Mapping urban–rural differences in the worldwide achievement of sustainable development goals: land-energy-air nexus

Yunyu Tian¹, Nandin-Erdene Tsendbazar¹, Eveline van Leeuwen² and Martin Herold¹

¹ Laboratory of Geo-information Science and Remote Sensing, Wageningen University & Research, Droevendaalsesteeg 3, 6708 PB Wageningen, The Netherlands
² Urban Economics, Wageningen University & Research, Hollandseweg 1, 6706 KN Wageningen, The Netherlands
* Author to whom any correspondence should be addressed.

E-mail: yunyu.tian@wur.nl

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Abstract

Land use efficiency (LUE), energy efficiency (EE), and air quality are key indicators when assessing urban-related Sustainable Development Goals, yet recent trends and trade-offs in and around urban areas worldwide remain largely unknown. We use an Earth Observation approach to map the land-energy-air sustainability nexus and highlight distinct urban–rural gradients worldwide (2000–2015). In the Global South, urban areas perform relatively better in land-energy-air sustainability trends than rural areas, which are the least sustainable in our global comparative analysis. Comparatively, urban areas in the Global North tend to be less sustainable than surrounding rural regions. Trade-offs among land-energy-air change directions are mostly related to EE versus air quality in urban areas, while spatial and temporal trade-offs between LUE and EE are more pronounced in suburban and rural areas. Integrating satellite data is crucial for tracking the progress of the land-energy-air nexus and can guide context-specific strategies to account for urban–rural differences in achieving sustainability and creating more livable environments.

1. Introduction

With unprecedented urbanization and related environmental problems, the United Nations (UN) proposed a specific goal for cities in the Sustainable Development Goals (SDGs)—‘SDG 11 Make cities and human settlements inclusive, safe, resilient and sustainable’ [1, 2]. Cities simultaneously consume most of the global resources and produce most of the air pollutants [3, 4]. Between 2010 and 2016, air quality deteriorated for more than half of the world’s population, jeopardizing people’s health [2]. With crises of natural resources and environmental quality [5, 6], we selected relevant SDG indicators—land use efficiency (LUE), energy efficiency (EE), and air quality—to track urban sustainability (figure 1). These indicators also have mature Earth Observation (EO) data for mapping global grid-level trends which is necessary for heterogeneous urban areas. The trends of these indicators are connected in several ways [7–9], and can only be jointly assessed by using a spatially disaggregated nexus approach; a rapidly expanding new concept for investigating trade-offs and synergies across multiple SDG targets [10]. Since this concept has been applied frequently to food–energy–water nexus [10, 11], we focus on the land-energy-air nexus which is a novel but central nexus to achieving urban-related SDGs.

As two distinct socioenvironmental systems, urban–rural differences reflect in population density, built-up patterns, and industrialization pathways, which would lead to contrasting land-energy-air trends and nexus [13–16]. Hence, SDG actions are expected to result in different outcomes for urban and rural regions [2, 16]. For instance, increased energy consumption (EC) in urban areas can deteriorate air quality [7], and decreased LUE due to disperse built-up expansion of tertiary industry can cause trade-offs between LUE and EE in suburbs [3]. Understanding the LUE-EE-air quality nexus is necessary for designing win-win strategies for the natural environment and socio-economic development. However,
previous land-energy-air studies only explored partial interactions in urban ecosystems, which hardly link with SDG indicators and remain limited in spatial and temporal scope [12]. Diverse social and geographical contexts make it precarious to generalize knowledge from individual projects/papers. We argue that understanding urban and rural land-energy-air SDG nexus from a global perspective can support win-win strategies for multiple SDG targets towards making sustainable cities.

Although SDGs are mainly policy tools and generally reported at a national level by the UN [17, 18], fine-grid-level SDG mapping allows movement beyond official reports and for exploring urban–rural differences [19, 20]. Recently, the UN called for a data revolution, in particular for the integration of various EO data for the timely monitoring of SDG indicators and nexuses in high spatial detail [21]. EO data are open, transparent, and can underpin sustainability analysis in a consistent way across the world [22]. Based on recent high-resolution EO data, global 1 km-grid-level SDG mapping can benefit every city and help address the inequality in data availability for the Global South [19, 21]. Additionally, integrating EO data to explore the land-energy-air nexus will contribute to ‘big nexus data’ for guiding strategies to minimize the trade-offs between SDG targets. However, no global grid-level nexus studies have linked with specific land-energy-air SDG indicators.

