Annex 3:
Global conversion of land to urban purposes

Method in brief

This analysis, produced for the Coalition's *Climate Emergency, Urban Opportunity*[1] report, and conducted by Alejandro Blei, Shlomo Angel and Xinyue Zhang, of the Marron Institute of Urban Management at New York University, estimates the extent to which urban settlements around the world expanded between the years 2000 and 2014, and what types of land cover were converted to urban use. The results presented in *Seizing the Urban Opportunity* and the six accompanying country reports are drawn directly from that analysis. However, since the methodology is reproduced here as it appeared in the original 2019 report, with only minimal edits, the illustrative figures and selected results provided are not specific to the six countries, but rather the same as were included in the original methodology.

Scope of analysis

Urban population growth and the outward expansion of cities and towns entail the conversion of land from rural to urban use. Yet knowledge of the land cover changes that underlie urban expansion, whether the amount of land or the type of land that is converted to urban use, such as forested areas or cultivated lands, remains poorly understood. A key obstacle to improving our understanding of the relationship between urban expansion and land cover change has been uncertainty surrounding the spatial representation of urban land. For example, while organisations such as the United Nations Population Division and the Food and Agriculture Organization (FAO) report time series data on the urban population in each country or on types of land cover in countries, these reports critically lack a spatial component. New datasets make possible the quantification of land cover change due to settlement expansion, globally, in a spatially explicit manner. Moreover, the new data sources allow for a targeted focus on different categories of human settlement, including an urban category. This analysis integrates those data sources to shed light on changes that have occurred as a result of urban settlement expansion specifically.

The goal of this analysis was to generate answers to the following questions:

- Over the 2000–2014 period, how much settlement expansion was urban, belonging to either the urban centres or urban clusters sub-classes in 2014?
- What types of land cover at the year 2000 were converted to urban use within these expansion areas?

The land cover impacts of urban expansion, globally, have been relatively unknown until now. This analysis provides a first attempt at documenting this dynamic. The results may be aggregated at any analysis level, whether the country, region, continent, or world. The analysis also raises questions about how the results should be interpreted and what actions, if any, should be taken in response to the observed trends. Addressing these questions in a comprehensive manner lies beyond the scope of the present analysis and remains a focus of subsequent study.

Data

The analysis combined datasets for built-up area, non-anthropogenic land cover and a settlement classification grid, to produce spatially explicit estimates of the amount of land that have been subsumed by urban settlement expansion, globally, over the 2000–2014 period.

A central concept throughout the analysis is the idea of settlement extent, which refers to a spatially explicit representation of human settlement. The basis for delineating settlement extent is a methodology created by the New York University Urban Expansion Program. This methodology was used to map and measure urban extent in *Atlas of Urban Expansion*.[2]

While the *Atlas* mapped settlements with populations of 100,000 or more, the model can also be applied to settlements with very small populations. In theory, and in practice – for we have observed as much in this analysis – the smallest settlement extent our model produces is on the order of 0.03 square kilometres, or approximately three hectares. Not all settlements with such small areas will classified as settlements by the model. For example, an isolated settlement of three hectares surrounded by open countryside in all directions would not meet the model's thresholds and would not be output as a settlement extent. A similarly sized settlement extent situated in close proximity to large or densely clustered settlements extents would, however.[3]

The basic input to the settlement extent model is the three-way classification of satellite imagery into built-up area, open space and water pixels. Whereas the *Atlas* relied on human-assisted classification of 30-metre resolution Landsat satellite imagery to generate input data for 200 cities, this analysis relied on the European Commission's Global Human Settlement Layer (GHSL) built up grid.[4] The GHSL built layer applies machine learning methods to Landsat satellite imagery to produce time series data (1975, 1990, 2000, and 2014) on the presence of built-up area across the entire planet at a resolution of 38 metres.[5]

The settlement extent model produced extents as large as several thousand square kilometres and as small as three hectares. Settlements may be more urban or more rural in character depending on a number of factors: the size and configuration of their built up areas, their populations, the types of economic activities in which residents are employed, connections to neighbouring settlements, and many others. At this stage of the analysis, we were unable to assign names or populations to settlement extents across all countries in a systematic manner and we knew little about the economic activities associated with individual settlements. We therefore looked to other data sources to help us differentiate urban settlement extent from rural settlement extent, and, ultimately, to help us identify urban settlement expansion.

