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# The number of forest- and tree-proximate people

## A new methodology and global estimates




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# The number of forest- and tree-proximate people

## A new methodology and global estimates

### Background Paper for The State of the World's Forests 2022 report

by

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# Abbreviations and acronyms

| | |
|---|---|
| **CGLC** | Copernicus Global Land Cover |
| **CPF** | Collaborative Partnership on Forests |
| **ESRI** | Environmental Systems Research Institute |
| **FAO** | Food and Agriculture Organization of the United Nations |
| **FPP** | forest-proximate people |
| **GCS** | Global Core Set of Forest-related Indicators |
| **GEE** | Google Earth Engine |
| **HRSL** | High Resolution Settlement Layer |
| **IFRI** | International Forestry Resources and Institutions |
| **LandSat** | land remote-sensing satellite |
| **MODIS** | moderate-resolution imaging spectroradiometer |
| **NGO** | non-governmental organization |
| **UNSPF** | United Nations Strategic Plan for Forests 2030 |

# Executive summary

Forests cover more than 30 percent of the Earth's surface and provide a diverse array of benefits to people around the world. There are also billions of trees that grow outside forests, including trees on farms, in cities, along roads and in many other locations that are not considered a forest. Mapping the spatial relationship between forests, trees and the people that live in and around them is key to understanding human–environment interactions. Evidence on the number and spatial distribution of people living within or near forests and trees outside forests may help decision-makers to target projects, programmes and strategies in priority areas, and to estimate the numbers of people that will be affected or have been affected as a result of an intervention.

The 2030 Agenda and the United Nations Strategic Plan for Forests 2030 (UNSPF) were the cornerstones for the Collaborative Partnership on Forests (CPF) in developing a concise Global Core Set of Forest-related Indicators (GCS). The Food and Agriculture Organization of the United Nations (FAO) has been leading on the development of some indicators, including the GCS indicator indicator No. 13: Number of forest-dependent people in extreme poverty. As a first step towards providing an estimate for this indicator, we developed a new methodology to quantify and map the number of people living in and around forests (forest-proximate people). We also estimated the number of people living outside urban areas close to trees outside forests (tree-proximate people). Estimations were produced by: i) combining forest cover and human population density data to map the spatial relationship between people and forests; and ii) combining tree cover, agricultural land cover and human population density data to map the spatial relationship between people and trees outside forests.

We estimated that 3.27 billion and 4.17 billion people outside urban areas lived within 1 km and 5 km, respectively, of a forest with a minimum size of 1 ha in 2019. These forest-proximate people correspond to 75 percent and 95 percent of the global non-urban population, respectively and to 42 percent and 54 percent of the total global population, respectively. We estimated that 3.5 billion people lived outside urban areas and within 1 km of agricultural lands (i.e. croplands plus grazing land) with at least 10 percent tree cover and a minimum size of 1 ha in 2019, and that 2.89 billion people lived outside urban areas and within 1 km of croplands (i.e. a subset of agricultural lands where crops are grown) with at least 10 percent tree cover and a minimum size of 1 ha in 2019. These tree-proximate people correspond to 80 percent and 66 percent of the global non-urban population, respectively. The vast majority of forest-proximate and tree-proximate people lived in low- and middle-income countries.

Our results shed new light on the spatial relationship between people, forests and trees, and suggest the importance of taking forests into consideration when designing poverty eradication strategies and developing sustainable landscapes. This work has also demonstrated a methodology that can be readily used to produce updated estimates based on publicly available data.

# 1. Introduction

## 1.1. THE IMPORTANCE AND DIVERSITY OF RELATIONSHIPS BETWEEN PEOPLE, FORESTS AND TREES

Forests cover 31 percent of the Earth's surface (FAO, 2020a) and provide a diverse array of benefits, services and values for human societies around the world on local to global scales. For example, forest ecosystems harbour the majority of terrestrial biodiversity, and contribute to the regulation of the global carbon cycle and climate change mitigation (Seymour and Busch, 2016). They also support the subsistence livelihoods of many people, including as a source of food, fuel, fodder and construction materials (Angelsen *et al.*, 2014; Byron and Arnold, 1999; Newton *et al.*, 2016). They also provide income-generating opportunities, including through the sale of timber, charcoal, medicinal products and food. Forests in many places have cultural significance, with aesthetic, recreational and spiritual value in many cultural and societal contexts. Many of the benefits of forests accrue primarily to people who live near them, but some benefits (e.g. timber) are also enjoyed by people living far from forests.

There are also billions of trees around the world that grow outside forests (Brandt *et al.*, 2020). These trees outside forests include trees on farms, in cities, along roads and in many other locations that are not considered a forest. They form part of agroforestry systems, home gardens, urban parks and isolated or small patches of trees. Trees outside forests are prevalent. In 2010, 43 percent of all agricultural land had at least 10 percent tree cover (Zomer *et al.*, 2016). In 2020, the Food and Agriculture Organization of the United Nations (FAO) estimated that there were at least 162 million ha of land with tree cover not classified as forests, based on reports from fewer than half of the world's countries (FAO and UNEP, 2020). Trees outside forests also make important contributions to human well-being and the wider environment. For example, trees outside forests on agricultural land can provide crop protection, carbon sequestration, conservation benefits and shade for livestock (Atangana *et al.*, 2014; Gordon, Newman and Coleman, eds., 2018).

Relationships between people, forests and trees are many and varied. They include the panoply of ways in which forests support human livelihoods, including by providing food and fuel, generating ecosystem services, and contributing to livelihoods and culture. They also include the many ways in which human activities affect forest and tree cover and forest ecology, including through deforestation and degradation, as well as through conservation and restoration. Critically, relationships between people, forests and trees also include the ways in which forests and trees can help alleviate poverty or serve as a safety net, not least because many people living in and around forests are living in poverty (Sunderlin, Dewi and Puntodewo, 2007; Wunder, 2001; Miller, Mansourian and Wildburger, eds., 2020).

## 1.2. THE NEED TO QUANTIFY AND MEASURE THE SPATIAL RELATIONSHIPS BETWEEN PEOPLE, FORESTS AND TREES

Mapping the spatial relationship between forests, trees and the people that live in and around them is key to understanding human–environment interactions. First, quantifying spatial relationships between humans and forests and trees outside forests can help decision makers develop spatially explicit conservation and sustainable development indicators and policies to target priority areas (Ellis and Ramankutty, 2008; Ferraro *et al.*, 2015; Waldron *et al.*, 2013). For example, many national and international governmental agencies, non-governmental organizations (NGOs) and donors concerned with forest conservation and development policies and programmes have launched initiatives that aim to improve the livelihoods of people living in and around forests and/or to change how people use forests and trees outside forests. Similarly, many donors and project implementers seek to quantify the impacts of projects designed to support the livelihoods of people living within intervention areas (Miller, Rana and Benson Wahlén, 2017).

Forests are also under increasing stress from anthropogenic and biophysical drivers (Oldekop *et al.*, 2020) and are central to global and national climate change mitigation efforts. This includes the deforestation that occurs when converting land for agricultural use (Buchadas *et al.*, 2022) and increasing wildfires (Halofsky, Peterson and Harvey, 2020) on the one hand, as well as increases in forest cover resulting from rapidly expanding climate change mitigation efforts on the other (Erbaugh *et al.*, 2020). Quantifying spatial relationships can help identify at-risk human populations, or those affected by forest changes (both positive and negative).

Evidence on the number and spatial distribution of people living within or near forests and trees outside forests may, therefore, support decision-makers to: 1) target projects in priority areas; 2) prioritize among alternative sites; 3) reduce the cost of achieving environmental or socio-economic objectives; 4) improve the effectiveness of monitoring, including by estimating the numbers of people who will be affected or have been affected as a result of an intervention or have been affected by biophysical changes to forests (e.g. deforestation, fire or floods); and/or 5) more effectively and assuredly reaching target populations.

Scholars have produced some data on the spatial relationships between people and forests. For example, Newton *et al.* (2020) estimated that 1.6 billion people lived within 5 km of a forest in rural areas globally in 2012. And Chao (2012) provided multiple coarse estimates of the number of forest-dependent people globally. However, these estimates are not up to date and did not use publicly available data, which enables easy replication. In contrast, little is known about the extent of trees outside forests and the number of people who use them to support their livelihoods and well-being globally. This paucity of knowledge may help explain the limited regard for trees outside forests in research and policy (Miller, Muñoz-Mora and Christiaensen, *et al.*, 2017).

## 1.3. CONCEPTS AND DEFINITIONS OF FOREST DEPENDENCE, FOREST PROXIMITY AND TREE PROXIMITY

***Forest dependence***

The term "forest-dependent people" is widely used to describe human populations that gain benefits from forests (Byron and Arnold, 1999; Newton *et al.*, 2016; Levers *et al.*, 2021). The term "forest-reliant people" is sometimes used as a synonym (e.g. Jagger *et al.*, 2022). In low- and middle-income countries, the term is often used to describe indigenous people and local communities living in or close to forests, though it can also be used to describe urban populations relying on forest products (e.g. wood fuel). In high-income countries, the term often describes people and/or communities that rely on forest-related industries (e.g. timber) for employment (Hajjar *et al.*, 2014). Given the multidimensional nature of forest dependency, the operationalization and estimation of a single, universal definition of forest-dependent people is extremely challenging.