In this study, we take the first global attempt to monitor land-energy-air SDGs: LUE, EE, and air quality at the 1 km resolution from 2000 to 2015, by performing an integrated analysis based on multiple EO-data (Global Human Settlements, Nighttime Lights, and Near-surface PM2.5). Synergies and trade-offs between the three SDG trends are explored using the nexus approach. SDG performances are further scored to analyze urban–rural gradients across continents. By doing so, we unravel co-occurrences of the land-energy-air nexus and provide high spatial detail that international policymakers can use to assess and achieve sustainability.

2. Methods

2.1. Improved calculation of LUE

SDG 11.3 aims to enhance sustainable urbanization by an orderly, built-up expansion that makes land use more efficient [17]. SDG indicator 11.3.1 is officially defined as the ratio of land consumption rate to population growth rate, referred to as LUE [23]. Since the official measurement is difficult to capture the dynamics of cities with negative or zero population growth [24, 25], the Joint Research Centre has developed the formulation to the built-up area per capita, which expresses a more indicative concept that increased built-up area occupied by each person means decreased LUE [24]. We used the developed formulation and adopted the calculation of annual change rates from the metadata of SDG 11.3.1:

$$\Delta \text{BPC} = \ln \frac{\text{BU}_{2015}}{\text{BU}_{2000}} \times \frac{\text{Pop}_{2015}}{\text{Pop}_{2000}} / 15$$

where $\Delta \text{BPC}$ represents the annual change rate of built-up area per capita, BU means the built-up area (m$^2$), and Pop means population. The Global
Human Settlement Layer (GHSL) is the official data source for monitoring SDG 11.3.1 [23], multi-temporal 38 m built-up pixels (GHS-BUILT) and 250 m population grids (GHS-POP) were used to calculate built-up area per capita in each 1 km grid cell. Technical detail of the data can be found in Pesaresi and Freire [26] and Freire et al [27]. We also defined ‘urban–suburban–rural’ based on the urban–suburban–rural classification in GHS-SMOD (https://ghsl.irc.ec.europa.eu/degruba.php) in 2000 except for urban–rural gradients in section 3.2 where we roughly observe the ‘rural’ as the surrounding exurbs for map interpretation.

2.2. Mapping EE
SDG 7.3 aims to double the global rate of improvement in EE by 2030, which requires tracking of SDG 7.3.1: energy intensity (EI) measured as the primary EC per GDP. The first step for mapping EE is to downscale the national EC to grid cells. National statistics of EC in 2000 and 2015 were obtained from the U.S. Energy Information Administration [28]. The statistics include coal, petroleum, natural gas, and renewable energy consisting of net nuclear, hydroelectric, and non-hydroelectric renewable electricity.

The most common proxy data is population distribution [29], and recently, nighttime light has been regarded as a proxy to downscale EC [30]. We combined population (GHS-POP) with nighttime light to downscale national EC to a 1 km resolution. The global nighttime light data we used have been harmonized into temporally consistent digital numbers for two sensors [31]. The assumption is the strong linear relationships between EC and population/nighttime lights, which have been proven in previous studies [32, 33] and this study (figure S6). We eliminated nighttime light emissions in non-populated regions to reduce the ‘blooming’ effect [34]. The remaining bright pixels are relevant to human activities, which can indicate the EC distribution.

