# Global distribution of forest classes and leaf biomass for use as alternative foods to minimize malnutrition

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## Abstract

Due to the ready availability of tree leaves in many geographies, the alternative food of leaf concentrate currently has the potential to alleviate hunger in over 800 million people. It is therefore potentially highly impactful to determine the edibility of leaf concentrates which are in the same regions as the world's most undernourished populations. Unfortunately, the toxicity of leaf concentrate for most common tree leaf types has not been screened and the cost of doing so demands a prioritization. This preliminary study explores this potential solution to world hunger by finding the forest classes most likely to offer proximate access to the world's hungry, thus providing the basis for a prioritized list of leaf types to screen for toxicity. Specifically, this study describes a novel methodology for mapping available green leaf biomass and corresponding forest classes (e.g. tropical moist deciduous forest), and their spatial relationship to the global distribution of people who are underweight. These results will be useful for developing a targeted list of tree species to conduct leaf toxicity analysis on, in the interest of developing leaves as an alternative food source for both current malnutrition problems and global catastrophic scenarios.

**Keywords** : agriculture; forests; GIS; edible leaves; hunger; global catastrophic risk

## 1. Introduction

More than 820 million people are currently undernourished and face chronic food deprivation throughout the world (FAO, 2018). Children under the age of five are the hardest hit (UNICEF, 2006; McDonald, et al., 2013; Bhutta, et al., 2017). According to the Global Nutrition Report (GNR)150.8 million are stunted (impaired growth and development that children experience from chronic poor nutrition) and 50.5 million children under five are wasted (acute malnutrition) (GNR, 2018). Overall, 20 million babies are born of low birth weight each year and a third of reproductive-age women are anaemic (GNR, 2018). This is unnecessary, as previous research has shown that alternative food supplies could support the entire human population even in the most extreme disaster that eliminates all conventional agriculture (Denkenberger & Pearce, 2014; 2015). In such a disaster, humanity's food intake could actually be improved over the current non-uniform distribution and all lives could be maintained based on caloric intake by converting carbon sources like dead trees (wood) and leaves to human-edible food (Denkenberger & Pearce, 2016; 2018). Even more surprisingly, preliminary calculations show that a modest diversity of alternative foods could supply a balanced diet of macronutrients and micronutrients (Denkenberger & Pearce, 2018) to maintain reasonable human health (Shenkin, 2006). Some alternative foods, including extracting calories from leaves, would be helpful in a different class of catastrophes; those that disrupt electricity such as an extreme solar storm (Cole 2016), or even a combination of catastrophes (Denkenberger 2017). Even without any extreme events, it is important that a resilient global food system is continuous (i.e. that it is able to maintain caloric intake consistently so that people do not starve or suffer from the detrimental effects of hunger intermittently) (Seekell, et al., 2017). In the most extreme circumstances of a sun-blocking global catastrophe, the largest challenge to feeding the global population lies in between the time that stored food is consumed (about six months) and the transition to alternative foods following the catastrophe (about 1 year) (Denkenberger & Pearce, 2014; 2015). Of the alternative food solutions that could be ramped up in this time period the best theoretical solution is to use leaves killed by the catastrophe (as opposed to leaves that are depleted of nutrients and shed naturally called leaf litter), because of their wide availability and reasonable price comparison to other alternative foods (Denkenberger et al., 2018). It is possible to grind and press leaves, boil the fluid and then coagulate the resultant liquid as leaf concentrate into food, which contains ~8% of the dry matter of the original leaves (Leaf for Life, 2019). The remaining unused liquid contains much of the toxins, and has been considered unfit for human consumption (Kennedy, 1993). Although yields of leaf concentrate made at the household scale are lower with nonindustrial techniques (Kennedy, 1993), conducting this process in households would be more widely accessible and could contribute to hunger alleviation now. However, making humanly consumable food at a global level from tree leaves in this manner or in teas is challenging because i) only a small fraction of the leaves' calories can be extracted (e.g. in black tea ~20% of the total calories of the proteins, carbohydrates, and lipids make it into the liquid (Belitz, et al., 2009)), ii) eating tree leaf-based teas is uncommon, although in some parts of the world pine needle tea is already consumed (Kim and Chung, 2000), iii) more information is needed on the percentage of existing tree leaves that could be harvested sustainably from the many types of trees, iv) there have not been enough studies to gauge the human toxicity leaf extract from common tree leaf types.

To overcome this last challenge (iv), a recent study (Pearce et al., 2019) provided a new methodology for obtaining rapid toxics screening of common leaf concentrates using a non-targeted approach with an ultra-high-resolution hybrid ion trap orbitrap mass spectrometer with electrospray ionization (ESI) coupled to an ultra-high pressure two-dimensional liquid chromatography system. Identified chemicals by the non-targeted approach are then cross-referenced with the OpenFoodTox database (Bassan et al., 2018) to identify toxic chemicals. Identified toxins are then screened for formula validation and evaluated for risk as a food and further analysis is needed with standards to rule out toxicity. Although this initial screening is faster and less expensive than past methods it still presents prohibitive costs for running against all of the world's tree species. Therefore the objective of this study is to provide a means of prioritization to identify the leaf types that should be screened first. Given that leaf concentrate as an alternative food has the potential to alleviate hunger in over 800 million people today (FAO, 2018), it appears appropriate to target leaf types where the most malnourished people live. With limited resources for leaf toxicity studies, which types of forests (forest classes) and the trees within them should have their leaves targeted first for toxilogical analysis? This is primarily an applied geography problem and this preliminary study seeks to solve that problem by determining these priorities. This study describes a methodology for mapping available green leaf biomass and forest classes, and their spatial relationship to the distribution of global malnutrition. It builds on methods described by (Ruesch et al., 2008, Doxsey-Whitfield et al., 2015, CIESIN, 2005). The output of this new methodology will be useful for developing more detailed tree species studies, which will form the basis for leaf toxicity screenings, in the interest of developing leaves as an alternative food source for both current malnutrition problems and catastrophic scenarios.

## 2. Methods

### 2.1 Data

Data were selected based on being open-accessible and the most recent high-quality available and are detailed below. Datasets have been chosen from the years 2000-2002, a date range with the most complete corresponding global data available for both leaf biomass and malnutrition. The data developed as part of this project are available open access in tabular format (Fist, 2019a) and users can look in detail at regions on an interactive map format housed at: [http://bit.ly/allfed-leaf-map](http://bit.ly/allfed-leaf-map)

#### 2.1.1. Global malnutrition

In order to estimate the global spatial data on malnutrition at a sub-national level, the global subnational prevalence of child malnutrition in 2002 developed by the NASA Socioeconomic Data and Applications Center (SEDAC) is used here (CIESIN, 2005). The total global population for 2000 broken down by region was also from SEDAC (2019).

#### 2.1.2 Leaf biomass

The Intergovernmental Panel on Climate Change (IPCC) provides a high resolution map of living biomass of carbon for the year 2000 (Ruesch et al., 2008).

### 2.2 Calculating total number of people suffering from malnutrition for each region

It is assumed that the SEDAC underweightness data within a region (which describes levels of underweightness in children under 5) is a good proxy for rates of malnutrition in general in that region. This is because children depend on adults for their care and they are not fed if there is not enough food in the region (LaFollette and May, 1996). It is also assumed that most of the regions with no SEDAC data or a poor sub-national data breakdown do not currently have significant malnutrition problems. For example, two such regions are the U.S. and Canada, which are both experiencing an epidemic of obesity (Upadhyay, et al., 2018; Pozza, & Isidori, 2018) and globally 38.9% of adults are overweight or obese (GNR, 2018).

To convert the general data into the total number of people suffering from malnutrition for each region, the total population in each region is multiplied by the fraction given by proportion of underweight children under 5. This assumes that if levels of childhood malnutrition are roughly similar to levels of adult malnutrition in each area, then this product will provide a reasonable first order approximation for the total number of people suffering from malnutrition in a given region. Next, the SEDAC population data (a 30 arc-second raster grid) is mapped onto the SEDAC malnutrition regions (a polygon vector dataset) in order to sum population in those regions to establish absolute levels of malnutrition.