***Forest proximity***

The term "forest-proximate people" refers to humans who live in or near forests (Newton *et al.*, 2020). In many contexts and for many (though not all) researchers and decision makers, forest proximity is an important but insufficient dimension of forest dependency (Newton *et al.*, 2016; Newton *et al.*, 2020). It is possible to live near a forest and not meaningfully rely on that forest for one's livelihood. Understanding the number and spatial distribution of forest-proximate people may be a useful step towards quantifying the number and spatial distribution of at least some forest-dependent people.

***Tree proximity***

The term "tree-proximate people" refers to people living near or within areas with trees on agricultural lands or lands that are not otherwise considered forests. "Trees outside forests" refers to trees within the agricultural landscape, including agroforestry, orchards, small woodlots on farms and other unmanaged trees on farms. Other definitions of trees outside forests include trees in cities and other locations that are not otherwise classified as forest areas. Here we focus on trees outside forests in rural areas (i.e. those areas not considered urban), particularly those areas that can be considered farm or agricultural land. Tree-proximate people may also be forest-proximate, and vice versa.

## 1.4. RESEARCH QUESTIONS

The 2030 Agenda and the United Nations Strategic Plan for Forests 2030 (UNSPF) were the cornerstones for the Collaborative Partnership on Forests (CPF) in developing a concise Global Core Set of Forest-related Indicators (GCS), a set of 21 indicators on the economic, social and environmental dimensions of sustainability. The GCS include a limited number of indicators that efficiently and comprehensively address the topics identified in high-level political commitments and serve countries to report international forest-related commitments and goals. One such indicator is GCS indicator No. 13: Number of forest-dependent people in extreme poverty. As a first step towards estimating this indicator, we address two closely related research questions: 1) How many people live in and around forests? 2) How many people live close to trees outside forests? To answer these questions, we developed a new methodology to quantify and map the number of people living in and around forests (forest-proximate people). We also estimated the number of people living close to trees outside forests (tree-proximate people). We note that these estimates do not in and of themselves provide evidence on the poverty dimension of the GCS Indicator No. 13; some forest-proximate or forest-dependent people may be in poverty or extreme poverty while others may not. While this analysis provides information necessary for GCS Indicator No. 13, it does not reveal anything about the proportion of forest-proximate people who live in poverty.

# 2. Methods

On a global scale, we generated spatial overlays using a distance buffer of: 1) forest cover and human population density data to map the spatial relationship between people and forests; and 2) tree cover, agricultural land cover and human population density data to map the spatial relationship between people and trees outside forests.

## 2.1. DATASETS

***Forest and tree cover***

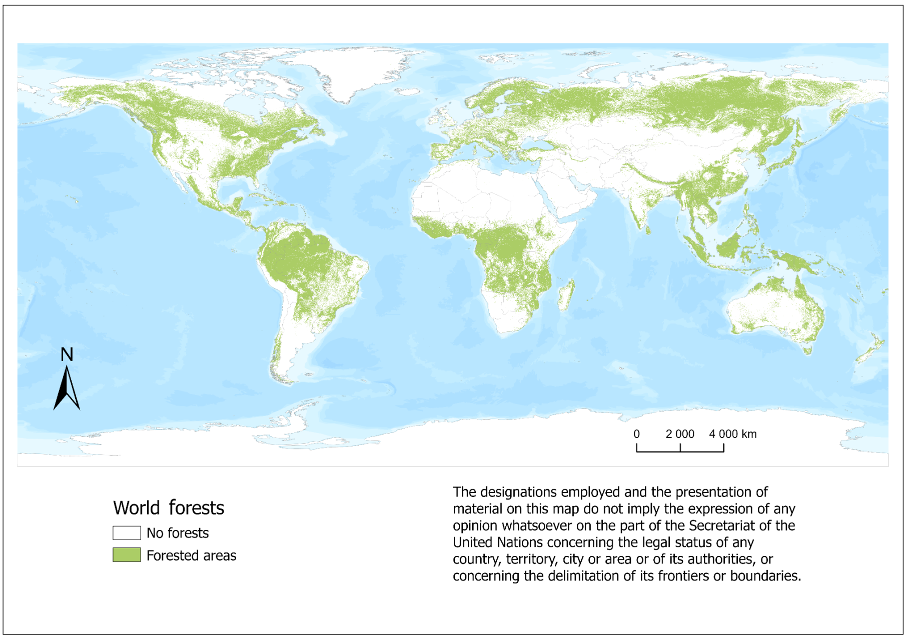
We used 100 m resolution global tree cover data from Copernicus Global Land Cover (CGLC) (Buchhorn *et al.*, 2020) for both analyses. The CGLC dataset is a global-scale, 100 m resolution land cover dataset and provides the best publicly available tree cover dataset for estimating the number of forest-proximate people. The data are available annually from 2015 onwards and differentiate between various forest cover classes. The CGLC product contains three relevant datasets: 1) a discrete land cover classification map using 23 classes (including 12 forest types); 2) fractional cover layers that provide the percentages of ten land cover classes in each pixel (including a percent forest cover land class that shows the percent tree cover, 0–100 percent, present in each pixel); and 3) a forest type data layer that provides discrete values for each of six forest types for all pixels where the tree cover fraction exceeds 1 percent (Buchhorn *et al.*, 2020). We used the first dataset, the discrete land cover classification map, to determine forest cover.

Other publicly available datasets have various limitations that make them less suitable than the CGLC data (Appendix 1). For example, the Landsat (land remote-sensing satellite system) based Global Forest Watch data (Hansen *et al.*, 2013) do not capture tree cover gains after 2012; the Moderate Resolution Image Spectrometer (MODIS) data have coarse (250–500 m) spatial resolution; and the recently released Environmental Systems Research Institute (ESRI) 2020 Land Cover data and the GlobeLand30 data have poor temporal resolution. The ESRI 2020 Land Cover dataset also has a restrictive definition of tree cover, defining tree cover as areas with dense, closed-canopy, tall (15 m or higher) vegetation. A more complete review of a range of alternative datasets is in Appendix 1.

For forests, we first created a global forest cover map (Figure 1) for the year 2019 by selecting all open and closed forest cover classes from the CGLC dataset (Appendix 1). We used the CGLC definition of forest cover (tree cover, ranging from 15 to 100 percent, with or without an understory of shrubs and grassland, and including both open and closed forests), and defined a forest as any area of tree cover ≥ 1 ha (1 pixel). This definition of forest differs from the one used by FAO by including tree stands in agricultural production systems, such as fruit tree plantations, oil palm plantations, olive orchards and agroforestry systems when crops are grown under tree cover, and by excluding temporarily unstocked forest areas, and a higher minimum tree cover density and area threshold (FAO, 2020b), among other factors.

For trees outside forests, we used the CGLC fractional tree cover dataset for the year 2019 and selected all fractional tree cover greater than 10 percent (see Appendix 1). We excluded tree cover that was otherwise classified as forest in the CGLC product (where forests were defined by tree cover greater than 15 percent with an understory layer or as a closed canopy with greater than 70 percent tree cover) (see Appendix 1). This definition differs from the one used by FAO, which defines "trees outside forests" as all trees excluded from FAO's definition of forest and other wooded lands.

**Figure 1. Global forest cover in 2019**




***Note*:** Forested areas (forest is defined as areas with >15% tree cover in 2019): tree cover data from 100 m CGLC fractional tree cover data for the year 2019.

***Source*:** Buchhorn, M., Smets, B., Bertels, L., De Roo, B., Lesiv, M., Tsendbazar, N.E., Herold, M. & Fritz, S. 2020. Copernicus Global Land Service: Land Cover 100m: collection 3: epoch 2019: Globe. In: *Zenodo*. Cited October 2021. https://doi.10.5281/zenodo.3939050

***Human population density***

We used 100 m resolution WorldPop global population density data for 2019 (WorldPop, 2021). WorldPop is a high-resolution population density estimate generated using machine learning approaches that disaggregate recent census data for administrative units using relationships with various geospatial covariate layers. Alternative datasets are compared in Appendix 2.