To downscale the national EC, we first built linear regression models between EC and two proxy indicators (population and nighttime lights) at the country level for the years 2000 and 2015 separately (equation (2)). Since the collinearity between built-up density and nighttime lights was significantly high, we excluded the built-up density from proxy indicators after model selection. We adopted a weighted linear downscale approach [14, 33], and standardized regression coefficients ($\beta_1$, $\beta_2$) in the models were used as weights of two proxy indicators. Different weights can reduce the dependency on the population of downscaled EC and the collinearity between two proxy indicators. Based on equation (3), we generated EC maps at the 1 km grid level for 2000 and 2015

$$EC_{country} = \beta_1 Light_{country} + \beta_2 Pop_{country} \quad (2)$$

$$EC_{grid-i} = EC_{country} \times \left( \frac{\beta_1 \times Light_{grid-i}}{Light_{country}} + \beta_2 \times \frac{Pop_{grid-i}}{Pop_{country}} \right). \quad (3)$$

We further validated the obtained gridded EC maps at the state level in the United States (US) and the neighborhood level in the Netherlands (figure S7) based on the local statistical EC data [35, 36]. The EC (MBtu) and a global gridded GDP (2011 dollars) dataset [37] (see supplementary section 3) were used to calculate the trend of SDG 7.3.1 between 2000 and 2015:

$$\Delta EI = \ln \frac{EC_{2015}}{EC_{2000}} / 15. \quad (4)$$

Negative change rates ($\Delta EI$) indicate improved EE (less energy is used to produce one unit of economic output), while positive numbers indicate decreased EE.

2.3. Air quality represented by PM2.5
According to the SDG indicator of air quality—SDG 11.6.2 annual mean levels of fine particulate matter (e.g. PM2.5 and PM10) in cities, we used the PM2.5 concentration to represent air quality. Such fine particles (less than 2.5 $\mu$m in diameter) can penetrate deeply into the respiratory tract and jeopardize people’s health [38].

The Global Annual PM2.5 Grids provide annual concentrations of ground-level PM2.5 at 1 km resolution from 1998 to 2019 [39]. The PM2.5 concentration was mainly estimated by aerosol optical depth from multiple satellite products. The resultant estimates were highly consistent ($R^2 > 0.8$) with cross-validated ground-based measurements and uncertainty estimates exhibit regional consistency [39]. With the relatively high accuracy for inhabited land, this product is widely used to analyze temporal dynamics of air quality in small to large cities internationally [40]. We used the 3 year average PM2.5 concentration ($\mu g m^{-3}$) for the initial year (PM2.5<sub>2000</sub>) and end year (PM2.5<sub>2015</sub>) separately to reduce the uncertainty in PM2.5 data

$$\Delta PM2.5 = \ln \frac{PM2.5_{2015}}{PM2.5_{2000}} / 15. \quad (5)$$

2.4. Mapping land-energy-air nexus
Nexus approaches are highly recommended for the analysis of trade-offs among SDG indicators [5, 10, 41]. Indicators that can combine nexus variables into a single number are common in nexus research for practical policy making [42]. Based on this theory, we combined the directions of multiple SDG trends into archetypes of land-energy-air nexus for each
1 km grid cell. Two fully synergy types with consistent change directions of land-energy-air targets, and six trade-off types with inconsistent change directions among land-energy-air nexus were detected. We further used the Pearson correlation coefficient, which has been widely used for SDG interactions [43], to analyze spatial variations of land-energy-air nexus in urban, suburban, and rural areas in the global North and South separately. A positive value represents a synergy while a negative value represents a trade-off, and the absolute value of the correlation coefficient represents the intensity of the nexus.

2.5. Scoring the performance of land-energy-air SDGs

Min–max normalized scores are typically used for comparing the performance of SDG targets and indicators across regions [6]. Here, we also produced normalized scores based on the change rate of each SDG indicator (equation (6)), ranging from 0 to 100

$$\text{SDGscore}_{\text{grid}-i} = \left(1 - \frac{x_{\text{grid}-i} - x_{\text{min}}}{x_{\text{max}} - x_{\text{min}}} \right) \times 100$$  \hspace{1cm} (6)

where \(x\) represents the annual change rate of the SDG indicator. Although the change rate was logged, outliers with extreme values remain in the obtained change rate map, which can influence the min–max normalization. Thus, we removed statistical outliers for each change rate map before the min–max normalization. Normalized change rates were inverted to get the final SDG score because an increasing SDG indicator (e.g. EI) signifies decreasing SDG target (e.g. EE). In doing so, higher scores represent better performance toward the SDG target. The overall SDG score was calculated by the average of three individual SDG scores, representing the overall performance of land-energy-air SDGs.