We employed the GHSL's settlement model (SMOD)[6] to help us distinguish urban from rural settlement. SMOD is a spatially explicit product with a resolution of one kilometre. Grid cells refer to areas of urban settlement, rural settlement or no settlement. Urban cells comprise two sub-classes: urban centres and urban clusters. Urban centres are roughly synonymous with cities and large urban areas, while urban clusters refer to towns and suburbs, peripheral or smaller urban areas. SMOD cell classification was generated by the OECD's degree of urbanisation model (DEGURBA),[7] which integrates data from global built-up and population grids, applying population and density thresholds, as well as spatial contiguity rules, to assign grid cells a settlement category value.

To assess land cover change due to urban settlement expansion, we identified a land cover dataset with more detailed information for the open space category for the year 2000. We used the GlobeLand30 (GL30) 30-metre dataset,[8] created by the National Geomatics Center of China, to obtain information about six land cover categories: cultivated land, forest, grassland, shrubland, wetland and bareland. We superimposed urban settlement expansion for the 2000–2014 period on this year 2000 GL30 data. Aggregating GL30 land cover data over the intersected area provided information about the categories of land cover, their areas and their relative shares that were subsumed by urban expansion across the 2000–2014 period.

Approach

The overall approach relied on spatial analysis techniques carried out in a GIS environment. Results may be summarised at the country, continental and global levels. Below, we describe the methodology and procedural steps in greater detail and use images to aid the reader's understanding of the input and output data. At the end of this section, a flowchart illustrates the data, procedures, and outputs associated with the analysis.