***Agricultural land cover***

We used 500 m resolution agricultural land cover data from MODIS Land Cover (MCD12Q1.006) (Friedl and Sulla-Menashe, 2015) for our primary analysis because it is linked to FAO land use classifications, rather than land cover classifications, and the coarser spatial resolution is more likely to capture trees outside forests in the agricultural land matrix. However, we also use the CGLC data as a sensitivity analysis (see below). We used the FAO-LCCS2 land use classification layer from MODIS Land Cover dataset, and we defined cropland as the sum of three classifications: 1) herbaceous croplands: dominated by herbaceous annuals (<2 m) with at least 60 percent cover and a cultivated fraction of >60 percent; 2) natural herbaceous/croplands mosaics: mosaics of small-scale cultivation 40–60 percent with natural shrub or herbaceous vegetation; and 3) forest/cropland mosaics: mosaics of small-scale cultivation 40–60 percent with >10 percent natural tree cover. We defined potential grazing land as the classification: natural herbaceous: dominated by herbaceous annuals (<2 m) with at least 10 percent cover. We defined agricultural land as the sum of the four classifications (i.e. cropland plus potential grazing land). Any pixel classified as agricultural per these definitions was included in the agricultural land cover data layer from which we identified trees on agricultural lands. While using herbaceous cover as a proxy for grazing lands was the best available option using these data, this assumption generates an overestimate of grazing lands since not all land with herbaceous cover is grazed. The cropland extent data is more accurate than the grazing extent. We present results for both agricultural land (cropland plus potential grazing land) and for cropland only. This definition of agricultural lands differs from the one used by FAO by excluding tree stands in agricultural production systems, such as fruit tree plantations, oil palm plantations, olive orchards and agroforestry systems when crops are grown under tree cover, which in this study are considered forests.

## 2.2. ANALYSIS

We generated spatial overlays that identified population subsets: 1) living in or close to forests in 2019; and 2) near agricultural lands with trees outside forests in 2019. We used Google Earth Engine (GEE) for our analysis because GEE is free to use and widely accessible, and because it already hosts the datasets we used. These data are all publicly available and can be used to update our estimates when new data become available (see "Data & Code Availability").

*Rural areas*

We focused on people living in rural areas, excluding urban areas from our analyses. We defined urban areas as any contiguous area with a total population of at least 50 000 people and comprised of pixels meeting at least one of two criteria: either the pixel 1) had at least 1 500 people per square km, or 2) was classified as "built-up" land use by the CGLC dataset (where "built-up" was defined as land covered by buildings and other manmade structures) (Dijkstra *et al.*, 2020). We take this definition from the "Degree of Urbanization" approach to defining urban centres (Dijkstra *et al.*, 2020), which is consistent with other definitions of urban centres (Cattaneo, Nelson and McMenomy, 2021; FAO, 2018; OECD, 2012; Pesaresi *et al.*, 2019). Cattaneo, Nelson and McMenomy (2021) considered contiguous areas with a total population of 20 000 people as urban, and we tested this alternative definition as a sensitivity analysis. All sensitivity analyses are reported in the Results section.

*Trees outside forests on agricultural lands*

For trees outside forests on agricultural lands, we identified trees within the agricultural landscape using the general approach taken by Zomer *et al.* (2016). They used 250 m resolution MOD44B MODIS Vegetation Continuous Field (2000–2010) Percent Tree Cover data aggregated to 1 km resolution to generate a percent tree cover data layer for the years 2000 and 2010. They then masked the percent tree cover layer with an agricultural land data layer for the year 2000. They defined agricultural lands at a 1 km resolution using the Global Land Cover 2000 database classes: 1) cultivated and managed areas; 2) cropland/other natural vegetation; and 3) cropland/mixed tree cover mosaic.

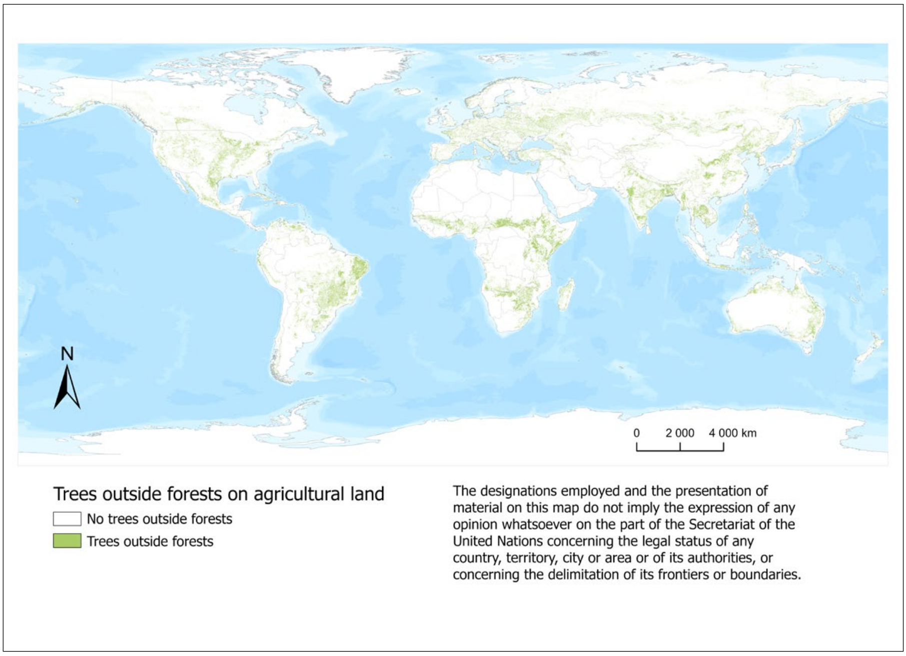
We deviated from this approach by using the most recent, highest resolution fractional tree cover data available. Specifically, we used the 100 m CGLC fractional tree cover data for the year 2019 with the 500 m MODIS Land Cover dataset for 2019. The CGLC fractional tree cover layer was masked by the MODIS agricultural (or cropland) land cover to exclude non-agricultural areas and create an estimate of trees outside forests on agricultural lands (or croplands) (Figure 2 and Figure 3).

*Proximity*

For our estimates of forest-proximate people, we used a Euclidean distance measure to create a 1 km and 5 km buffer zone around each forest cover pixel. There is no established definition of forest proximity, so we report estimates for both 1 km and 5 km. There is some precedence for 5 km, from the methodology deployed in hundreds of sites globally by the International Forestry Resources and Institutions (IFRI) research network, which records the number of people who "reside in or very close to the forest(s) (within 5 km)" (IFRI, 2011). Analyses for both distances serve as a sensitivity analysis to understand the effects of buffer distance on our estimates. Populations living in high density urban areas were masked from the forest-proximate people proximity analysis.

For our estimates of tree-proximate people, we used a Euclidean distance measure to create a 500 m, 1 km, and 5 km buffer zone around each pixel with trees outside forests. We then calculated the population living within those buffers and summed the total for each country. We present the results using a 1 km buffer distance and include the results using the different buffer distances to serve as a sensitivity analysis. Populations living in high density urban areas were masked from the tree-proximate people proximity analysis.

**Figure 2. Global trees outside forests on agricultural lands in 2019**



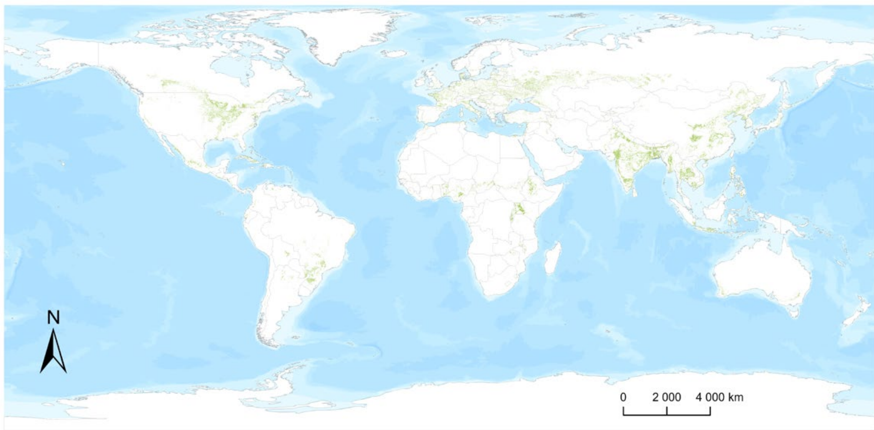

***Note***: Trees outside forests: tree cover data from the 100 m CGLC fractional tree cover data for the year 2019.

***Source***: Buchhorn, M., Smets, B., Bertels, L., De Roo, B., Lesiv, M., Tsendbazar, N.E., Herold, M. & Fritz, S. 2020. Copernicus Global Land Service: Land Cover 100m: collection 3: epoch 2019: Globe. In: *Zenodo*. Cited October 2021. https://doi.10.5281/zenodo.3939050

***Note***: Agricultural land: land cover data from the 500 m MODIS Land Cover Type dataset (MCD12Q1) for 2019.

***Source***: Friedl, M. & Sulla-Menashe, D. 2015. MCD12Q1 MODIS/Terra+Aqua Land Cover Type Yearly L3 Global 500m SIN Grid V006. NASA EOSDIS Land Processes DAAC. In: *USGS (United States Geological Survey)*. Cited October 2021. https://doi.org/10.5067/MODIS/MCD12Q1.006

**Figure 3. Global trees outside forests on croplands in 2019**




***Note***: Trees outside forests on croplands: tree cover data from the 100 m CGLC fractional tree cover data for the year 2019.