3. Results

3.1. Global maps of sustainability trends

We reveal that, at the global scale, EE (SDG 7.3.1) performs better than LUE (SDG 11.3.1) and air quality (SDG 11.6.2) between 2000 and 2015 (figure 2). In nearly 60% of the global inhabited grid cells, EE has improved by using less primary energy to produce one unit of economic output. In contrast, LUE has only increased in 34% of the cells, with less built-up land consumption per capita. Improved air quality appears in about 37%, while in nearly 57% of global inhabited grid cells, PM2.5 concentrations exceed the WHO guideline level of 10 µg m\(^{-3}\) in 2015 (figure S1(d)).

With relatively low LUE in 2015 and an enlarged built-up area per capita since 2000 (figures S1(a) and S2(a)), the rural areas of Europe, Northeast US, and South Africa need more policy attention to enhance sustainable urbanization (Target 11.3). According to the current status and changes in EI (figures 2(b), S1(c) and S2(c)), the US and rural areas in the Global South need better energy policies to improve their relatively low EE (Target 7.3). With high PM2.5 concentration in 2015 and aggravated air pollution since 2000 (figures 2(c), S1(d) and S2(d)), Asian countries such as India and China should be targeted for extra efforts to improve air quality (Target 11.6).

3.2. Complex patterns in urban–rural gradients

Regarding LUE, worldwide, we observe better performance in urban areas compared to rural areas between 2000 and 2015 (figures 2(a) and S2(a)) as has previously been reported [13], except for some cities in North America. Specifically, LUE in most city centers is stable or has increased, while it has decreased in most rural areas. Stable-decrease is a common urban–rural gradient in Europe, and increase–decrease is common in Asia, Africa, and Australia. Different reasons for decreased LUE in the Global North (population declines) and South (dispersed built-up expansion) are elaborated in supplementary section 2.

Regarding EE, measured by primary EC/GDP, urban–rural gradient patterns are opposite in the Global North and South (figures 2(b) and S2(c)). In North US, Canada, and Europe, decreased EE mostly occurs in metropolitan city centers such as Toronto, Detroit, Los Angeles, Chicago, Paris, and Berlin. Improved EE in North US, Europe, and Japan can be mainly attributed to decreased EC (figure S2(b)). In contrast, EE in South Asia and Africa increased particularly in urban centers but decreased in their surrounding exurbias (figure 2(b)). Examples include Johannesburg, New Delhi, and Beijing. Improved EE in China and India mainly results from increased GDP rates, since the EC in most cells increased as well (figure S2(b)).

Concerning our third SDG, air quality, we did not find a clear urban–rural divide. Instead, our general observation is that air quality is strongly affected by geographical and climate conditions (figure 2(c)). Moderate urban–rural gradients are observed in certain Chinese cities. In 2015, air pollution is largely higher in urban centers than in the surrounding suburbs (figure S1(d)), but since 2000, increased rates of PM2.5 concentrations in the suburbs have outweighed those in urban centers (e.g. Shenzhen and Chengdu) (figure S2(d)). Therefore, improving rural air quality is as important as mitigating urban air pollution for the currently most polluted continent: Asia.

3.3. Different sustainability trade-offs in urban, suburban, and rural areas

We identified eight synergy/trade-off types for the land-energy-air nexus based on changes in LUE, EE, and air quality (figure 3), including two fully synergy types: win-win-win type (green areas) and lose-lose-lost type (red areas), as well as six trade-off types.
In synergy types, the win-win-win type is mainly found in North America and Europe, while the lose-lose-lose type primarily occurs in Asia, Africa, and South America. Furthermore, the lose-lose-lose type makes up a larger proportion in rural areas than in urban areas.

Urban–suburban–rural and North–South differences are observed in trade-off types. First, most identified trade-offs in urban areas concern EE versus air quality, while land-energy trade-offs are common in suburban and rural areas (figures 3(b) and 4(c)). Suburban–rural differences are mainly observed in
Figure 3. Land-energy-air nexus between 2000 and 2015.