The resulting dataset can be analyzed at both a global and regional level. Here the regions of Uttar Pradesh in India and North East Nigeria are used as examples, being two regions with high levels of malnutrition. They also represent areas where this approach would be most viable as poor people live within or near forests.

### 2.3 Estimating the spatial distribution of tree species and leaf biomass

The total biomass of carbon from Lawrence Berkeley National Laboratory (Ruesch et al., 2008) needs to be translated into a reasonably accurate estimate leaf biomass, broken down by forest type. First, the amount of this carbon which is above ground in trees is determined. Second, the proportion of a tree's biomass that is carbon is found. Finally, the proportion of a tree's biomass which is made up of leaves is applied to determine the total leaf biomass available in each region.

The majority of the biomass determined by Ruesch et al. (2008) is contained in trees, rather than grasses, crops, etc. To determine the specific amount of tree biomass in the dataset, the global spatial distribution of trees is required, for which the European Space Agency Global Land Cover (ESA, 2019) dataset was used. The relevant land classes for tree cover are mapped noting that the following classes have been excluded: mountain systems, polar regions, desert regions, steppes, shrubland and water. These classes were excluded due to their geographic isolation, hostility, and difficulty of leaf harvesting (e.g. it would be impractical to assume widespread leaf harvesting). The proportion of a tree's dry biomass that is carbon is assumed to be 47% (Sabah et al., 2006), whereas the percentage of a tree's biomass which is made up of leaves is assumed to be 1% (Poorter et al., 2012). It should be pointed out that for the purposes of this study the rapid ramp rates of leaf concentrate make the 1% leaf biomass of most interest, but that remaining wood could be used for alternative foods by for example feeding it to beetles and mushrooms and the remaining material to rats.

These values are combined to generate a map of leaf biomass across different forest classifications.

### 2.4 Combining malnutrition density and leaf biomass to determine forest zones to evaluate

First, forest types which are most common in regions with high levels of malnutrition are determined by taking the earlier generated regional under-weightness data, and referencing it against forest zone data (ESA, 2019). These data can be closely examined to understand which forest classifications are most prevalent in the areas suffering most from malnutrition. Again, regions in India and Nigeria are used as examples. Next, the most common forest class by population region area is mapped based on 1) total forest area and 2) total leaf biomass. This analysis can provide a priority list for both global and regional forest type to concentrate alternative food research upon, based on potential lives saved. However, to determine if there are actually enough leaves to be useful, a final analysis is made to derive the total leaf biomass available in each region across all forest classes, per individual suffering from malnutrition.

These data are available in tabular format (Fist, 2019a) and users can look in detail at regions on an interactive map format housed at: [http://bit.ly/allfed-leaf-map](http://bit.ly/allfed-leaf-map)

## 3. Results

Following the methods outlined above, the proportion of children who are both under five years old and underweight is mapped in Figure 1a and the proportion of the total population who are under five years old is shown in Figure 1b. The proxy for general malnutrition in a region is described by the black-outlined boundaries in Figure 1. The results, being derived from SEDAC region boundaries, have a higher resolution in areas with a larger malnutrition problem, such as Sub-Saharan Africa. As Figure 1 shows, these boundaries do not give a particularly good idea of how malnutrition levels break down within certain regions, such as Russia. In addition, these results do not provide any information for countries where no malnutrition data are present, which covers North America, Western Europe, Australia/New Zealand as well as several others.

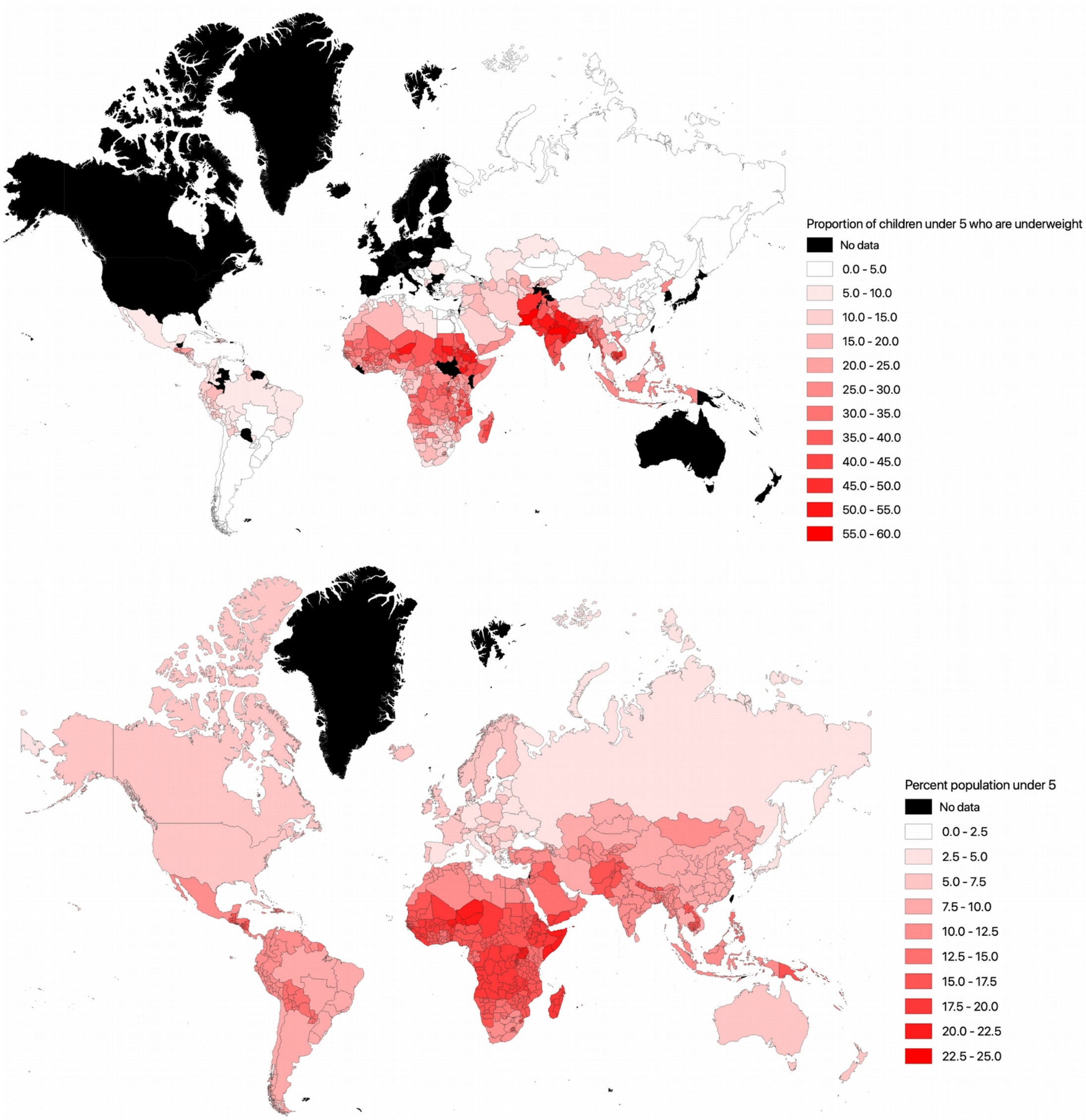



*Figure 1a. Proportion of children who are both under five years old and underweight and b.*

*Proportion of the total population who are under five years old.*

The global population for 2000 is shown in Figure 2. The population data is mapped onto the malnutrition regions shown in Figure 1a and 1b in Figure 3a and 3b. The maps in Figure 3 emphasize the large number of children suffering from malnutrition in South and Southeast Asia, in particular India and Indonesia.