***Source***: Buchhorn, M., Smets, B., Bertels, L., De Roo, B., Lesiv, M., Tsendbazar, N.E., Herold, M. & Fritz, S. 2020. Copernicus Global Land Service: Land Cover 100m: collection 3: epoch 2019: Globe. In: *Zenodo*. Cited October 2021. https://doi.10.5281/zenodo.3939050

***Note***: Croplands: land cover data from the 500 m MODIS Land Cover Type dataset (MCD12Q1) for 2019.

***Source***: Friedl, M. & Sulla-Menashe, D. 2015. MCD12Q1 MODIS/Terra+Aqua Land Cover Type Yearly L3 Global 500m SIN Grid V006. NASA EOSDIS Land Processes DAAC. In: *USGS (United States Geological Survey)*. Cited October 2021. https://doi.org/10.5067/MODIS/MCD12Q1.006

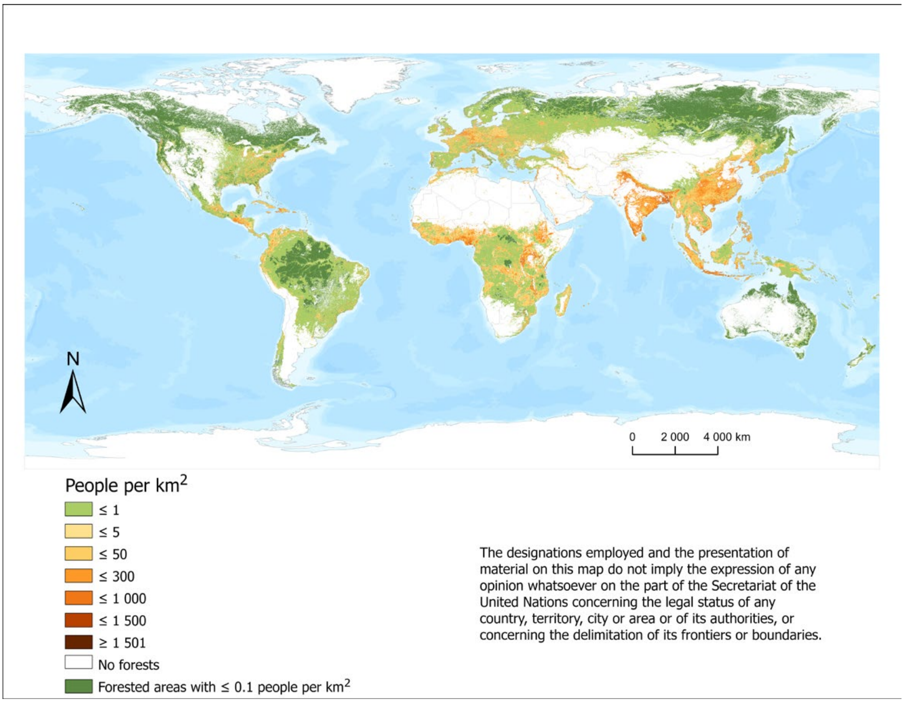
# 3. Results

## 3.1. ESTIMATES, MAPS AND SENSITIVITY ANALYSES OF FOREST-PROXIMATE PEOPLE

Globally, 3.27 billion and 4.17 billion people lived outside urban areas and within 1 km and 5 km, respectively, of a forest (minimum 1 ha) in 2019 (Figure 4). The world's total population (based on WorldPop data) in 2019 was 7.79 billion people. Of these, 4.38 billion people (56 percent) lived outside urban areas. Of those people who lived outside urban areas, the percentage of people who lived within 1 km and 5 km of a forest (minimum 1 ha) was 75 percent and 95 percent, respectively. The distribution of these people by region and subregion is indicated in Table 1 and Table 2, respectively.

Of the 3.27 billion people who lived outside urban areas and within 1 km of a forest in 2019, 2.74 billion lived in low-income, lower-middle-income or upper-middle-income countries, as classified by the World Bank, while 528 million lived in countries classified as high-income (the remaining 2.04 million lived in territories not included in the World Bank's classification system). The distribution of forest-proximate people by World Bank income category is indicated in Table 3. Of the 4.17 billion people who lived outside urban areas and within 5 km of a forest in 2019, 3.61 billion lived in low-income, lower-middle-income or upper-middle-income countries, while 552 million lived in high-income countries (the remaining 2.09 million lived in territories not included in the World Bank's classification system).

**Figure 4. Forest-proximate people. Number of people living outside urban areas and within 5 km of a ≥1 ha forest in 2019**




***Note:*** People per km². Forested areas (forest is defined as areas with >15% tree cover) and tree cover data from the 100 m CGLC fractional tree cover data for the year 2019.

***Source:*** WorldPop (2021). Buchhorn, M., Smets, B., Bertels, L., De Roo, B., Lesiv, M., Tsendbazar, N.E., Herold, M. & Fritz, S. 2020. Copernicus Global Land Service: Land Cover 100m: collection 3: epoch 2019: Globe. In: *Zenodo*. Cited October 2021. https://doi.10.5281/zenodo.3939050

TABLE **1**.
## Number of people living outside urban areas and within 1 km or 5 km of a forest ≥1 ha in 2019, subdivided by region

| Region | Number of people living outside urban areas and within x km of a forest ≥1 ha in 2019 | |
|---|---|---|
| | 1 km | 5 km |
| Africa | 572 137 442 | 719 524 627 |
| Asia | 1 883 003 640 | 2 590 448 825 |
| Europe | 388 352 892 | 399 172 871 |
| North and Central America | 261 112 381 | 274 051 044 |
| Oceania | 15 509 762 | 15 625 783 |
| South America | 149 303 110 | 167 556 307 |
| Total | 3 269 419 227 | 4 166 379 458 |

***Source*** *of regions*: FAO. 2020c. Global Forest Resources Assessment. In: *FAO.* Cited October 2021. https://fra-platform.herokuapp.com/

TABLE **2**.
## Number of people living outside urban areas and within 1 km or 5 km of a forest ≥1 ha in 2019, subdivided by subregion

| Subregion | Number of people living outside urban areas and within x km of a forest ≥1 ha in 2019 | |
|---|---|---|
| | 1 km | 5 km |
| Caribbean | 25 553 440 | 25 987 123 |
| Central America | 30 078 753 | 30 545 787 |
| East Asia | 625 640 067 | 812 057 367 |
| Eastern and Southern Africa | 247 298 202 | 288 102 065 |
| Europe | 388 352 892 | 399 172 871 |
| North America | 205 480 187 | 217 518 134 |
| Northern Africa | 58 612 464 | 99 628 647 |
| Oceania | 15 509 762 | 15 625 783 |
| South America | 149 303 110 | 167 556 307 |
| South and South-east Asia | 1 159 044 785 | 1 586 432 762 |
| Western and Central Africa | 266 226 776 | 331 793 915 |
| Western and Central Asia | 98 318 788 | 191 958 696 |
| **Total** | **3 269 419 227** | **4 166 379 458** |

***Source*** *of subregions*: FAO. 2020c. Global Forest Resources Assessment. In: *FAO*. Cited October 2021.https://fra-platform.herokuapp.com/

TABLE **3**.
**Number of people living outside urban areas and within 1 km or 5 km of a forest ≥1 ha in 2019, subdivided by 2019 World Bank income classification**

| World Bank income category 2019 | Number of people living outside urban areas and within x km of a forest ≥1 ha in 2019 | |
|---|---|---|
| | 1 km | 5 km |
| High | 523 028 854 | 551 803 677 |
| Lower | 311 119 817 | 388 268 542 |
| Lower-middle | 1 297 926 633 | 1 812 152 418 |
| N/A | 2 040 797 | 2 094 360 |
| Upper-middle | 1 135 303 126 | 1 412 060 460 |
| **Total** | **3 269 419 227** | **4 166 379 458** |

Source of World Bank income classification: World Bank. 2019. World Bank Country and Lending Groups. In: *World Bank*. Cited October 2021. https://datahelpdesk.worldbank.org/knowledgebase/articles/906519-world-bank-country-and-lending-groups

## *Sensitivity analyses*

### *Urban areas*

We ran our analysis using a more expansive definition of urban areas, excluding from our analysis all contiguous areas with a total population of at least 20 000 people (rather than at least 50 000 people, per the original analysis above) as considered by Cattaneo, Nelson and McMenomy (2021). A more expansive definition of urban areas reduced the number of non-urban people included in the subsequent analysis, and generated a more conservative estimate of the number of people living outside urban areas and near to a forest. Using the urban threshold of 20 000 people, we found that 3.95 billion people lived within 5 km of a forest in 2019, compared to the 4.17 billion people who lived within 5 km of a forest in 2019 based on the urban threshold of 50 000 people. A relatively large increase in the threshold for defining urban areas had relatively little impact on the estimates of the number of people living near a forest.

### *Forest definitions*

We ran our analysis using only the closed forest categories in the CGLC dataset and excluding the open forest categories (see Appendix 1). We did this to understand the degree to which the relatively low canopy cover definition of 15 percent for open forests was affecting our estimates. Using this definition of only closed forests (>70 percent tree cover, as defined by CGLC), we found that 3.16 billion people lived outside urban areas and within 5 km of a forest in 2019 when urban areas were defined as contiguous areas with a total population of at least 50 000 people. This number was 2.98 billion people when we used the urban threshold of 20 000 people (instead of 50 000).