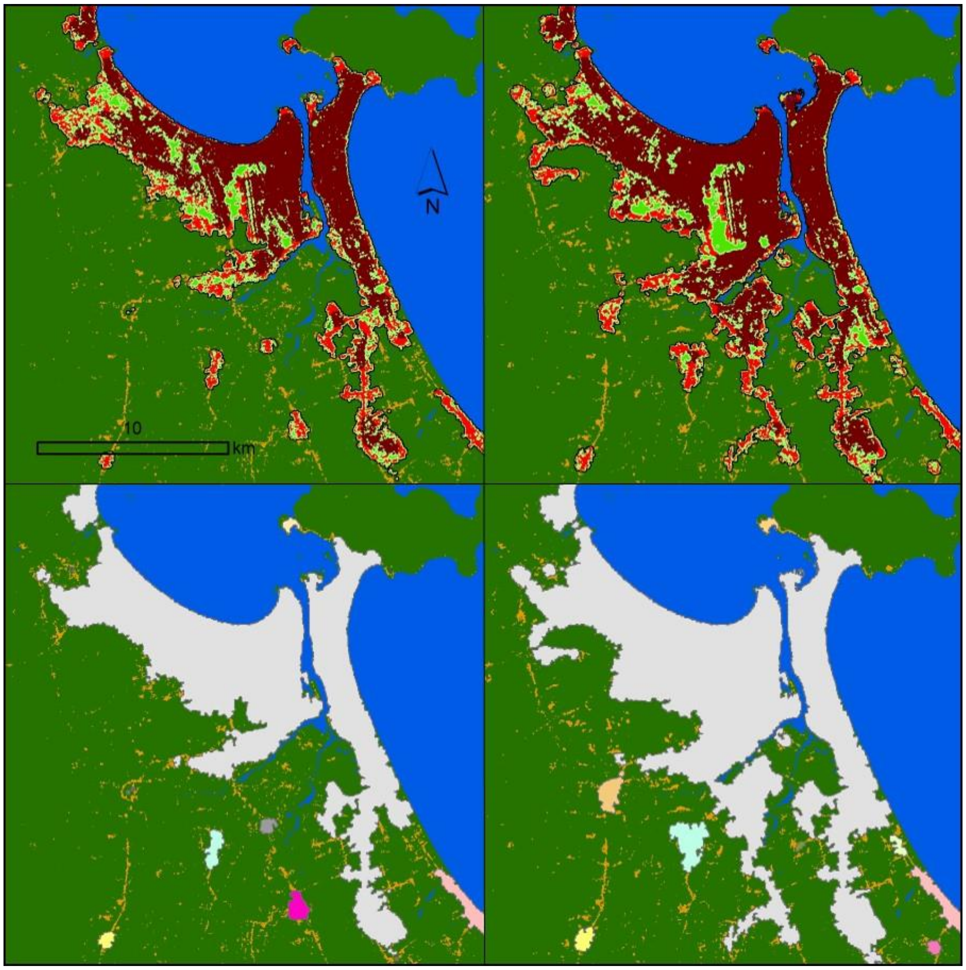
Settlement extent

While a built-up grid was a fundamental input for the generation of settlement extent, extracting information that would allow for the segmentation and clustering of this data required additional analysis. The first step of this information extraction procedure was to obtain the three-way classification of built- up area, open space and water pixels. The GHSL built layer already contained these divisions. The second step of this procedure was to create information for each built-up and open space pixel that would allow for subclassification into one of three categories of built-up area: urban, suburban or rural; and one of three categories of open space: fringe open space, captured open space and rural open space.

Around each built-up pixel, we calculated the share of built-up area within its one square kilometre Walking Distance Circle, a circle with a radius of 584 metres, roughly a 10-minute walk. Cut-offs for the share of built-up area within this circle provide a measure of the spatial density of built-up area and defined the different categories of built-up pixels. If more than 50% of the circle was built-up, the target pixel was labelled urban; if more than 25% but less than 50%, the target pixel was labelled suburban; if less than 25%, the target pixel was labelled rural. Open space pixels within 100 metres of urban and suburban pixels are likely to be degraded by their proximity to development and were labelled fringe open space. Captured open space patches less than 200 hectares in area – patches that are completely surrounded by urban and suburban pixels – are likely to be degraded by their isolation from other open spaces and were labelled captured open space. Fringe and captured open space comprise urbanised open space. Open space pixels that are neither fringe nor captured were labelled rural open space.

This segmentation of imagery pixels allowed for the third step of the procedure: the identification of settlement clusters. These are discrete clusters of built-up area and their urbanised open space pixels surrounded by rural open space or rural built-up. The fourth and final step of the procedure grouped settlement clusters into settlement extents. Discrete clusters of built-up area and urbanised open space may be unioned into the same settlement extent, a type of meta-cluster, depending on the size and geographic proximity of settlement clusters to each other. A settlement extent may be composed of a single, hundreds or thousands of settlement clusters, depending on spatial relationships of clusters across the analysis area as seen in Figure A3.1.

Figure A.1. The sub-classification of built-up area and open space and the identification of settlement in Da Nang, Vietnam for 2000 and 2014.