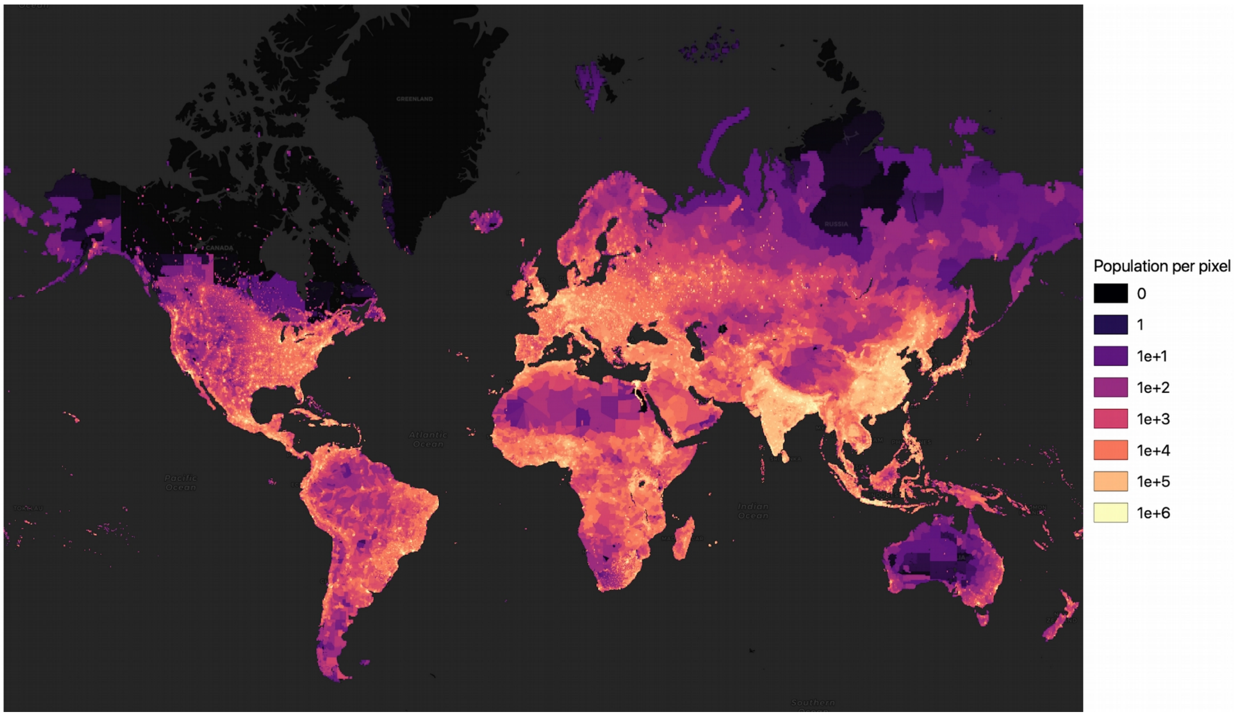



*Figure 2) The global population in 2000. Note that the legend values for each color are on a log scale.*