*Most conservative estimate*
To generate an estimate using conservative assumptions, we ran an analysis that included only closed forests (>70 percent tree cover), defined urban areas as contiguous areas with a total population of at least 20 000 people (rather than 50 000 people), and a distance to forest cutoff of 1 km (rather than 5 km). Using these parameters, we found that 1.95 billion people lived outside urban areas and within 1 km of a closed forest in 2019.

## 3.2. ESTIMATES, MAPS AND SENSITIVITY ANALYSES OF TREE-PROXIMATE PEOPLE

An estimated 3.5 billion people across the world lived outside urban areas and within 1 km of agricultural land (cropland plus potential grazing land) with trees outside forests of at least 1 ha in 2019 (Figure 5). Globally, 2.89 billion people lived outside urban areas and within 1 km of cropland (excluding potential grazing land) with trees outside forests of at least 1 ha in 2019 (Figure 6). The distribution of these people by region and subregion is indicated in Table 4 and Table 5, respectively. Of those people who lived outside urban areas, the percentage of people who lived within 1 km of trees outside forests on agricultural land and of trees outside forests on cropland (minimum 1 ha) was 80 percent and 66 percent, respectively.

TABLE **4**.
**Number of people living outside urban areas and within 500 m or 1 km of ≥1 ha of agricultural land or cropland with ≥10 percent tree cover in 2019, subdivided by region**

| Region | Number of people living outside urban areas and within 500 m of ≥1 ha land with ≥10% tree cover in 2019 | | Number of people living outside urban areas and within 1 km of ≥1 ha land with ≥10% tree cover in 2019 | |
|---|---|---|---|---|
| | Agricultural land | Crop land | Agricultural land | Crop land |
| Africa | 431 044 201 | 252 685 717 | 538 475 524 | 340 856 697 |
| Asia | 1 964 955 915 | 1 781 626 910 | 2 315 709 501 | 2 126 250 287 |
| Europe | 256 831 497 | 185 969 399 | 339 253 493 | 255 853 249 |
| North and Central America | 133 298 437 | 89 291 313 | 178 721 482 | 121 867 806 |
| Oceania | 5 706 463 | 1 331 448 | 8 517 867 | 2 425 283 |
| South America | 88 949 073 | 25 867 215 | 123 283 661 | 43 124 592 |
| **Total** | **2 880 785 586** | **2 336 772 002** | **3 503 961 528** | **2 890 377 914** |

Source of regions: FAO. 2020c. Global Forest Resources Assessment. In: *FAO*. Cited October 2021. https://fra-platform.herokuapp.com

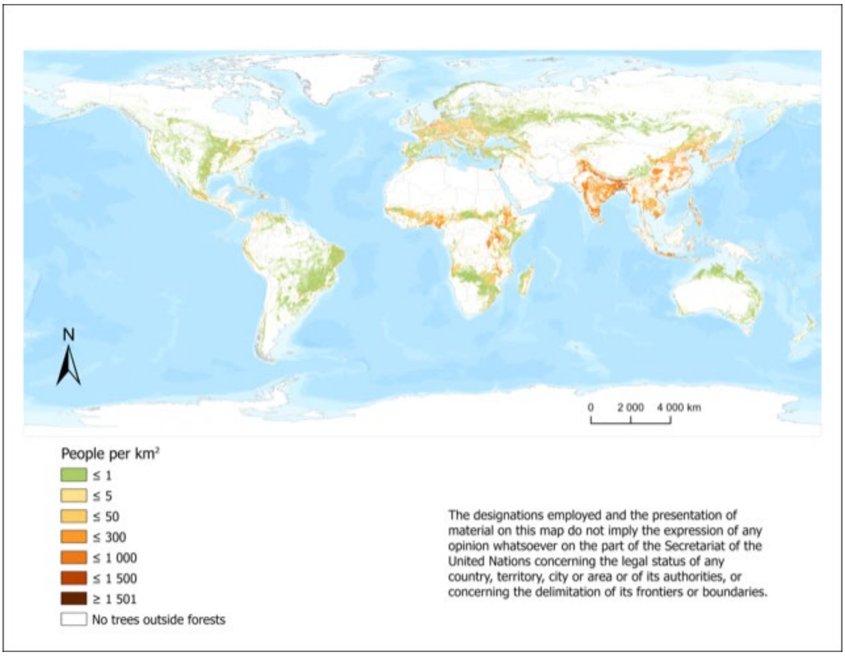
TABLE **5.**

**Number of people living outside urban areas and within 500 m or 1 km of ≥1 ha of agricultural land or cropland with ≥10 percent tree cover in 2019, subdivided by subregion**

| Subregion | Number of people living outside urban areas and within 500 m of ≥1 ha land with ≥10% tree cover in 2019 | | Number of people living outside urban areas and within 1 km of ≥1 ha land with ≥10% tree cover in 2019 | |
|---|---|---|---|---|
| | Agricultural land | Crop land | Agricultural land | Crop land |
| Caribbean | 15 623 077 | 11 805 517 | 19 804 551 | 15 314 411 |
| Central America | 9 986 396 | 7 037 137 | 14 571 180 | 10 472 411 |
| East Asia | 577 711 226 | 523 865 053 | 695 465 521 | 642 385 265 |
| Eastern and Southern Africa | 207 577 058 | 103 321 218 | 241 532 662 | 127 679 566 |
| Europe | 256 831 497 | 185 969 399 | 339 253 493 | 255 853 249 |
| North America | 107 688 965 | 70 448 660 | 144 345 751 | 96 080 983 |
| Northern Africa | 60 951 772 | 43 598 559 | 79 221 813 | 58 092 214 |
| Oceania | 5 706 463 | 1 331 448 | 8 517 867 | 2 425 283 |
| South America | 88 949 073 | 25 867 215 | 123 283 661 | 43 124 592 |
| South and South-east Asia | 1 272 734 964 | 1 185 756 152 | 1 464 287 425 | 1 380 318 571 |
| Western and Central Africa | 162 515 370 | 105 765 940 | 217 721 048 | 155 084 917 |
| Western and Central Asia | 114 509 726 | 72 005 705 | 155 956 555 | 103 546 451 |
| **Total** | **2 880 785 586** | **2 336 772 002** | **3 503 961 528** | **2 890 377 914** |

*Source of subregions*: FAO. 2020c. Global Forest Resources Assessment. In: *FAO*. Cited October 2021. https://fra-platform.herokuapp.com

**Figure 5. Tree-proximate people. Number of people living outside urban areas and near trees on agricultural land in 2019**



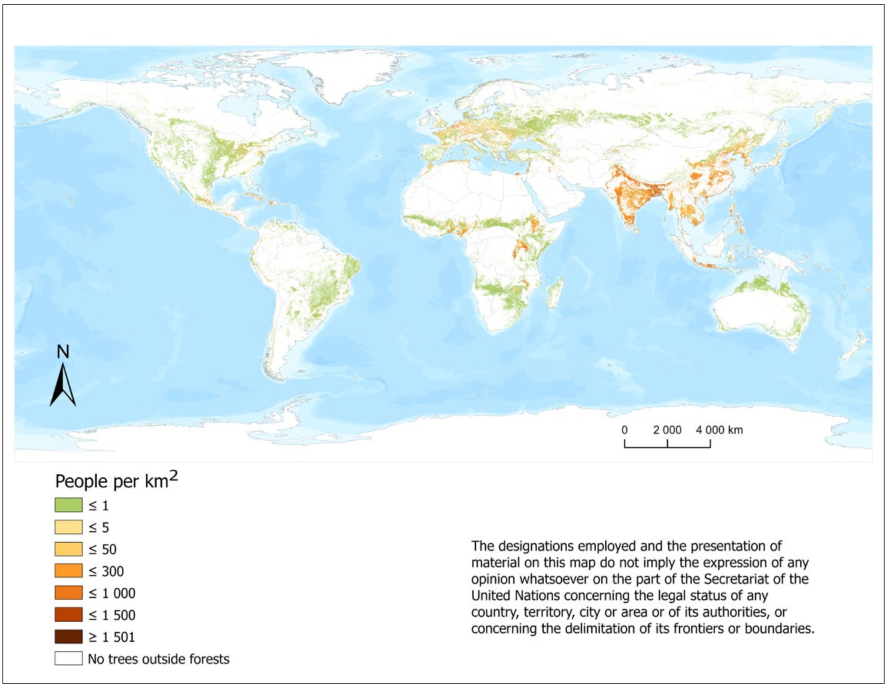

***Note:*** People per km². Trees outside forests: tree cover data from the 100 m CGLC fractional tree cover data for the year 2019.