Figure 4. Urban–suburban–rural gradients and continental differences in SDG scores.
Asia and Africa with opposite directions of land-energy trade-offs (figures 3(c) and (d)). Pearson correlation coefficients for spatial variations also show that land-air and land-energy trade-offs were greater across rural grids than suburban and urban grids (table 1). Second, the Global North and South experience opposite directions in trade-offs between resource use efficiency and air quality. In the Global North, in urban areas, especially in megacities such as Los Angeles and Chicago, EE declined but air quality improved (orange and yellow areas), while in the Global South, EE improved, but air quality still declined (chocolate and plum areas).

### 3.4. The least sustainable: rural areas in the Global South

In terms of overall land-energy-air SDG trends, the Global South is less sustainable than the Global North during 2000–2015 (figures 4 and S4). Specifically, the North is more sustainable in air quality and EE than the South, while the South performs better in LUE than the North (figure S8). We also found more dramatic North–South differences in rural areas compared to the small North–South difference in urban areas, in terms of LUE and EE. In general, air quality is the dominant factor in North–South differences, especially in urban and suburban areas.

In addition to the urban–rural heterogeneity observed for individual SDG trends, the overall scores of SDG trends show significant urban–suburban–rural differences (P < 0.05), and urban–rural gradients in the Global North and South are opposite (figure 4). In the Global North, rural areas are significantly more sustainable than urban areas according to overall SDG scores (p < 0.05), dominated by EE. In contrast, urban areas are more sustainable than suburban and rural areas in the South, dominated by EE. These results reveal that EE is the dominant factor in urban–rural gradients in both the Global North and South.

Overall, rural areas in the Global South are the least sustainable regions (figure 4(a)). In the South, although urban residents consume more natural resources than rural residents currently, rural resource use (energy & land) efficiency is lower compared to urban areas in 2015 and has decreased more since 2000 (figures S1, 2(a) and (b)). Furthermore, cities that we identified as more sustainable in land-energy-air SDGs are also those that people find more livable (figure S5). Thus, improving resource use efficiency and air quality in rural areas of the Global South is crucial for reaching global land-energy-air targets and livable settlements.

### 4. Discussion

#### 4.1. Implications of 1 km-gridded SDG maps

SDG trends we observed are generally in line with the global SDG reports [17]. Compared to robust national reports, uncertainties might be exacerbated by applying SDG indicators at a fine scale (see supplementary section 3). However, our 1 km-gridded maps provide essential spatially detailed information on the land-energy-air nexus, and for informing policymakers of effective local actions. First, our global maps contribute to the SDG data revolution [21]. They consistently cover every inhabited cell, which is beneficial for ‘data-poor’ regions and support their efforts toward the SDGs [19]. Second, our maps go beyond existing national reports by revealing diverse urban and rural issues for the Global North and South, such as deteriorated air quality in the urban South, declined EE in the urban North and rural South, and decreased LUE in the rural North (figures 2 and 3). National SDG strategies can be more effective when local sustainability challenges are known, i.e. it is important to be aware of differences within megacities or small-sized cities. Third, despite various land-energy-air trade-offs across regions, win-win-win regions exist (see parts of London and Sydney as green areas in figure 3(a)) and should be studied in more detail on why they can perform better than others. Local trade-offs reflected by our map (figure 3) can guide the context-specific strategies to transform all inhabited areas into win-win-win regions.

Despite urban sustainability being high on national and international policy agendas [19, 44], our 1 km-gridded maps reveal that rural areas have become critical for land-energy-air SDGs in the Global South (figure 4(a)). Since rural areas occupy...
more land than urban centers, rural low-resource-use-efficient activities could lead to more unsustainable inhabited areas overall. Low LUE in newly urbanized areas could replace significant surfaces of agricultural land and therefore has more adverse environmental impacts than for established urban land [3, 45]. Furthermore, it is important to revisit the tendency of moving manufacturing from urban to rural areas, which can improve urban air quality and EE in the city of origin but jeopardizes rural sustainability in the longer term [15]. With rapid urbanization and industrialization increasingly occurring in rural regions [3], enhancing resource use efficiency is crucial for turning urbanization into an opportunity for sustainable development in the rural Global South [46–48].