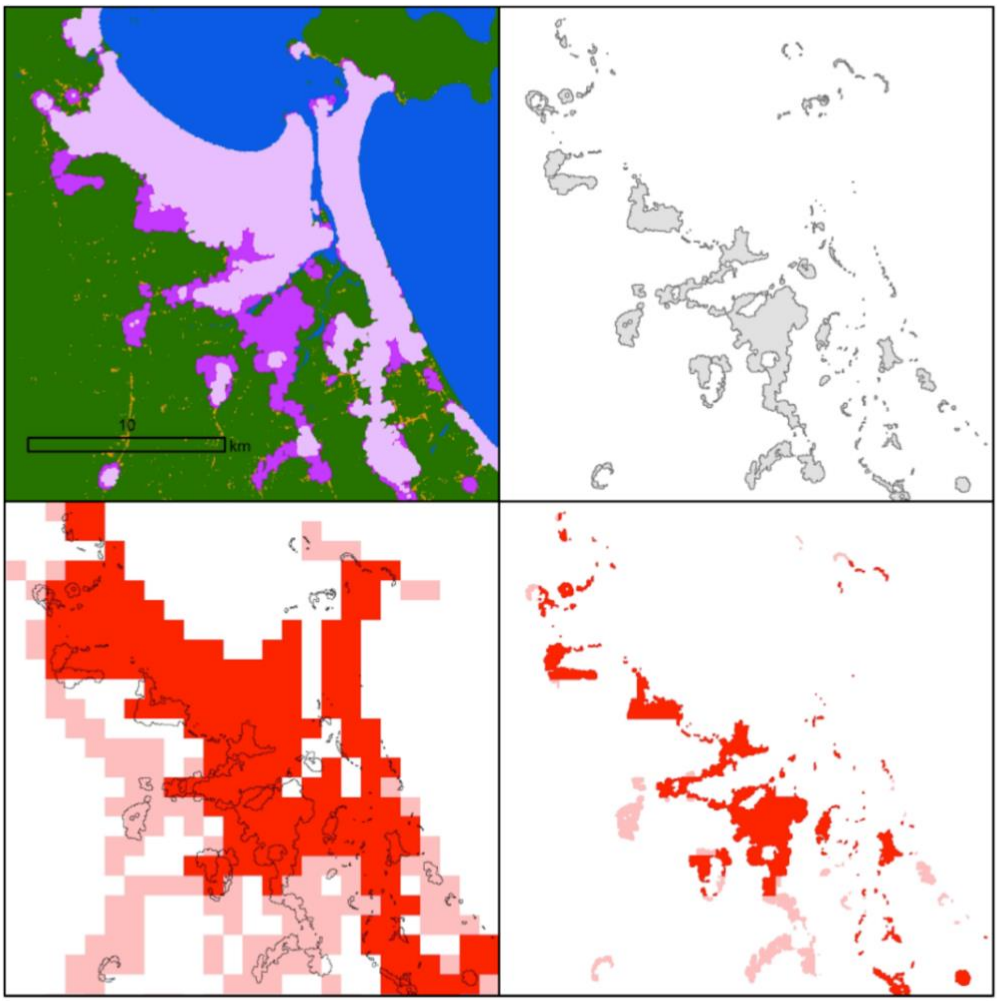


Top row: *The vicinity of Da Nang, Vietnam and the sub-classification of built-up pixels into urban (dark red), suburban (red) and rural (ochre); and open space pixels into fringe (light green), captured (bright green) and rural open space (dark green) for the years 2000 (left) and 2014 (right).*
Bottom row: *The extraction of settlement extent for the years 2000 (left) and 2014 (right) after applying the settlement extent methodology. The different colours refer to individual settlement extents identified at each time period. Note that bright pink settlement extent in 2000 is absorbed into the larger grey settlement extent in 2014. The yellow, light green and pink settlements in 2000 grow larger in 2014. Three new settlements appear in 2014.*

Urban settlement expansion

Repeating the procedure at 2000 and 2014 produced two sets of settlement extents. Subtracting the 2000 area from 2014 area resulted in the settlement expansion area. This area may include both built-up area and urbanised open space. To identify urban settlement expansion and to distinguish urban center settlement expansion from urban cluster settlement expansion, we superimposed the SMOD urban layer on settlement expansion and obtained the intersections of these areas. In *Figure A.2*, bottom left, the GHS-SMOD layer appears much larger than the urban expansion area because it has a resolution of 1km and it describes all settlement within the cells regardless of the amount of built-up within a cell.

Figure A.2. The vicinity of Da Nang, Vietnam, and its different type of settlements – continued



Top row, left: *Year 2000 settlement extent (light purple) and year 2014 settlement extent (dark purple).* ***Top row, right:*** *Settlement expansion over the 2000–2014 obtained by subtracting year 2000 extent from year 2014 extent.* ***Bottom row, left:*** *Overlaying SMOD urban centre cells (red) and urban cluster cells (pink) on 2000–2014 settlement expansion.* ***Bottom row, right:*** *Extracting the intersections of settlement expansion with urban centres (red) and urban clusters (pink) to identify all urban settlement expansion in the vicinity of Da Nang, Vietnam.*

Land cover change

Assessing land cover change within the two types of urban settlement expansion required intersecting these areas with year 2000 land cover data. Figure A3.3 depicts GL30 land cover within all urban settlement expansion in the vicinity of Da Nang, Vietnam. Land cover totals within urban centre expansion and urban cluster expansion individually may be obtained by aggregating GL30 pixels within these respective areas. The presence of built-up pixels in expansion areas, as shown in the bottom left corner of Figure A3.3, may be explained by rural built-up pixels that were absorbed by the outward expansion of urban settlements. Since built-up is a GL30 category (labelled "artificial surfaces" in the GL30 dataset), it comprises a land cover category within expansion areas, although the interpretation of this category is rather nuanced, as described in the Limitations section. To illustrate the data inputs, procedures, and outputs see the flowchart (Figure A3.4).