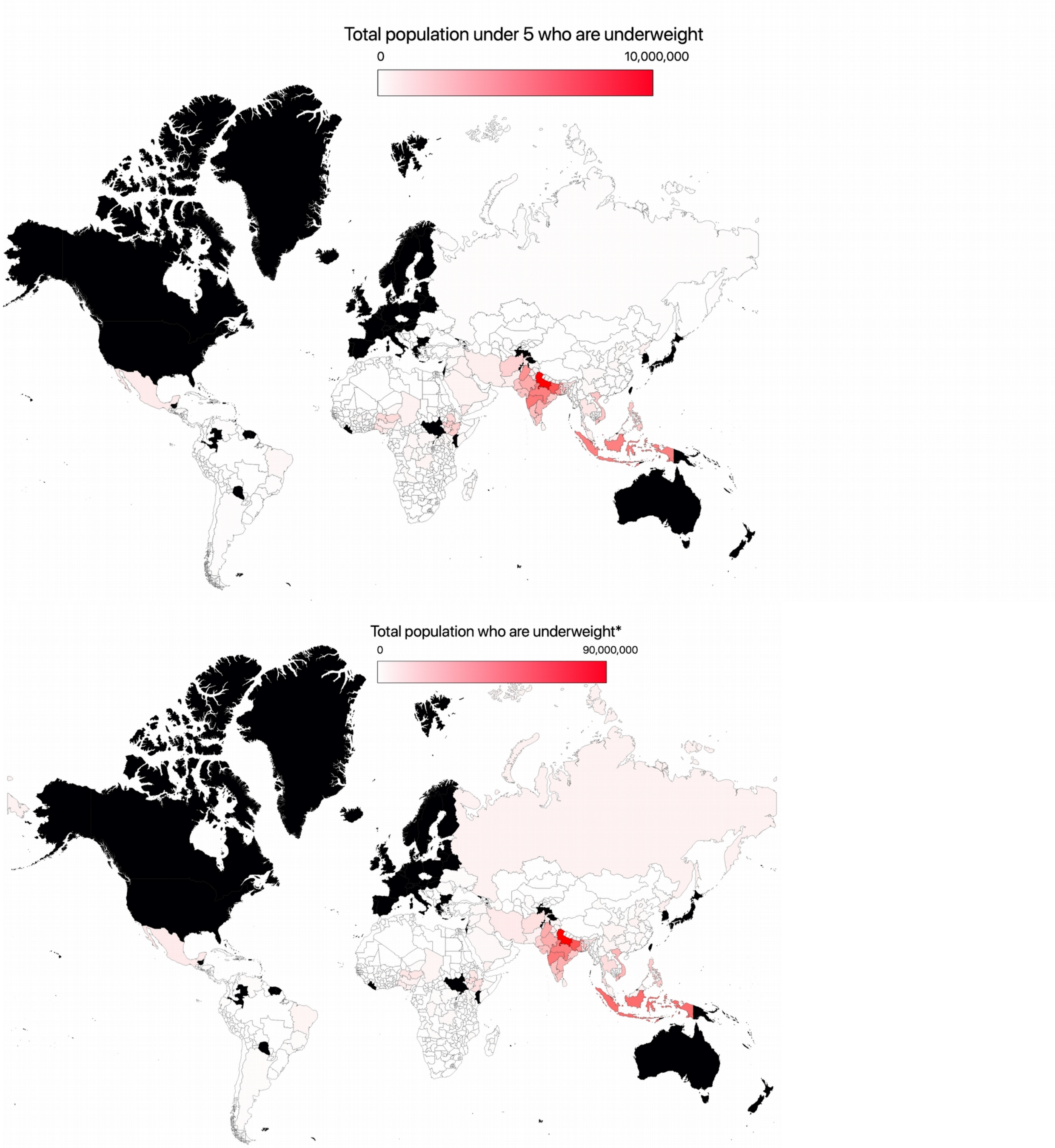


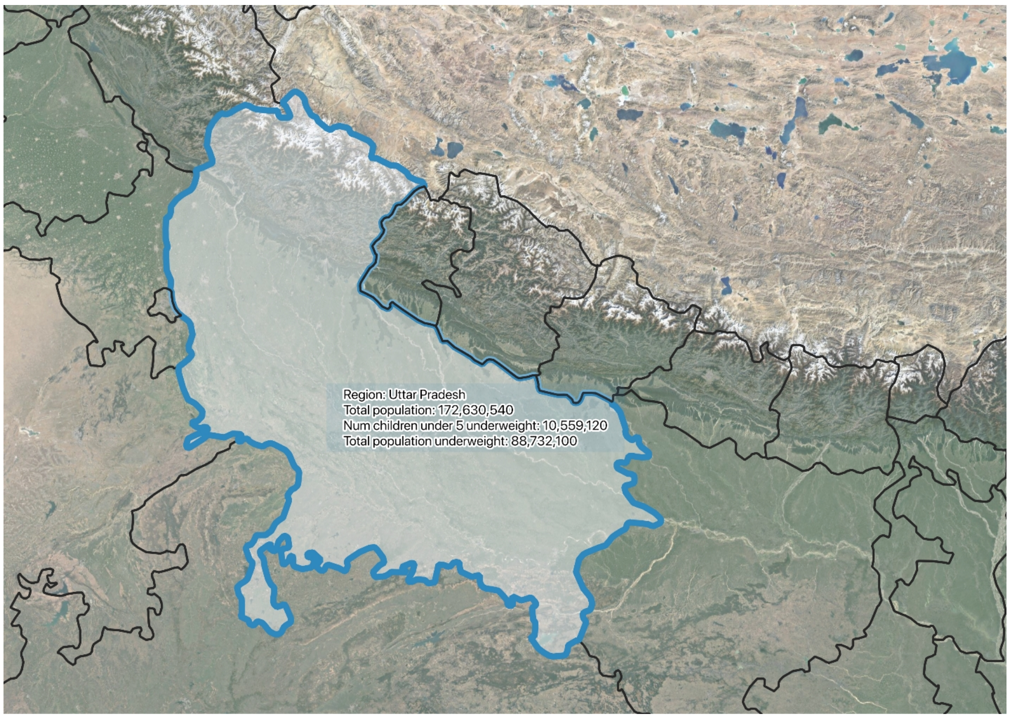

*Figure 3a) Total population who are both under five years old and underweight. 3b) Total population who are underweight, assuming that the percent children who are underweight can be extrapolated to the total population. Regions with no data available are shown in black.*

With this data set, individual regions can be analyzed. This is shown in Figure 4 for the state of Uttar Pradesh in India and in Figure 5 for North East Nigeria.

In Uttar Pradesh alone (Figure 4a) there are over 10 million underweight children under 5, composing a shocking 51% of the total number of children under 5. Using the methodology described above, the inferred total underweight population in this region is 89 million, in a total population of 173 million.

Figure 4b shows the same set of data for North East Nigeria, where the total population is 22 million, the percent of children under 5 who are underweight is 38%, and the subsequent inferred underweight population under 5 and in general are 1.4 million and 8.3 million respectively.

The next step is to supplement the analysis of the global distribution of hunger with information available for leaf biomass in each of these regions.



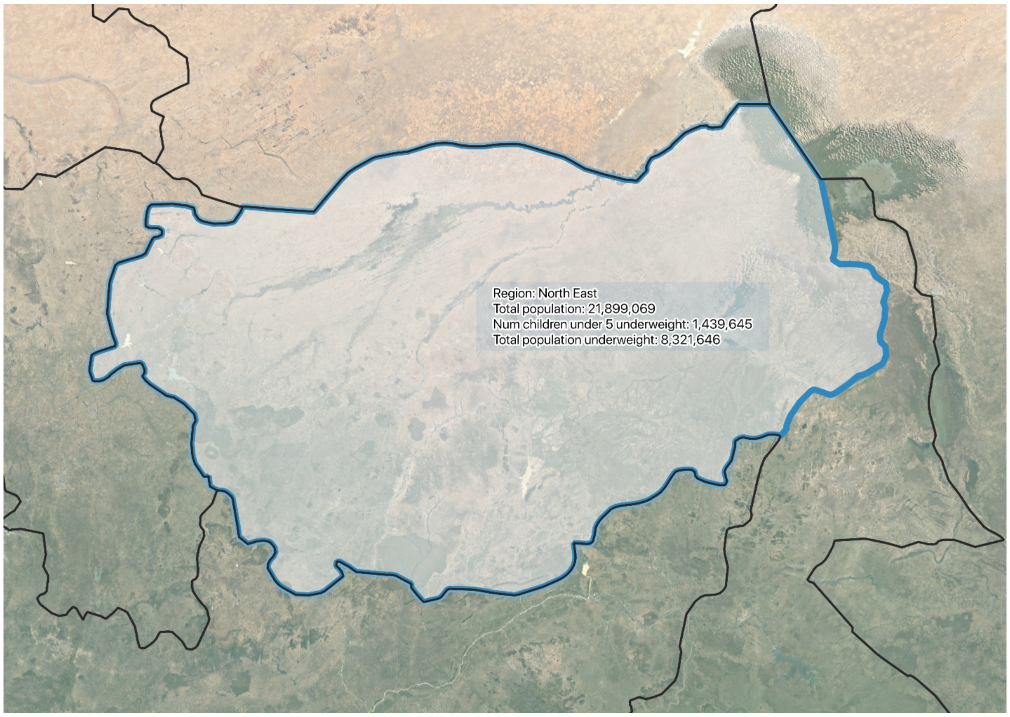
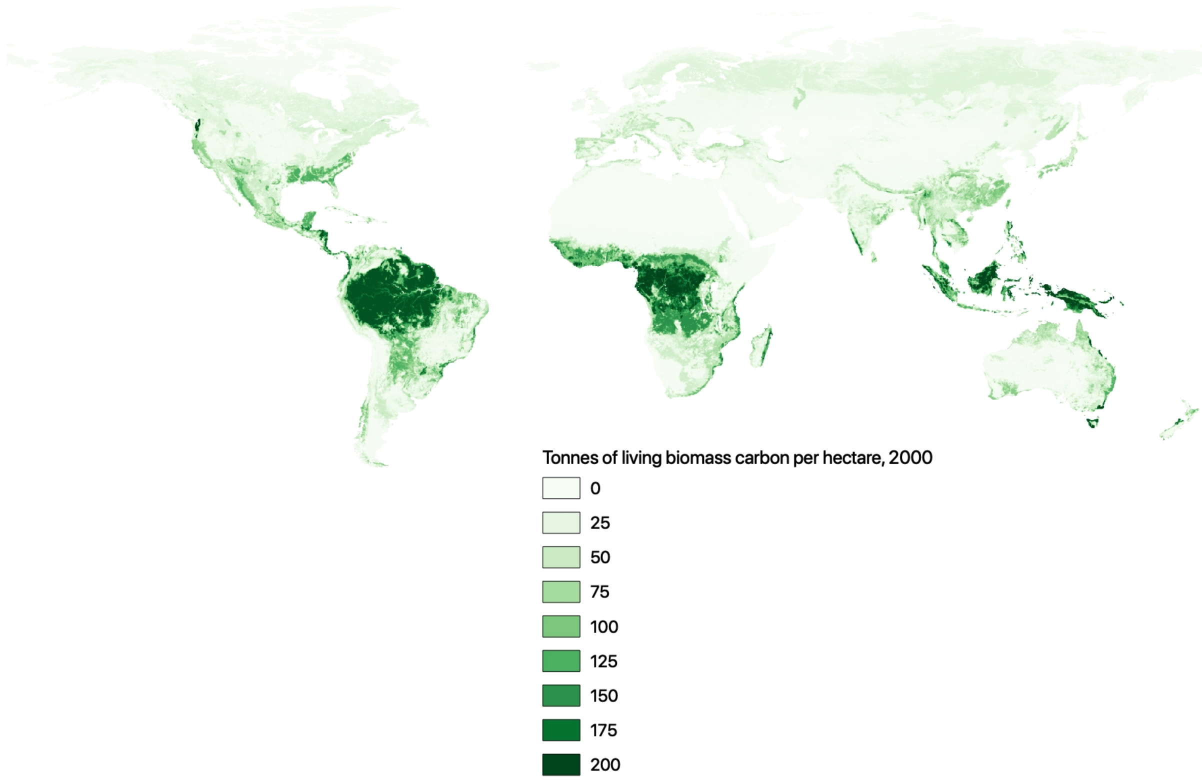
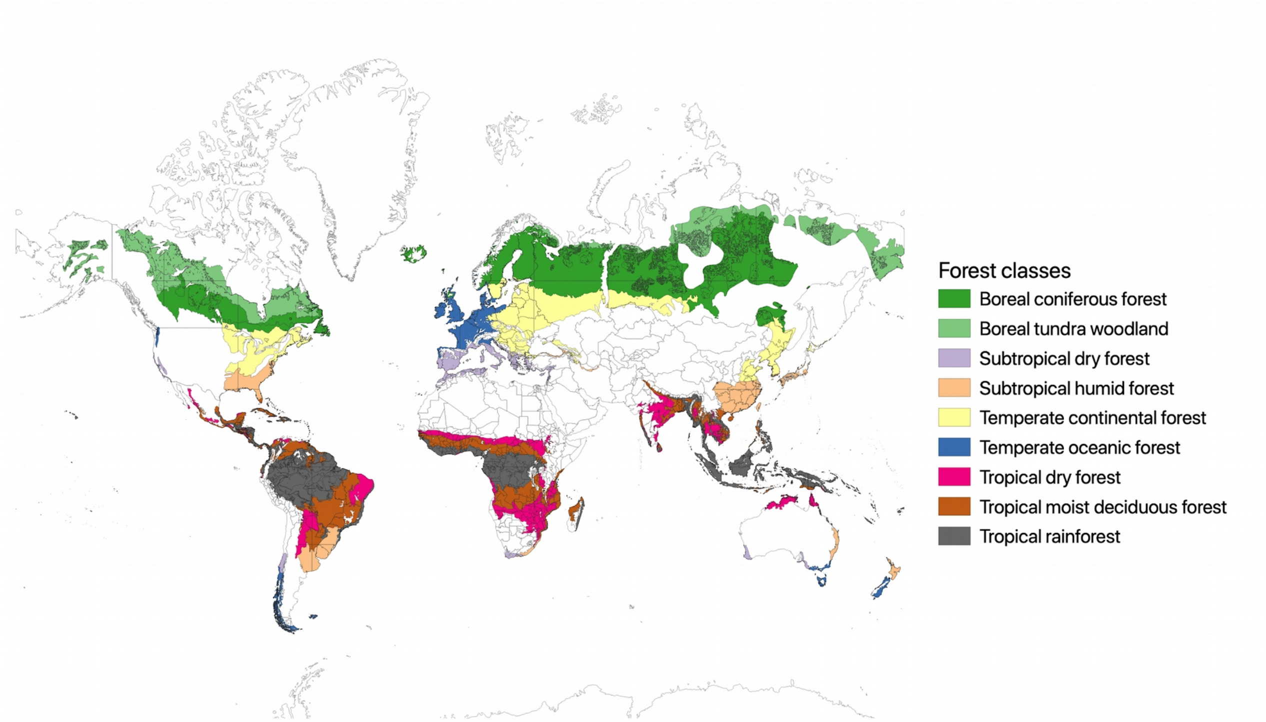