4.2. Mechanisms behind the North–South differences and urban–rural gradients

We found that the less sustainable Global South compared to the Global North is primarily reflected by EE and air quality (figure 4), which are possibly explained by the inequality between developing countries in the South and developed countries in the North. Previous research has revealed that socioeconomic development and environmental quality are lower in the developing Global South compared with the developed Global North [19]. The developed countries have shifted their focus toward improving environmental quality such as greenness (figure S9), while the developing countries tend to attract foreign investment and factories to boost the economy [48, 49]. Such inequality allows the relocation of production from developed to developing countries resulting in outsourcing of environmental costs, i.e. improved air quality in the North but deteriorated air pollution in the South [50, 51]. Nevertheless, EE in many cities in China and India still improved since they consume similar energy to produce much more economic output (figures 2(b) and S2(b)). This is a win-win situation for both sustainability and economic development which is especially crucial for developing countries.

Our analysis not only highlights more dramatic North–South differences in suburban and rural areas compared to the small North–South difference in urban areas (figures 4 and S4) but reveals opposite urban–rural gradients in the North and South. As contrasting settlement types, urban–suburban–rural differences reflect in built-up patterns and population density, which lead to distinct human activities, energy behaviors, and industrial structures. In the Global North where most developed countries are located, urban areas are noticeable indicated by the decreased urban EE (figure 4), which is possibly related to the high urban EC and declining economy caused by urban shrinkage in the US and Europe [52]. Taking Detroit city as an example, the major industrial sector is automotive, and Detroit has suffered a long economic decline [53]. In the Global South where most developing countries are located, urban sustainability has been improved, whereas rural EE has decreased which might be due to extensive rural industrialization [54]. Thus, industrial urban areas in the developed North and industrializing rural areas in the developing South are expected to be noticed for achieving SDG 7.3.1. Previous discussions on SDG trade-offs have mostly concerned resource use for social development and adverse environmental impacts [12, 42]. Our study adds the spatially detailed trade-offs between resource use efficiencies and air quality. In the developed North, we observed that EE decreased but air quality still improved in urban centers (figure 3(a)). In addition to the favorable geographical conditions with enhanced atmospheric ventilation in coastal cities [55], increased renewable energy share and dense renewable power plants might be an important reason (figure S3). On the contrary, in most urban areas of the developing South, such as Johannesburg and Beijing, air quality declined even when EE improved (figures 3(a) and (b)), implying other drivers of declined air quality except for high EI. Such an energy-air trade-off inspires governments of developing countries to rethink if the efforts undertaken for improving air quality are taking effect and to seek more effective actions [48], such as increasing the share of renewable energy in South Africa and developing solar power plants in China (figure S3). Nevertheless, increasing EE is still effective for improving air quality according to the positive energy-air correlation across urban grid cells in Asia and Africa (table 1). Moreover, land-energy trade-offs in suburban and rural areas in Asia and Africa have opposite directions (figures 3(c) and (d)), which is likely to be related to different industrialization pathways and human activities (see supplementary section 2).

4.3. Uncertainties and limitations

Although the EO data we used are the best options for monitoring the SDG indicators, there are several uncertainties in data sources and approaches. For instance, the GHS-BUILT is less accurate in rural areas compared to urban areas, and the disaggregation process for GHS-POP neglects building height. Uncertainty in the GDP data can be found in both statistical reports of sub-national GDP per capita and gridded population data. The drastic rural-to-urban transformation in developing counties over 15 years contributes to the uncertainty in urban–rural differences in SDG trends. More detailed uncertainties are provided in the supplementary.

The rationale of SDG 11.3.1 is that cities require orderly urban expansion that makes the land use more efficient since dispersed built-up expansion can occupy more natural habitats and farmland compared to the compact pattern. However, the over-densification in crowded city centers and related poor
livability in slums are not considered. Future research can explore the SDG trade-offs between efficient built-up expansion and livability to provide more comprehensive knowledge about how to make sustainable and livable cities.

We only focus on land-energy-air nexus based on three SDG indicators, while urban sustainability involves other indicators within and outside the SDGs. For air quality, carbon monoxide, nitrogen/sulfur dioxide, and ozone are also critical air pollutants. For EE, EC per capita is an important indicator to reflect sustainable behaviors such as public transportation instead of cars. Despite the LUE and EE, water use efficiency (SDG 6.4.1) is another important indicator of resource use efficiency in cities. Urban environmental problems involve other aspects such as urban green degradation, urban heat island, and flooding which can be obtained through EO but are not included in SDGs. Future research could monitor more urban sustainability indicators and SDG 11 is highly recommended to involve urban greenspace and urban heat island. Moreover, further analysis of socio-economic drivers of SDG trends and trade-offs is highly recommended for providing specific advice for reversing the trend and win-win-win strategies.