***Source:*** WorldPop (2021). Buchhorn, M., Smets, B., Bertels, L., De Roo, B., Lesiv, M., Tsendbazar, N.E., Herold, M. & Fritz, S. 2020. Copernicus Global Land Service: Land Cover 100m: collection 3: epoch 2019: Globe. In: *Zenodo*. Cited October 2021. https://doi.10.5281/zenodo.3939050

***Note:*** Agricultural land: land cover data from the 500 m MODIS Land Cover Type dataset (MCD12Q1) for 2019.

***Source:*** Friedl, M. & Sulla-Menashe, D. 2015. MCD12Q1 MODIS/Terra+Aqua Land Cover Type Yearly L3 Global 500m SIN Grid V006. NASA EOSDIS Land Processes DAAC. In: *USGS (United States Geological Survey)*. Cited October 2021. https://doi.org/10.5067/MODIS/MCD12Q1.006

**Figure 6. Tree-proximate people. Number of people living outside urban areas and within 1 km of trees on cropland (excluding potential grazing land) in 2019**




***Note:*** People per km². Trees outside forests: tree cover data from the 100 m CGLC fractional tree cover data for the year 2019.

***Source:*** WorldPop (2021). Buchhorn, M., Smets, B., Bertels, L., De Roo, B., Lesiv, M., Tsendbazar, N.E., Herold, M. & Fritz, S. 2020. Copernicus Global Land Service: Land Cover 100m: collection 3: epoch 2019: Globe. In: *Zenodo*. Cited October 2021. https://doi.10.5281/zenodo.3939050

***Note:*** Cropland: land cover data from the 500 m MODIS Land Cover Type dataset (MCD12Q1) for 2019.

***Source:*** Friedl, M. & Sulla-Menashe, D. 2015. MCD12Q1 MODIS/Terra+Aqua Land Cover Type Yearly L3 Global 500m SIN Grid V006. NASA EOSDIS Land Processes DAAC. In: *USGS (United States Geological Survey)*. Cited October 2021. https://doi.org/10.5067/MODIS/MCD12Q1.006

The distribution of tree-proximate people by World Bank income category is indicated in Table 6. Of the 3.5 billion people who lived outside urban areas and within 1 km of agricultural lands with greater than 10 percent tree cover in 2019, 3.1 billion lived in countries classified as low-income, lower-middle-income, or upper-middle-income by the World Bank, while 403 million lived in countries classified as high-income (the remaining 1.68 million lived in territories not included in the World Bank's classification system). Of the 2.89 billion people who lived outside urban areas and within 1 km of cropland with greater than 10 percent tree cover in 2019, 2.6 billion lived in low-income, lower-middle-income, or upper-middle-income countries, while 292 million lived in high-income countries (the remaining 1.08 million lived in territories not included in the World Bank's classification system).

TABLE 6.
**Number of people living outside urban areas and within 500 m or 1 km of ≥1 ha of agricultural land or cropland with ≥10 percent tree cover in 2019, subdivided by 2019 World Bank income classification**

| World Bank income category 2019 | Number of people living outside urban areas and within x km of ≥1 ha land with ≥10% tree cover in 2019 | | | |
|---|---|---|---|---|
| | 500 m | | 1 km | |
| | Agricultural land | Cropland | Agricultural land | Cropland |
| High | 295 372 455 | 208 956 410 | 403 270 775 | 291 888 714 |
| Lower | 239 447 618 | 136 797 886 | 290 122 053 | 172 047 087 |
| Lower-middle | 1 407 600 361 | 1 253 366 825 | 1 649 420 205 | 1 498 846 358 |
| N/A | 1 327 369 | 698 145 | 1 681 364 | 1 076 730 |
| Upper-middle | 937 037 784 | 736 952 736 | 1 159 467 131 | 926 519 025 |
| **Total** | **2 880 785 586** | **2 336 772 002** | **3 503 961 528** | **2 890 377 914** |

***Source** of World Bank income category*: World Bank. 2019. World Bank Country and Lending Groups. In: *World Bank*. Cited October 2021. https://datahelpdesk.worldbank.org/knowledgebase/articles/906519-world-bank-country-and-lending-groups

### *Sensitivity analyses*

#### *Trees outside forests definitions*

We conducted an additional analysis using fractional tree cover between 1 and 15 percent (rather than between 10 and 15 percent as above) to include all trees on agricultural lands otherwise not classified as forests. We did so to generate a more encompassing estimate where agricultural areas with very low tree cover were included. Using this definition of trees outside forests, we found that 3.64 billion people lived outside urban areas and within 1 km of agricultural land with 1–15 percent tree cover in 2019. For cropland only, this estimate was 2.98 billion people.

#### *Agricultural land definition*

We also conducted an analysis that used the CGLC data as an alternative method for defining agricultural lands. We used the "cultivated and managed vegetation / agriculture" classification to define cropland and the "herbaceous vegetation" classification to define potential grazing lands, which again is an overestimation of grazing lands, since not all land with herbaceous cover is used for grazing. Using CGLC to define agricultural lands (cropland plus potential grazing lands), an estimated 3.96 billion people lived near agricultural land with at least 10 percent tree cover in 2019. For cropland only, this estimate was 2.86 billion people.

*Buffer distance*

Finally, we ran the analyses using a 500 m and 5 km buffer distance instead of the 1 km buffer distance. Using the 500 m buffer distance, we estimated that 2.88 billion people lived near agricultural land with at least 10 percent tree cover. Using the 5 km buffer distance, we estimated that 4.21 billion people lived near agricultural land with at least 10 percent tree cover.

# 4. Discussion

## 4.1. SUMMARY OF RESULTS

We estimated that 3.27 billion and 4.17 billion people lived outside urban areas and within 1 km and 5 km, respectively, of a forest of a minimum size of 1 ha in 2019. These numbers correspond to 75 percent and 95 percent of the global non-urban population, respectively. That is, we found that a large majority of people living outside urban areas lived near a forest. Of these people, the vast majority (3.61 billion or 87 percent of the total 4.17 billion) lived in low- and middle-income countries.

We estimated that 3.5 billion people lived outside urban areas and within 1 km of agricultural lands with at least 10 percent tree cover and a minimum size of 1 ha in 2019, and that 2.89 billion people lived outside urban areas and within 1 km of croplands with at least 10 percent tree cover and a minimum size of 1 ha in 2019. These numbers correspond to 80 percent and 66 percent of the global non-urban population, respectively. That is, we found that a large majority of people living outside urban areas lived near agricultural lands with trees. Of these people, the vast majority (3.09 billion or 88 percent of the total 3.5 billion) lived in low and middle income countries.

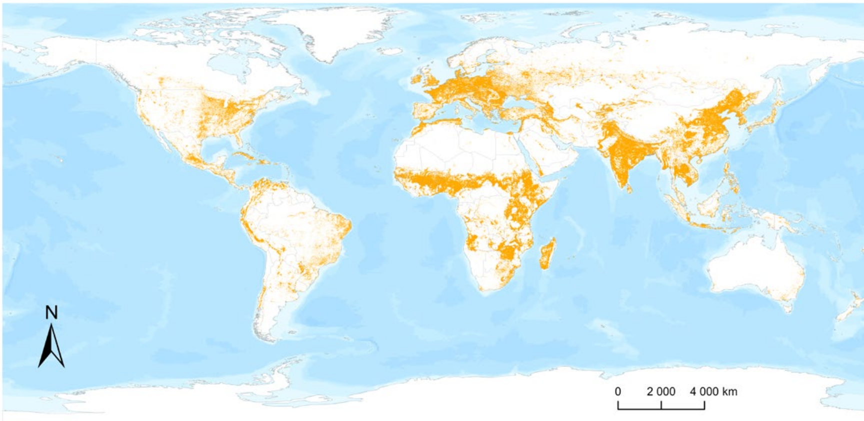
## 4.2. IMPLICATIONS FOR UNDERSTANDING THE RELATIONSHIPS BETWEEN FORESTS, TREES AND PEOPLE

Our results shed new light on the spatial relationship between people, forests and trees, and our methodology can be readily used to produce updated estimates based on publicly available data. Our estimate is considerably higher than some previous estimates (e.g. 1.60 billion people within 5 km of a forest in rural areas in 2012 [Newton *et al.*, 2020]). Further, we provide the first global scale estimate of people in rural areas living near trees outside forests. Putting people's relationships to both forests and trees in the same frame (Figure 7) enables a more complete picture of the relevance and potential importance of trees (both in and outside forests) and the goods and services they provide to people. Doing so can help raise awareness among the general public, policymakers and researchers about these relationships. Such awareness and understanding are particularly salient in the context of national and global initiatives to conserve and restore forests, mitigate climate change, reduce poverty and support the livelihoods of rural people, including recent financial commitments made by international donors at the 26th United Nations Climate Change Conference of the Parties (COP26) in Glasgow, 2021.

Many people living in and around forests live in poverty (Sunderlin *et al.*, 2007). Further, the GCS Indicator that motivated this work is concerned with the number of forest-dependent people living in poverty. Poverty among forest-dependent people can manifest both as low income and/or poor access to infrastructure and services. As such, poverty metrics that include both income thresholds and multidimensional poverty indices can both be useful ways of measuring and monitoring poverty among forest-proximate people. Our data do not reveal anything about the number or proportion of forest- or tree-proximate people who are poor. But the interrelationships between forests and poverty are complex and dynamic, and forests can play important roles in the lives of the rural poor (Miller, Mansourian and Wildburger, eds., 2020; Wunder, 2001). Further, forest policies and programmes can help to alleviate poverty among forest-dependent people (Hajjar *et al.*, 2021). Understanding the number of people living in and around forests, which will likely include many people who are living in poverty, may thus serve to motivate governments and other stakeholders to include forests in their poverty alleviation strategies.