Figure A3.3. Year 2000 land cover within the 2000–2014 urban expansion area in the vicinity of Da Nang, Vietnam

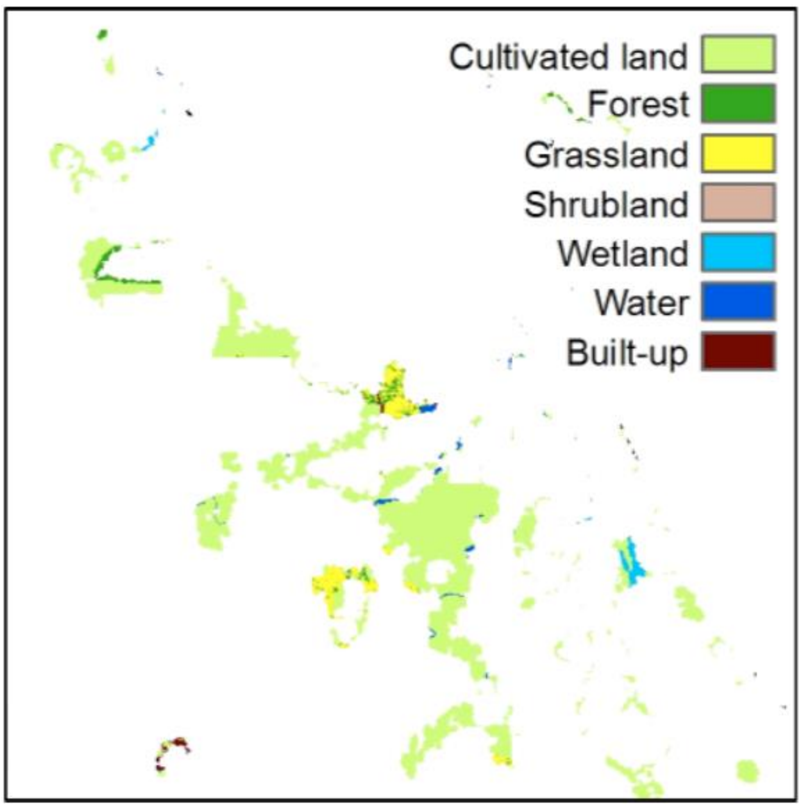
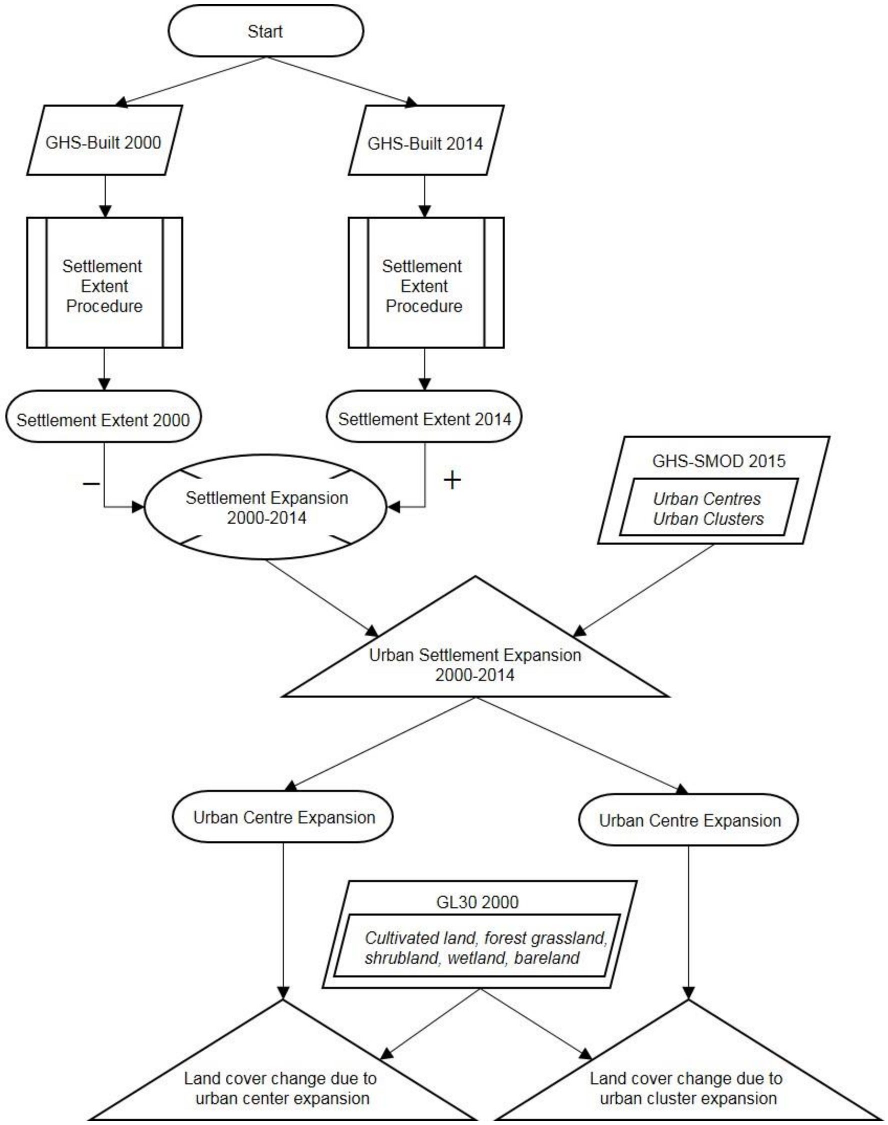