*Figure 4a. Details of the output from the calculations for Uttar Pradesh. 4b. Details of the output from the calculations for North East Nigeria.*

Figure 5a shows a map of living biomass of carbon for the year 2000, which includes. From this data, it is clear that the majority of global living biomass is in the equatorial region with a typical factor of ~2x higher biomass per hectare than even the most biomass-dense northern or southern regions.





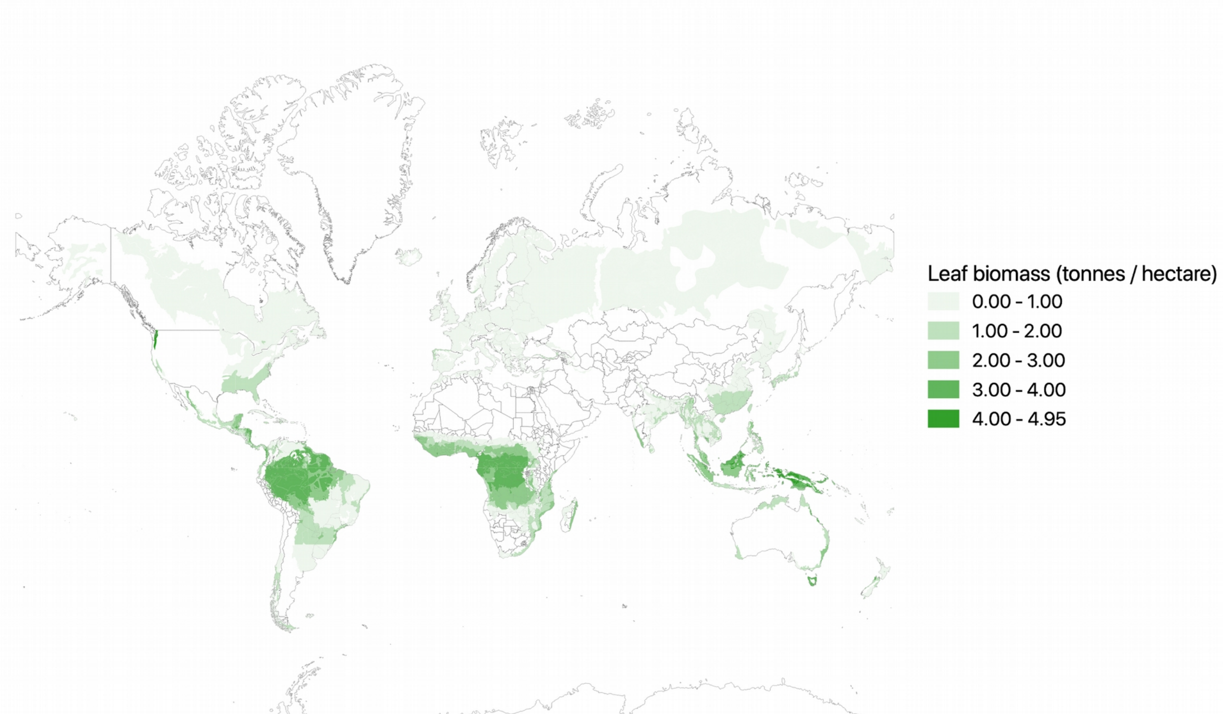



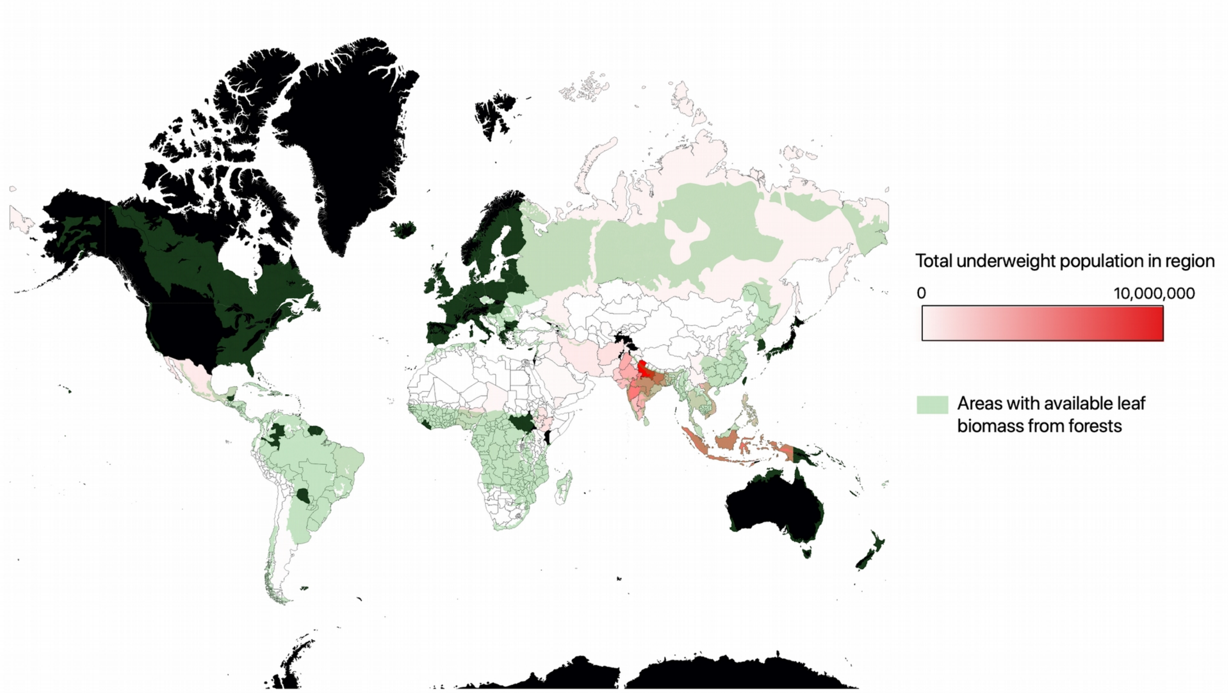

*Figure 5a. Tonnes of living biomass of carbon per hectare in 2000. b. The regions in the globe covered with forests and broken down by type of forest zone, c. Leaf biomass across different forest classifications shown in b.*