Since urban sustainability is driven by human activities, further dividing the Global North and South into different development levels is recommended for analyzing urban SDG nexuses. More in-depth statistical analysis can shed more light on non-linear interactions and the intensity of the SDG nexus [10, 43] (see supplementary).

5. Conclusion

This global study of land-energy-air SDG trends at 1 km resolution (2000–2015) goes beyond the UN country-level SDG reports, case studies of land-energy-air interactions, and limited global city-level mapping of individual SDG indicators. Our global 1 km-griddeds maps highlight the distinct urban–rural gradients of SDG trends in the Global North and South, particularly for the diverse trade-offs in the land-energy-air nexus across the world. The North performs better than the South in EE and air quality, and rural areas in the South are the least sustainable in our global comparative analysis. Trade-offs among land-energy-air trends are mostly related to EE versus air quality in urban areas, while spatial relations show energy-air synergy and land-energy and land-air trade-offs in all settlement types. Our results can guide context-specific and win-win-win strategies from a global perspective for land-energy-air SDGs, which are important considering that limited resources and air pollution will continue to be critical sustainability issues in the context of urbanization. Future research can include more satellite-based information (e.g. building height) to improve the disaggregation of social statistics for monitoring fine-scale SDGs and explore in-depth land-energy-air nexus based on long-time-series data and machine learning models.

Data availability statement

All data that support the findings of this study are included within the article (and any supplementary files).

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References

[1] United Nations 2020 Global indicator framework for the Sustainable Development Goals and targets of the 2030 Agenda for Sustainable Development (available at: https://unstats.un.org/sdgs/indicators/Global%20Indicator%20Framework%20after%202020%20Review_Eng.pdf)
[2] United Nations 2019 The Sustainable Development Goals report United Nations Publ. issued by Dep. Econ. Soc. Aff. 64 (available at: https://undocs.org/E/2019/68)
[3] Jiang G, Ma W, Dingyang Z, Qinglei Z and Ruijuan Z 2017 Agglomeration or dispersion? Industrial land-use pattern and its impacts in rural areas from China’s township and village enterprises perspective J. Clean. Prod. 159 207–19
[4] Wang H, Wang L, Su F and Tao R 2012 Rural residential properties in China: land use patterns, efficiency and prospects for reform Habitat Int. 36 201–9
[5] Bleischwitz R, Spataru C, VanDeveer S D, Obersteiner M, van der Voet E, Johnson C, Andrews-Speed P, Boersma T, Hof H and van Vuuren D P 2018 Resource nexus perspectives towards the United Nations Sustainable Development Goals Nat. Sustain. 1 737–43
[6] Zeng Y, Maxwell S, Runting R K, Venter O, Watson J E M and Carrasco L R 2020 Environmental destruction not avoided with the Sustainable Development Goals Nat. Sustain. 3 795–8
[7] Shikwambana L and Tooleleng L T 2020 Impacts of population growth and land use on air quality. A case study of Tshwane, Rustenburg and Emalahleni, South Africa S. Afr. Geogr. J. 102 209–22
[8] Rafaj P, Amann M, Siri J and Wuester H 2014 Changes in European greenhouse gas and air pollutant emissions 1960–2010: decomposition of determining factors Clim. Change 124 477–504
[9] Hou J, Wang J, Chen J and He F 2020 Does urban haze pollution inversely drive down the energy intensity? A perspective from environmental regulation Sustain. Dev. 28 343–51
[10] Liu J et al 2018 Nexus approaches to global sustainable development Nat. Sustain. 1 466–76
[11] Torhan S et al 2022 Tradeoffs and synergies across global climate change adaptations in the food-energy-water nexus Earth’s Future 10 e2021EF002301
[12] Maes M J A, Jones K E, Toldano M B and Milligan B 2019 Mapping synergies and trade-offs between urban ecosystems and the Sustainable Development Goals Environ. Sci. Policy 93 181–8
[13] Schiavina M et al 2019 Multi-scale estimation of land use efficiency (SDG 11.3.1) across 25 years using global open and free data Sustainable 11 1–25

