / main roads. The remaining part covered by local roads and walking pathways contained considerable SOC stocks even though they were lower compared to the unsealed areas. Ignorance of these “hidden” SOC stocks underestimated the role of urban soils in C sequestration (Dolgikh and Aleksandrovskii, 2010; Piotrowska-Długosz and Charzyński, 2015).

5. Conclusion

Urbanization has a considerable impact on soil resources, changing soil functions and ecosystem services. Changes of soil organic carbon (SOC) stocks by urbanization arises attention of scientist, policy makers and urban planners. Considering high heterogeneity of urban soils and multiple factors influencing C stocks and fluxes in cities, spatial analysis and mapping of urban SOC stocks is highly relevant. Conventional digital soil mapping of SOC stocks in cities is limited by legacy data, which is scarce for many regional cities. In the research we implemented an alternative approach and projected urban SOC stocks based on the medium-resolution (10 m) land cover map derived from the Sentinel-2 images and correction coefficients estimated for different urbanization pathways based on the literature data and independent soil surveys. This approach was implemented for the two cities located in polar and steppe conditions of European Russia and based on the global, national and regional soil maps. The results revealed the urbanization effect on SOC in different bioclimatic regions, but also highlighted the limitations of the available soil data. In Murmansk SOC stocks increased on 35-50%, whereas in Rostov-on-Don SOC stocks in 0-100 cm increased on 21-16%, whereas the topsoil SOC stocks decreased on 18%. The difference can be explained by slower mineralization of SOC stocks in colder conditions as well as by higher initial SOC stocks in Chernozems dominating soils of the Rostov region. Soil sealing had the most negative effect, however the actual level of build-up and main road areas resulting to complete loss of SOC stocks turned to be less than 10%, showing that regional and global models likely underestimate the negative effect of soil sealing. A considerable decrease of SOC stocks was obtained for the bare soils in Rostov-on-Don, whereas development of green infrastructures (e.g., district parks and green lawns) had a clear positive effect on SOC stocks in both cities. Data scarcity was a limitation for the accurate estimation of the SOC stocks. Only the regional soil map of Rostov was a sufficient source of the pre-urban SOC stocks, whereas the soil map of the Murmansk region didn’t allow improving estimated based in the national and even global sources. Although, the absolute values of SOC stocks were likely uncertain, the outcomes clearly show the patterns in SOC transformations induced by different urbanization pathways and in different regions. The research also confirms the possibility of the positive effect on urbanization on SOC stocks, which can be considered as a target for sustainable development strategies aiming to enhance ecosystem services of urban soils among which C sequestration is one of the most important.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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