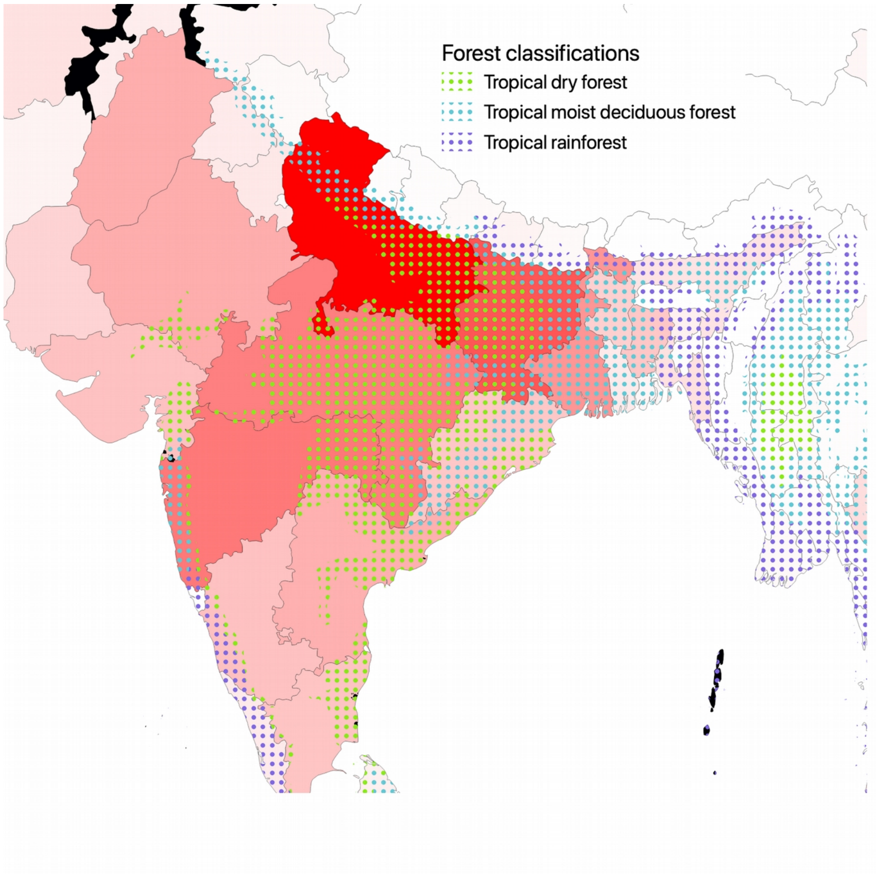
Using the European Space Agency (ESA) global land cover data (2019), the forested regions of the world broken down by broad class are shown in Figure 5b. This data was cross validated against datasets from the Global Forest Watch Tree Cover (2000) and NASA MODIS Land

Cover (2019). Of the forest classes excluded as per the methodology described above, mountain systems are the classes with the most forest cover based on biomass. However, for this analysis the mountain regions were still excluded due to the relative difficulty of harvesting leaves in such environments.

Combining the data shown in Figure 5a and Figure 5b, by using the carbon proportion of a tree's biomass together with the proportion of a tree's biomass which is made up of leaves gives us the data shown in Figure 5c: a map of leaf biomass in tonnes/hectare across different forest classifications.

The population-underweight data is overlaid with regions of available forest and shown in Figure 6a.




Forest classifications
Tropical dry forest
Tropical moist deciduous forest
Tropical rainforest

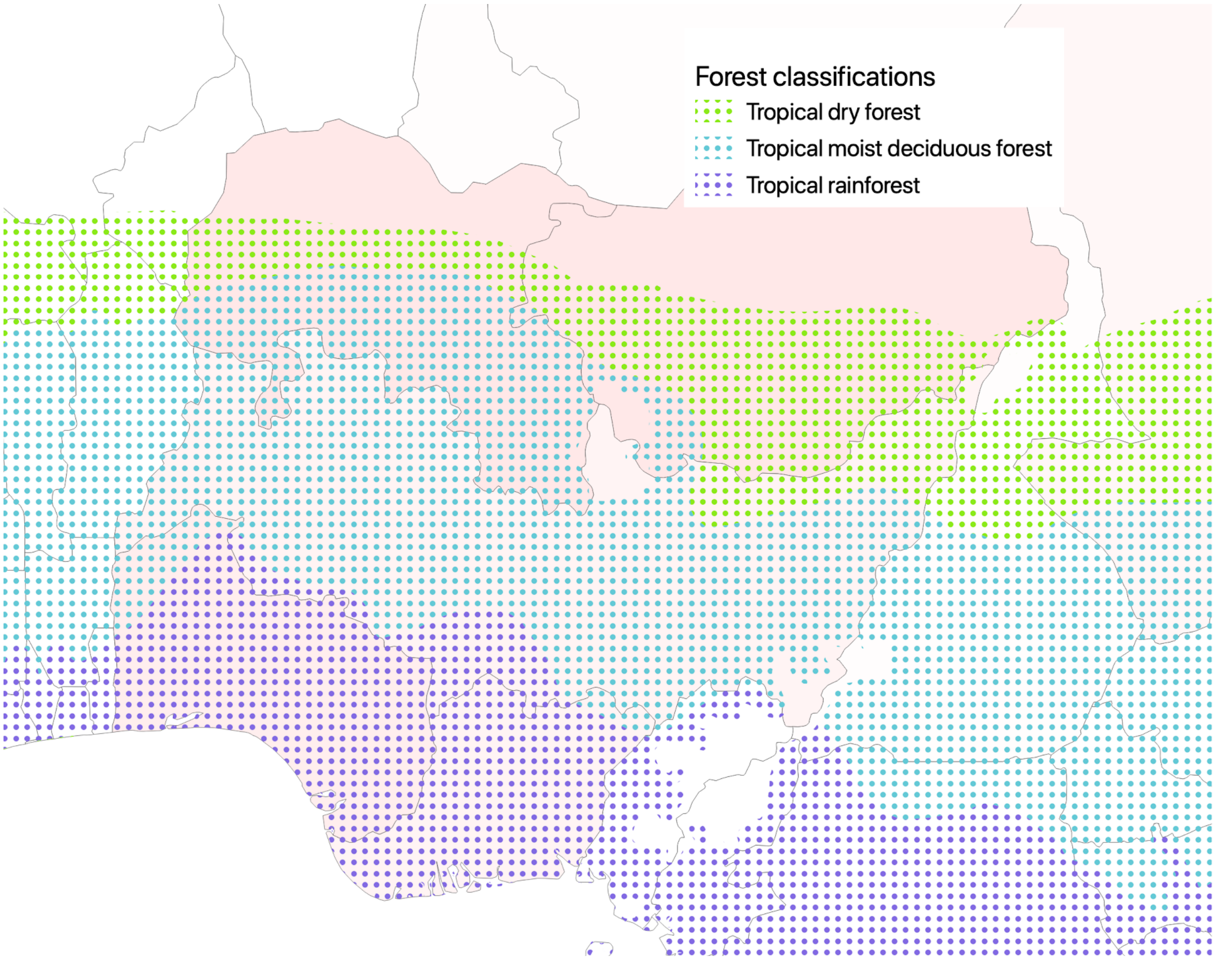



*Figure 6a. Population-underweight data (white → red, black where no data) overlaid with regions of available forest (green). 6b. Population underweight data (white → red, black where no data) vs. forest classifications (dots), India. 6c. Population underweight data (white → red, black where no data) vs. forest classifications in Nigeria.*

Figure 6b zooms in on the forest class and malnutrition data in India. There are three primary forest classifications for India: tropical dry forests, tropical moist deciduous forests and tropical rainforests. Figure 6b indicates that concentrating on leaves of trees common to tropical dry forests would provide the most malnutrition reduction potential in this region, as this forest class has the most local; coverage and total leaf biomass. This data can also be found in tabular format (Fist, 2019a). In addition, as can be seen in Figure 6b, leaf extract could not be used to reduce malnutrition in all regions in India (most notably in the west) unless leaf biomass is transported as there are regions which are suffering from malnutrition issues (shown in red) with no forests available.