The number of people living in and around forests, and near to trees on agricultural land, could change because of demographic or biophysical dynamics. Demographically, rural–urban migration, changes in birth and death rates, low-density urban sprawl, and other drivers of changes to population dynamics, could increase or decrease the number of forest- and tree-proximate people (Oldekop *et al.*, 2020). Biophysically, deforestation, reforestation, tree-planting on farmland, fires and other drivers of tree cover change could similarly increase or decrease the number of forest- and tree-proximate people. Many of these dynamics may in turn be influenced by policies, programmes and strategies implemented by governmental agencies, NGOs, communities, or the private sector. For example, protected areas, REDD+ and other payments for environmental services programmes, reforestation projects, poverty alleviation initiatives, or programmes that incentivize or prohibit agricultural expansion could all affect the relative spatial distribution of forests, trees and people.

**Figure 7. Overlap of forest-proximate people and tree-proximate people on agricultural lands in 2019**




***Note:*** FPP = forest-proximate people; TPP = tree-proximate people.
People per km2. Forested areas and trees outside forests: (forest is defined as areas with >15% tree cover) and tree cover data from 100 m CGLC fractional tree cover data for the year 2019.
***Source:*** WorldPop (2021). Buchhorn, M., Smets, B., Bertels, L., De Roo, B., Lesiv, M., Tsendbazar, N.E., Herold, M. & Fritz, S. 2020. Copernicus Global Land Service: Land Cover 100m: collection 3: epoch 2019. Globe. In: *Zenodo*. Cited October 2021. https://doi.org/10.5281/zenodo.3939050
***Note:*** Agricultural land: land cover data from the 500 m MODIS Land Cover Type dataset (MCD12Q1) for 2019.
***Source:*** Friedl, M. & Sulla-Menashe, D. 2015. MCD12Q1 MODIS/Terra+Aqua Land Cover Type Yearly L3 Global 500m SIN Grid V006. NASA EOSDIS Land Processes DAAC. In: *USGS (United States Geological Survey)*. Cited October 2021. https://doi.org/10.5067/MODIS/MCD12Q1.006

## 4.3. STRENGTHS OF THE METHODS

The data and methods we used to generate these estimates have several strengths. These strengths include their replicability, and the possibility of building on them with additional data layers.

Foremost, our analyses are replicable. First, the key datasets used for these analyses are currently updated periodically (usually, annually). The data are suitable for estimates that need to be regularly updated, including for use as part of an indicator such as GCS Indicator No. 13. Second, all data used to generate these estimates are publicly available and free to use. Third, all datasets are contained within GEE and so require little processing to use.

Fourth, we have published the code necessary to run the analyses, thus making replicability easier by users including those with less experience of coding.

Our approach also allows for additional data layers to be overlaid on top of the current analysis. A user could add other variables (e.g. poverty, environmental income), if they had access to a global spatially explicit dataset of similar resolution. However, these types of high-resolution gridded data are currently unavailable at the global level.

## 4.4. LIMITATIONS OF AND CAVEATS TO THE METHODS

Here, we suggest six important factors to consider when interpreting and reporting on these estimates of forest-proximate and tree-proximate people.

First, estimates of the number of forest-proximate and tree-proximate people are heavily influenced by the datasets, definitions and parameters used in the analysis. A previous analysis (Newton *et al.*, 2020) estimated that there were 1.6 billion forest-proximate people in the world in 2012. That analysis used a methodology that was conceptually very similar to this one, but used different datasets, definitions and parameters. For example, the CGLC data used for forest cover in this analysis includes open forests with as little as 15 percent canopy cover, whereas the Landsat data used by Newton *et al.* (2020) had a minimum canopy cover threshold of 50 percent and largely excluded dryland forests. Based on a sensitivity analysis that used parameters as close as possible to those used by Newton *et al.* (2020), we believe that these data differences led to very different estimates. Therefore, we do not believe that it is insightful or meaningful to compare the estimates generated by Newton *et al.* (2020) for 2012 to the estimates contained in this paper for 2019.

Second, the CGLC data, which we used to define forest cover, defined forests broadly to include areas with low tree cover (≥15 percent) as well as those with high tree cover (up to 100 percent). The dataset includes open forests (with canopy cover as low as 15 percent) as well as closed forests. The CGLC data also does not perfectly capture tree cover extent, particularly for lower fractional tree cover values. For our estimates of tree-proximate people we presented the results using greater than 10 percent tree cover as the primary results, as used in previous work by Zomer *et al.* (2016). Other global forest products use different definitions of forests, use different classification algorithms and are available at different spatial resolutions. Different definitions and resolutions of forest cover are likely to substantially influence estimates within and between countries. A relatively coarse resolution may be appropriate for global-scale analyses but may lead to higher estimation errors for more local analyses.

Third, an important limitation is that we use a global tree cover dataset to represent forests. Tree cover is widely used by researchers as a proxy for forests. However, it is important to note that tree cover data include forest plantations and plantations of tree crops (e.g. oil palm). People living near such a plantation but not near a forest would still be counted as forest proximate using our data and methods. Thus, our estimates of the number of forest-proximate people include people living near forest plantations and plantations of tree crops (e.g. oil palm) in addition to people living near natural forests.

Fourth, our gridded population data estimates are derived from the WorldPop database. These estimates, like other gridded population estimates (e.g. Landscan), combine various datasets (including census data) and algorithms to model the spatial distribution of population densities. These modelled estimates are sensitive to both the data and methods that are used to generate them and, like our choice of forest data, are likely to influence our results. Additionally, many people who seasonally live on or near agricultural lands with trees may not be captured by the WorldPop dataset since WorldPop relies on census data.

Fifth, our estimates do not provide any information about the proportion of people living within 1 km or 5 km of a forest, or within 1 km of agricultural land with trees outside forests, who rely on or interact with those forests, or trees outside forests, to any degree. That is, it is not possible to infer dependency on forests or trees outside forests from these data. Many forest-proximate people may not be forest-dependent: many people live near a forest, but do not meet additional criteria for dependence. For example, many common interpretations of forest dependence do not include people living in relatively densely populated areas (e.g. on the periphery of the densely populated urban areas that we excluded in this analysis), nor those living in higher-income countries, nor those living in non-tropical countries. Rather, many common interpretations of forest dependence instead refer to indigenous, traditional and other communities living in relatively remote forested regions in tropical low-income, lower-middle-income, or upper-middle-income countries. In relation to such interpretations, only a subset of all people who live near a forest are also forest dependent. Since it is very unlikely that global data on many of these variables will ever be available, some of the caveats will likely persist. It is also not possible to determine the degree of management of trees outside forests included in our analysis (i.e. not all trees counted would be managed as an agroforestry system, orchard or woodlot). Our estimates also do not include all types of agricultural production systems with trees. For example, not all agroforestry systems would be captured by our analysis (e.g. shade-grown coffee systems that may look like forests from satellite imagery).

Sixth, some authors have used definitions of forest dependence that explicitly do not include forest proximity as a necessary condition for forest dependence. That is, some authors identify forest-dependent people who do not live near forests (e.g. people working in the timber sector). Of course, estimating the number of people who live near a forest will not reveal anything about the number or spatial distribution of forest-dependent people in cases where forest proximity is not a condition of forest dependence. See Newton *et al*. (2016) and (2020) for further discussion on this point. Relatedly, Euclidean distance is not always a good proxy for accessibility (see the discussion of this point in Newton *et al*., 2020).

# 5. Conclusions and future research directions

Our findings suggest that many people around the world may rely on and help shape the dynamics of forests and trees outside forests. Several lines of research may help to better understand the relationships between forests, trees outside forests and people living near them in rural areas across the globe.

First, our work was largely motivated by the need to begin to develop a practical means for measuring GCS Indicator No. 13: Number of forest-dependent people in extreme poverty. Our method represents a necessary step toward this goal. However, our analysis estimates the number of forest-proximate people, but not the proportion of these people who are forest dependent nor the proportion who live in poverty. To make such estimates would require integrating a) forest-dependence data, and b) poverty data with the spatial map and estimates of forest-proximate people we have presented. No such data currently exist at the global scale for either forest-dependence or poverty. However, machine learning and other methods are helping to develop datasets that could be useful in pursuit of this objective (e.g. Chi *et al.*, 2022).

Second, more research is needed on the specific relationships between people, forests and trees beyond just the spatial dimension of these relationships. Our analyses show the spatial overlap between forests, trees and people. But our work does not explore the kinds of relationships people actually have with forests and trees either in terms of the different benefits that people derive from forests or different demographics of people (e.g. nationality, class, gender, ethnicity), or in terms of different kinds of forests or trees (or both). Finer grained research, including spatially explicit and detailed data on the livelihoods of forest-dependent people, would complement our global analysis and could explore these relationships, including in a comparative way.