Figure A3.4. Flowchart of data inputs, procedures and outputs



Limitations

Studying spatially explicit land cover change requires careful consideration of the advantages and disadvantages of different data sources. The desire for a globally comprehensive analysis required the use of datasets generated by automatic detection methods and gains in geographic coverage may have come at the expense of gains in accuracy that may have been attained by using localised land cover data generated by labour-intensive, human-assisted procedures. Overall classification accuracies are generally high across datasets, but aggregate classification accuracy may mask variation in regional accuracy, which may in turn render estimates for certain regions more accurate than others. In Bhutan, for example, our procedures did not yield a single settlement extent for either 2000 or 2014. Even though Bhutan is a small and sparsely populated country, we know it contained several human settlements. We failed to create settlement extents because the input data contained virtually no built-up pixels, and the ones that existed were too small in number and too sparsely arranged. This example highlights the difficulties of developing automatic detection methods that can be applied globally with high accuracy. Methods that are highly accurate in one context may be less accurate in another.

We limited the study period to 2000–2014 to make use of a single data source (GHSL) with a consistent spatial resolution, despite the existence of more recent global built-up datasets, some of which were released over the course of this analysis. This study window placed constraints on the data that could be used to assess the different land cover categories subsumed by urban settlement expansion. Namely, the window required locating a global dataset with fine-grained land cover data for circa 2000. We integrated information from the GL30 dataset for this purpose. Combining the two datasets carried the potential for spatial irregularities or contradictions, perhaps an unavoidable consequence of integrating two different global datasets. For example, pixels that are classified as built-up in the year 2000 by GHSL may not be classified as built-up in GL30 in the year 2000 and vice versa. These differences may be at least partly explained by different assumptions built into each product’s classification algorithms.

Uncertainties surrounding thematic accuracies in each dataset means that the amount of urban expansion and the breakdown and totals of land cover categories within expansion areas must be treated as estimates. We were unable to determine confidence intervals around these estimates, as doing so would require additional analysis that lay beyond the scope of this present study. We also recognise that different urban definitions will inevitably lead to different estimates of the amount of urban expansion. Our focus on settlement expansion within GHSL urban centres and urban clusters to deepens our understanding of the impact of these two definitions on outcome measures.

Endnotes

[1] CUT, 2019, “Climate Emergency, Urban Opportunity.”

[2] Angel et al., 2016, *Atlas of Urban Expansion–2016 Edition, Volume 1: Areas and Densities*..

[3] For a detailed explanation the settlement extent methodology, see Blei et al., 2018, “Urban Expansion in a Global Sample of Cities, 1990–2014.”

[4] Corbane et al., 2018, “GHS-BUILT R2018A – GHS Built-up Grid, Derived from Landsat, Multitemporal (1975-1990-2000-2014).”

[5] Corbane et al., 2019, “Automated Global Delineation of Human Settlements from 40 Years of Landsat Satellite Data Archives,” *Big Earth Data*.

[6] Pesaresi et al., 2019, “GHS-SMOD R2019A – GHS Settlement Layers, Updated and Refined REGIO Model 2014 in Application to GHS-BUILT R2018A and GHS-POP R2019A, Multitemporal (1975-1990-2000-2015).”

[7] Dijkstra and Poelman, 2014, “A Harmonised Definition of Cities and Rural Areas: The New Degree of Urbanisation.”

[8] See the GlobeLand30 Data Platform at http://www.globallandcover.com.

Selected results

Table A3.1. Year 2000 land cover converted to urban area between 2000 and 2014 (km^2 and %), by continent and subregion.