Nigeria shares the same types of forests with India. Similarly not all of the parts of Nigeria suffering from malnutrition have access to forests (see Figure 6c). Transportation would be necessary to use leaf extract to control malnutrition within Nigeria. This is complicated by the sub-regional distribution of linguistic groups (Hansford, et al., 1976). Figure 6c indicates that trees with tropical moist deciduous forests should be evaluated first to use leaf extract as an

alternative food in Nigeria. Other countries can use the data sets provided with this study to evaluate priority lists for their own regions.
The most common forest class by region are shown in Figures 7a) and 7b), by area and by total biomass respectively. Note the priorities for some regions like Argentina.

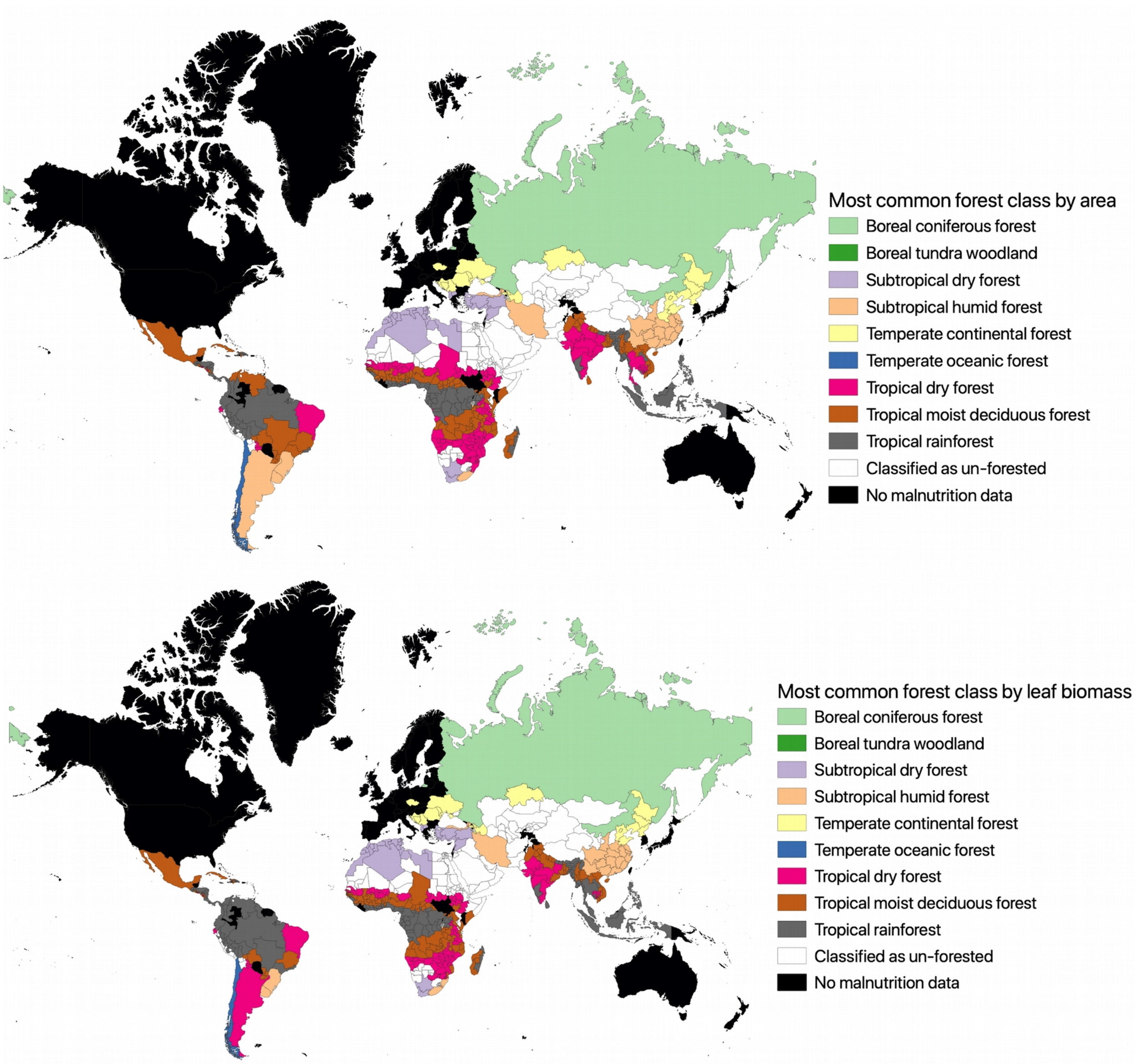



*Figure 7. a) The most prevalent forest classification by population region based on a) total forested area and 7) total leaf biomass available.*

Finally, the total leaf biomass available in each region across all forest classes, per individual suffering from malnutrition is shown in Figure 8