[14] van Vuuren D P, Lucas P. J. and Hilderink H 2007 Downscaling drivers of global environmental change: enabling use of global SRES scenarios at the national and grid levels Glob. Environ. Change 17 114–30

[15] Yan L. M., Arzabi H, Densley Tingley D, Brockway P E and Mayfield M 2021 Mapping resource effectiveness across urban systems npj Urban Sustain. 1 1–14

[16] Malashock D A et al 2022 Estimates of ozone concentrations and attributable mortality in urban, peri-urban and rural areas worldwide in 2019 Environ. Res. Lett. 17 050423

[17] United Nations 2020 SDG Progress Report 2020 (available at: https://unstats.un.org/sdgs/report/2020/)

[18] The World Bank and International Energy Agency 2017 Global Tracking Framework 2017 - Progress Toward Sustainable Energy (available at: https://www.worldbank.org/en/topic/energy/publication/global-tracking-framework-2017)

[19] Nagendra H, Bai X, Brondizio E S and Lwasa S 2018 The urban south and the predicament of global sustainability Nat. Sustain. 1 341–9

[20] Blanchard J L et al 2017 Linked sustainability challenges and trade-offs among fisheries, aquaculture and agriculture Nat. Ecol. Evol. 1 1240–9

[21] United Nations 2020 A World that Counts: Mobilising the Data Revolution for Sustainable Development (The United Nations Secretary-General’s Independent Expert Advisory Group) (https://doi.org/10.7551/mitpress/12439.003.00118)

[22] Cochrane F, Daniel J, Jackson L and Neale A 2020 Earth observation-based ecosystem services indicators for national and subnational reporting of the Sustainable Development Goals Remote Sens. Environ. 244 111796

[23] UN-Habitat 2018 SDG indicator 11.3.1 metadata (available at: https://unstats.un.org/sdgs/metadata/files/Metadata-11-03-01.pdf)

[24] Pesaresi M et al 2017 Atlas of the Human Planet 2016. Mapping Human Presence on Earth with the Global Human Settlement Layer (https://doi.org/10.2788/889483)

[25] Melchiorri M, Pesaresi M, Florczyk A, Corbane C and Kemper T 2019 Principles and applications of the global human settlement layer as baseline for the land use efficiency indicator—SDG 11.3.1 ISPRS Int. J. Geo-Inf. 8 96

[26] Pesaresi M and Freire S 2016 GHS-SMORD R2016A—GHS settlement grid, following the REGIO model 2014 in application to GHSL Landsat and CIESIN GPW v4-multipletemporal (1975–1990–2000–2015) Eur. Comm. Jt. Res. Cent. (available at: http://data.europa.eu/89h/roc-gshl-glb_smol_pop Globe_r2016a)

[27] Freire S et al 2015 Combining GHSL and GPW to improve global population mapping Int. Geoscience and Remote Sensing Symp. (IGARSS) (https://doi.org/10.1109/IGARSS.2015.7326329)

[28] U.S. Energy Information Administration (EIA) International energy statistics: total primary energy consumption (available at: https://www.eia.gov/international/data/world/total-energy/)

[29] Jin K, Wang F, Chen D, Liu H, Ding W and Shi S 2019 A new global gridded anthropogenic heat flux dataset with high spatial resolution and long-term time series Sci. Data 6 1–14

[30] Yang W, Luan Y, Liu X, Yu X, Miao L and Cui X 2017 Data descriptor: a new global anthropogenic heat estimation based on high-resolution nighttime light data Sci. Data 4 1–11

[31] Li X, Zhou Y, Zhao M and Zhao X 2020 A harmonized global nighttime light dataset 1992–2018 Sci. Data 7 1–9

[32] Xiao H, Ma Z, Mi Z, Kelsey J, Zheng J, Yin W and Yan M 2018 Spatio-temporal simulation of energy consumption in China’s provinces based on satellite night-time light data Appl. Energy 231 1070–8