Third, identifying a means to disaggregate or exclude tree-cover data from forest plantations and tree crops (e.g. oil palm) would enable researchers to generate more accurate estimates of the number of people who live near natural forests. The estimates of forest-proximate people presented here include people living near forest plantations and areas of tree crops. This is a challenge that is common for much research that uses global tree-cover data. As such, the development of data on natural forests, or of analytical means to reliably disaggregate such data from total tree-cover, would be a significant development. In this case, it would enable a more precise exploration of the spatial relationships between people and different types of forest and tree cover.

Fourth, research is needed to look at change over time and how the number and spatial distribution of forest- and tree-proximate people has changed either as a function of population dynamics or changes in forest- and tree-cover. Such change may also be induced by policy interventions that aim to conserve forests and/or support rural livelihoods.

Finally, our method, dataset and findings open several other avenues for research related to the effectiveness and equity of different forest-related funding and policy mechanisms. For example, spatially explicit data on protected areas (UNEP-WCMC and IUCN, 2021) and funding for them (Waldron *et al.*, 2013) could be overlaid with the data we present here to shed new light on the number of people likely to be affected by protected areas at different spatial scales, from specific sites to countries to the globe. Such analysis could then inform evaluations of the social-ecological impacts of protected areas. More generally, this approach could be applied to many other forest policy instruments for which spatially explicit data are available. Doing so remains an urgent task as the international community seeks to address the profound and interlinked challenges facing people and forests worldwide.

# 6. Data and code availability

The maps produced in this analysis are openly available at FAO's Hand-in-Hand Geospatial Platform:

*Forest-proximate people:* https://data.apps.fao.org/catalog/dcat/forest-proximate-people

*Tree-proximate people*: https://data.apps.fao.org/catalog/dcat/tree-proximate-people

All programming code necessary to reproduce the analysis in Google Earth Engine is available at: https://bitbucket.org/cioapps/sofo2022/src/master/.

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# Appendix 1. Copernicus Global Land Cover classes

| Copernicus Global Land Cover (CGLC) class | Definition |
|---|---|
| Shrubs | Woody perennial plants with persistent and woody stems and without any defined main stem being less than 5 m tall. The shrub foliage can be either evergreen or deciduous. |
| Herbaceous vegetation | Plants without persistent stem or shoots above ground and lacking definite firm structure. Tree and shrub cover is less than 10%. |
| Cultivated and managed vegetation / agriculture | Lands covered with temporary crops followed by harvest and a bare soil period (e.g. single and multiple cropping systems). Note that perennial woody crops will be classified as the appropriate forest or shrub land cover type. |
| Urban / built up | Land covered by buildings and other man-made structures. |
| Bare / sparse vegetation | Lands with exposed soil, sand, or rocks and never has more than 10% vegetated cover during any time of the year. |
| Snow and ice | Lands under snow or ice cover throughout the year. |
| Permanent water bodies | Lakes, reservoirs, and rivers. Can be either fresh or salt-water bodies. |
| Herbaceous wetland | Lands with a permanent mixture of water and herbaceous or woody vegetation. The vegetation can be present in either salt, brackish, or fresh water. |
| Moss and lichen | Moss and lichen. |
| Closed forest, evergreen needle leaf | Tree canopy >70%, almost all needle leaf trees remain green all year. Canopy is never without green foliage. |
| Closed forest, evergreen broad leaf | Tree canopy >70%, almost all broadleaf trees remain green year round. Canopy is never without green foliage. |
| Closed forest, deciduous needle leaf | Tree canopy >70%, consists of seasonal needle leaf tree communities with an annual cycle of leaf-on and leaf-off periods. |
| Closed forest, deciduous broad leaf | Tree canopy >70%, consists of seasonal broadleaf tree communities with an annual cycle of leaf-on and leaf-off periods. |
| Closed forest, mixed | Tree canopy >70%, mixed type. |
| Closed forest, other | Tree canopy >70%, not matching any of the other definitions. |

| | |
|---|---|
| Open forest, evergreen needle leaf | Top layer- trees 15–70% and second layer- mixed of shrubs and grassland, almost all needle leaf trees remain green all year. Canopy is never without green foliage. |
| Open forest, evergreen broad leaf | Top layer- trees 15–70% and second layer- mixed of shrubs and grassland, almost all broadleaf trees remain green year round. Canopy is never without green foliage. |
| Open forest, deciduous needle leaf | Top layer- trees 15–70% and second layer- mixed of shrubs and grassland, consists of seasonal needle leaf tree communities with an annual cycle of leaf-on and leaf-off periods. |
| Open forest, deciduous broad leaf | Top layer- trees 15–70% and second layer- mixed of shrubs and grassland, consists of seasonal broadleaf tree communities with an annual cycle of leaf-on and leaf-off periods. |
| Open forest, mixed | Tree canopy >70%, mixed type. |
| Open forest, other | Tree canopy >70%, not matching any of the other definitions. |
| Oceans, seas | Can be either fresh or salt-water bodies. |

| CGLC tree cover fractional layer | Definition |
|---|---|
| Tree-cover fraction | Percent vegetation cover for forest land cover class (0–100%) |

# Appendix 2. Alternative global population density datasets

| Database name | Geographical coverage | Spatial resolution | Temporal resolution | Time span | Conclusions of viability for estimating the number of forest-proximate people (FPP) | Citation |
|---|---|---|---|---|---|---|
| WorldPop Global Project Population Data | Global | 3 arc-seconds (approx. 100 m), 30 arc-seconds (approx. 1 km) | Every year | 2000–2020 | A viable data source to estimate FPP. | WorldPop. 2021. WorldPop Hub. In: *WorldPop*. Cited August 2021. https://dx.doi.org/10.5258/SOTON/WP00647 |
| GPWv411: Population Count (Gridded Population of the World Version 4.11) | Global | 30 arc-seconds (approximately 1 km) | Every 5 years | 2000–2020 | A potentially viable data source to estimate FPP, but only updated every 5 years. | CIESIN. 2022. Socioeconomic Data and Applications Center. In: *NASA EarthData*. Cited August 2021. https://doi.org/10.7927/H4JW8BX5 |
| LandScan | Global | 30 arc-seconds (approx. 1 km) | Every year | 2000–2020 | A potentially viable data source to estimate FPP; it is not currently open access, though there are plans to move to fully open access. | Rose, A.N., McKee, J.J., Sims, K.M., Bright, E.A., Reith, A E. & Urban, M.L. 2020. LandScan 2019. LandScan Global. In: *Oak Ridge National Laboratory*. Cited August 2021. https://landscan.ornl.gov/ |

| Database name | Geographical coverage | Spatial resolution | Temporal resolution | Time span | Conclusions of viability for estimating the number of forest-proximate people (FPP) | Citation |
|---|---|---|---|---|---|---|
| Facebook's and CIESIN's High Resolution Settlement Layer (HRSL) | 160 countries | 30 m | Inconsistent release and available years (estimates are generally available for only one year, mostly 2015) | 2015–2021 | Not a viable data source to estimate FPP since it does not have global coverage and estimates only represent single years (mostly 2015). This may become a best option once it is globally and annually available. | Facebook Connectivity Lab and Center for International Earth Science Information Network - CIESIN - Columbia University. 2016. High Resolution Settlement Layer (HRSL). Source imagery for HRSL ©2016 DigitalGlobe. In: *Columbia Climate School*. Cited August 2021. https://ciesin.columbia.edu/data/hrsl/ |
| GHSL: Global Human Settlement Layers Population Grid 1975–1990–2000–2015 (P2016) | Global | 9 arc-seconds (250 m), 30 arc-seconds (1 km) | Every 15 years (1975, 1990, 2000, 2015) | 1975–2015 | Not a viable data source to estimate FPP, since it is only updated every 15 years. | Schiavina, M., Freire, S. & MacManus, K. 2019. GHS population grid multitemporal (1975, 1990, 2000, 2015) R2019A. European Commission, Joint Research Centre (JRC). In: *European Commission Joint Research Centre Catalogue*. Cited August 2021.<br>https://doi.org/10.2905/0C6B9751-A71F-4062-830B-43C9F432370F or http://data.europa.eu/89h/0c6b9751-a71f-4062-830b-43c9f432370f |

| Database name | Geographical coverage | Spatial resolution | Temporal resolution | Time span | Conclusions of viability for estimating the number of forest-proximate people (FPP) | Citation |
|---|---|---|---|---|---|---|
| ESRI World Population Estimate | Global | 162 m | Inconsistent | 2013, 2015 and 2016 | Not a viable data source to estimate FPP since it is updated inconsistently and has not been updated since 2016. | Frye, C., Wright, D.J., Nordstrand, E., Terborgh, C. & Foust, J. 2018. Using Classified and Unclassified Land Cover Data to Estimate the Footprint of Human Settlement. *Data Science Journal*, 17: 20. https://doi.org/10.5334/dsj-2018-020 |

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