Region	Cultivated Land	Forest	Grassland	Shrubland	Wetland	Rural Built-Up	Water	Bareland	No Data	Total
Africa	**5,590 (30%)**	**3,930 (21%)**	**4,338 (23%)**	**620 (3%)**	**366 (2%)**	**3,282 (17%)**	**254 (1%)**	**544 (3%)**	**15 (0%)**	**18,939 (100%)**
Eastern Africa	1,642 (43%)	541 (14%)	830 (22%)	50 (1%)	26 (1%)	705 (18%)	21 (1%)	15 (0%)	2 (0%)	3,832 (100%)
Middle Africa	527 (24%)	330 (15%)	926 (42%)	23 (1%)	25 (1%)	334 (15%)	19 (1%)	31 (1%)	0 (0%)	2,217 (100%)
Northern Africa	1,427 (48%)	50 (2%)	257 (9%)	98 (3%)	3 (0%)	691 (23%)	36 (1%)	407 (14%)	7 (0%)	2,975 (100%)
Southern Africa	219 (13%)	144 (9%)	651 (40%)	90 (5%)	3 (0%)	511 (31%)	15 (1%)	5 (0%)	1 (0%)	1,639 (100%)
Western Africa	1,775 (21%)	2,865 (35%)	1,673 (20%)	359 (4%)	309 (4%)	1,041 (13%)	163 (2%)	86 (1%)	5 (0%)	8,276 (100%)
Asia	**39,833 (65%)**	**3,852 (6%)**	**2,996 (5%)**	**420 (1%)**	**212 (0%)**	**11,678 (19%)**	**1,973 (3%)**	**658 (1%)**	**53 (0%)**	**61,676 (100%)**
Central Asia	245 (33%)	6 (1%)	33 (4%)	2 (0%)	1 (0%)	448 (60%)	3 (0%)	4 (1%)	0 (0%)	742 (100%)
Eastern Asia	27,711 (71%)	1,746 (4%)	1,532 (4%)	80 (0%)	101 (0%)	6,130 (16%)	1,559 (4%)	33 (0%)	32 (0%)	38,923 (100%)
SE Asia	3,202 (64%)	773 (15%)	138 (3%)	10 (0%)	42 (1%)	697 (14%)	129 (3%)	3 (0%)	7 (0%)	5,002 (100%)
Southern Asia	6,698 (54%)	1,136 (9%)	919 (7%)	194 (2%)	60 (0%)	3,030 (24%)	251 (2%)	135 (1%)	6 (0%)	12,428 (100%)
Western Asia	1,977 (43%)	192 (4%)	374 (8%)	134 (3%)	8 (0%)	1,373 (30%)	30 (1%)	485 (11%)	8 (0%)	4,582 (100%)
Europe	**7,334 (63%)**	**791 (7%)**	**202 (2%)**	**154 (1%)**	**36 (0%)**	**2,959 (25%)**	**177 (2%)**	**34 (0%)**	**16 (0%)**	**11,704 (100%)**
Eastern Europe	1,266 (55%)	127 (6%)	94 (4%)	15 (1%)	12 (1%)	738 (32%)	42 (2%)	8 (0%)	0 (0%)	2,302 (100%)
Northern Europe	618 (51%)	117 (10%)	20 (2%)	15 (1%)	3 (0%)	418 (34%)	16 (1%)	3 (0%)	5 (0%)	1,215 (100%)
Southern Europe	2,206 (66%)	194 (6%)	32 (1%)	85 (3%)	8 (0%)	772 (23%)	19 (1%)	15 (0%)	9 (0%)	3,339 (100%)
Western Europe	3,245 (67%)	354 (7%)	57 (1%)	39 (1%)	13 (0%)	1,031 (21%)	101 (2%)	8 (0%)	1 (0%)	4,848 (100%)
Latin Am. & Carib.	**1,504 (26%)**	**846 (14%)**	**996 (17%)**	**580 (10%)**	**41 (1%)**	**1,784 (30%)**	**42 (1%)**	**54 (1%)**	**7 (0%)**	**5,854 (100%)**
Caribbean	81 (17%)	193 (41%)	99 (21%)	3 (1%)	4 (1%)	83 (17%)	2 (0%)	9 (2%)	2 (0%)	476 (100%)
Central America	652 (30%)	247 (11%)	220 (10%)	315 (14%)	11 (0%)	738 (34%)	12 (1%)	6 (0%)	1 (0%)	2,201 (100%)
South America	771 (24%)	406 (13%)	677 (21%)	262 (8%)	26 (1%)	963 (30%)	28 (1%)	39 (1%)	4 (0%)	3,177 (100%)
Northern America	**2,512 (18%)**	**2,835 (21%)**	**1,372 (10%)**	**749 (5%)**	**715 (5%)**	**5,240 (38%)**	**148 (1%)**	**88 (1%)**	**7 (0%)**	**13,665 (100%)**
Oceania	**334 (49%)**	**121 (18%)**	**80 (12%)**	**9 (1%)**	**1 (0%)**	**125 (18%)**	**3 (0%)**	**3 (0%)**	**1 (0%)**	**687 (100%)**
Aus. & NZ	291 (49%)	102 (17%)	78 (13%)	7 (1%)	1 (0%)	104 (18%)	3 (1%)	3 (1%)	1 (0%)	591 (100%)
Melanesia/FSM	53 (55%)	19 (20%)	1 (1%)	1 (1%)	0 (0%)	20 (21%)	0 (0%)	0 (0%)	0 (0%)	96 (100%)
GRAND TOTAL	**57,117 (51%)**	**12,376 (11%)**	**9,984 (9%)**	**2532 (2%)**	**1371 (1%)**	**25,068 (22%)**	**2,598 (2%)**	**1381 (1%)**	**98 (0%)**	**112,524 (100%)**

Table A3.2. Year 2000 land cover converted to urban area between 2000 and 2014 (km^2 and %), select countries of interest

Country	Cultivated Land		Forest		Grassland		Shrubland		Wetland		Rural Built-Up		Water		Bareland		No Data		Total	
China	25,495	(71%)	1,539	(4%)	1,468	(4%)	47	(0%)	97	(0%)	1,517	(4%)	5,628	(16%)	18	(0%)	21	(0%)	35,830	(100%)
Ghana	97	(8%)	597	(47%)	264	(21%)	29	(2%)	27	(2%)	19	(2%)	224	(18%)	0	(0%)	1	(0%)	1,258	(100%)
India	5,591	(57%)	928	(9%)	763	(8%)	156	(2%)	52	(1%)	215	(2%)	2,057	(21%)	57	(1%)	4	(0%)	9,822	(100%)
Indonesia	122	(57%)	40	(19%)	3	(1%)	3	(1%)	0	(0%)	0	(0%)	44	(21%)	0	(0%)	0	(0%)	213	(100%)
Mexico	552	(30%)	157	(9%)	138	(8%)	308	(17%)	9	(0%)	10	(1%)	641	(35%)	6	(0%)	0	(0%)	1,821	(100%)
Tanzania	100	(25%)	33	(8%)	161	(40%)	4	(1%)	2	(0%)	1	(0%)	102	(25%)	0	(0%)	1	(0%)	404	(100%)

Table A3.3. Top five countries, cultivated land converted to urban area, 2000–2014 (gross area)

Rank	Country	Cultivated land converted to urban area, km^2
1	China	25,495
2	India	5,591
3	USA	2,237
4	Japan	1,368
5	Italy	1,310

Table A3.4. Top five countries, cultivated land converted to urban area, 2000–2014 (as a share of urban expansion area)

Rank	Country	Share of urban expansion area that was cultivated land in 2000
1	Nepal	89%
2	North Korea	81%
3	Taiwan	79%
4	Myanmar	79%
5	Slovakia	77%

Note: Ranking includes only countries where at least 50 square kilometres of cultivated lands were converted to urban areas between 2000 and 2014.

Table A3.5. Top five countries, forest converted to urban area, 2000–2014 (gross area)

Rank	Country	Forest converted to urban areas, km^2
1	USA	2,762
2	China	1,539
3	Nigeria	1,327
4	India	928
5	Ghana	597

Table A3.6. Top five countries, forest converted to urban area, 2000–2014 (as a share of urban expansion area)

Rank	Country	Share of urban expansion area that was forest in 2000
1	Liberia	80%
2	Cote d'Ivoire	73%
3	Sierra Leone	67%
4	Sri Lanka	64%
5	Senegal	60%

Note: Ranking includes only countries where at least 50 square kilometres of forests were converted to urban areas between 2000 and 2014.

Table A.7. Top Five Countries, Wetlands Converted to Urban Area, 2000–2014 (gross area).

Rank	Country	Wetland converted to urban area, km^2
1	USA	714
2	Nigeria	251
3	China	97
4	India	52
5	Ghana	27

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