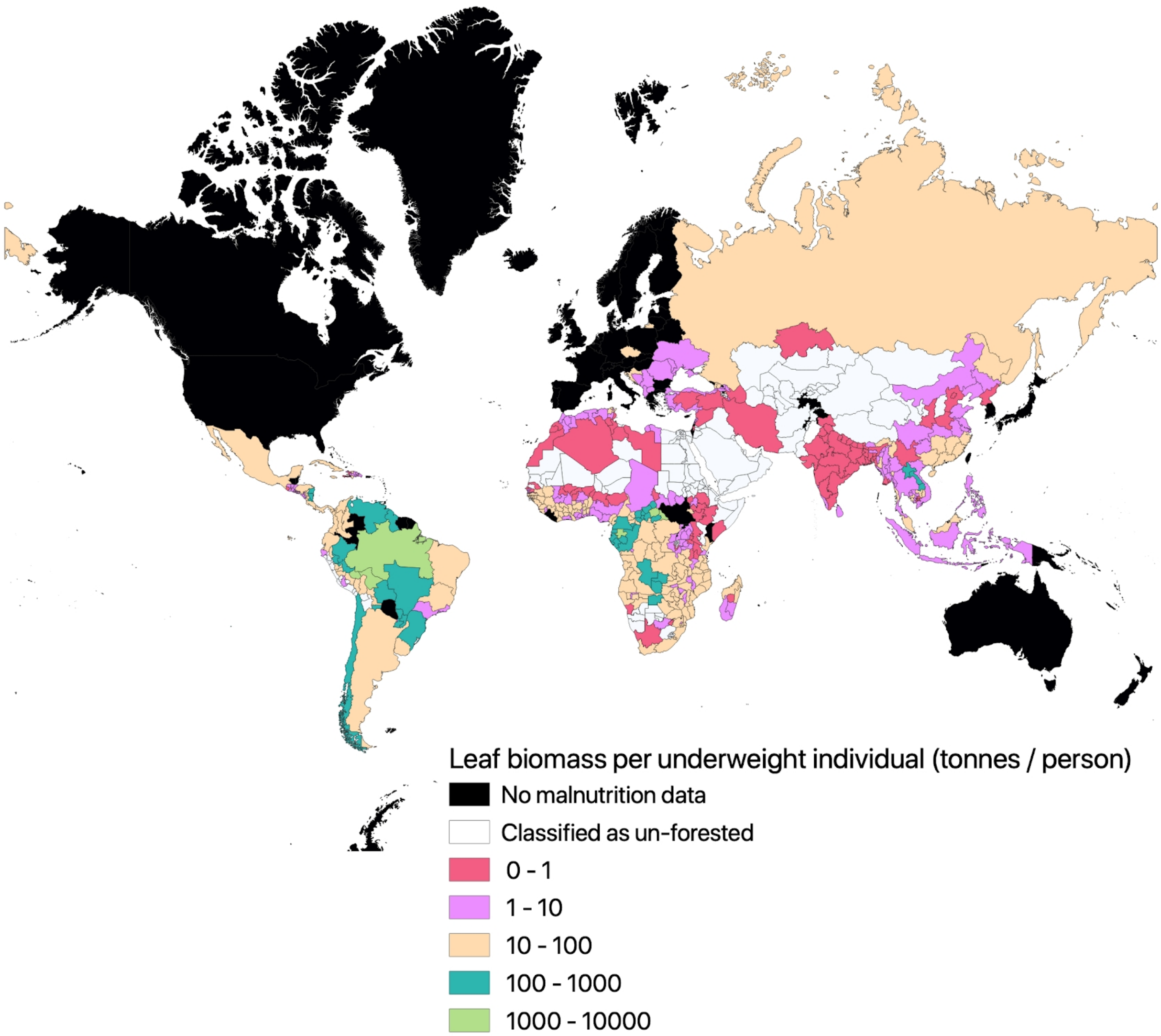



*Figure 8. Leaf dry biomass per underweight individual in tonnes/person shown i n the populations regions. Note that the categories in the legend are on a log scale.*

Over the entire Earth the forest classifications that could provide alternative food with leaf extract to people suffering from malnutrition are shown in Table 1. As can be seen in Table 1 the forest types, which should be more closely evaluated to end acute hunger with leaf extract are all tropical: moist deciduous forests, dry forests and rainforests account for the vast majority of underweight global population.

*Table 1. Forest classifications that could provide alternative food with leaf extract to the most number of people suffering from malnutrition.*

| **Forest classification** | **Global underweight population in region where forest classification is the most prevalent** |
|---|---:|
| Tropical moist deciduous forest | 348,514,567 |

| | |
|---|---|
| Tropical dry forest | 309,536,295 |
| Tropical rainforest | 226,873,692 |
| Subtropical humid forest | 37,503,126 |
| Temperate continental forest | 17,900,192 |
| Subtropical dry forest | 12,574,476 |
| Boreal coniferous forest | 4,988,328 |
| Temperate oceanic forest | 117,119 |
| *Total* | *958,007,795* |

Table 2 shows the total available amount of dry leaf biomass across each of the forest classes considered in this study. This data is especially relevant for sun-obscuring global catastrophe scenarios, where a large amount of alternative food would be required to feed the world's population.

*Table 2. The total dry leaf biomass in tonnes as a function of forest classification.*

| **Forest classification** | **Total dry leaf biomass (tonnes)** |
|---|---|
| Tropical rainforest | 4,383,160,948 |
| Tropical moist deciduous forest | 1,545,050,205 |
| Tropical dry forest | 621,972,869 |
| Subtropical humid forest | 521,891,853 |
| Boreal coniferous forest | 432,035,896 |
| Temperate continental forest | 186,085,629 |
| Boreal tundra woodland | 112,470,103 |
| Temperate oceanic forest | 120,400,200 |
| Subtropical dry forest | 95,440,491 |
| *Total* | *8,018,508,194* |

## 4. Discussion

The analysis presented in this study has several limitations. First, it is limited by the timeliness of datasets, with all datasets having reference years within 2000-2002, which affect the results as all inputs have changed. Global population, number of malnourished individuals, and tree cover would all reasonably be expected to have changed in the intervening time period. However, this was the best available complete data and provides good semi-quantitative indicators for both research and policy action. Future work is recommended that would utilize remote sensing (Drake, et al., 2003; Zheng, et al., 2007; Heiskanen, 2006; Djomoand Chimi, 2017; Halme, et al., 2019) and normalized hotspot-signature vegetation index (NHVI), leaf area index (LAI), normalized difference vegetation index (NDVI), and bi-directional reflectance distribution function (BRDF) techniques to estimate leaf biomass (Hasegawa,  et al., 2010; Zhu and Liu, 2015; Cunliffe, et al., 2020; Sader, et al., 1989).

In addition, not all areas had data available (black regions in Figures). With global climate change accelerating (Houghton, 1996; Edenhofer, 2015; Schuur, et al., 2015; Bevis et al., 2019; Turetsky, et al., 2019) the coverage of forest area dataset (forest classes) would also be expected to change into the future (Gatti et al., 2019). The methodology to calculate leaf biomass from the global carbon stock data has several sources of assumption that could be further refined when detailed mass ratio analyses of leaves for trees in specific regions have been conducted. Additionally, in this study mountain regions were excluded, but if technically viable means was found to harvest leaves in those regions, they should be included in future analysis. Furthermore, other types of leaves could be evaluated (e.g. on shrubs) that may alter the priority list.

The results of this study are useful as they give a strong indication of the types of forests that should be concentrated on for future research surrounding using leaves as alternative foods to help reduce malnutrition in the short term. There are also clear areas where future spatial work is desired to make further use of this study. The suggested next step in this analysis is to break down the forest classes in this study into individual tree species in different regions and/or develop a global dataset showing tree species distribution. The overall technical viability of this approach to solving current hunger issues needs considerably more study as current hunger is primarily a social construction (Maurer & Sobal, 1995) due to poor governance (Birner, 2007) or war (Toole & Waldman, 1993), even short distances for transport can be technically or economically prohibitive for the world's poor. This analysis could thus be enhanced by considering the impact of both property (e.g. who owns the forests) as well as shipping both across regions internally in a country as well as international shipping and the impact of regional vs distributed processing. In addition, the methods of leaf harvesting and processing to make LPC needs considerably more technical investigation to find the most efficient and sustainable methods to determine viability particularly for acute hunger. For example, what percent of leaves can be easily harvested from specific tree species in specific regions without leading to tree death and deforestation for current hunger? It can be noted, that after a major GCR event the trees would be dead anyway. Future work is also necessary to evaluate the impact of unintended consequences (e.g. deforestation and carbon emissions as a result of widespread LPC extraction using felling methods).  Future work could also update the input data used in this analysis. For example, malnutrition data is now available from the Food Security Portal (2019).

In addition, these same methods as used in this study could be used for priority determination of forest types to study for the viability of leaf concentrate as an alternative food in sun-obscuring global catastrophic risk (GCR) scenarios. In these cases, a more global view of leaf biomass availability would be important, rather than one specifically targeted towards more malnourished regions.

Finally, additional work is needed to be able to determine how many people could be fed on the existing leaf biomass in a region, harvested to address acute malnutrition sustainably (e.g. harvesting some percentage of leaves by pulling them off the tree) as well as using more extreme methods for sun-obscuring GCR scenarios (e.g. cut the trees down and harvest all leaves, as trees will die regardless in such an event). For the former, the percentage of leaves that can be sustainably harvested from the relevant different tree species is needed. For both scenarios, the percentage of dry weight of leaves that can be extracted as edible food for different tree species would also need to be experimentally determined. These techniques would need to be weighed against other solutions previosulsy discussed in a partial sun-obscuring disaster as well as new solutions such as scaling up greenhouse crop production (Alvarado, et al., 2020), microbial protein production from hydrogen conversion (Martínez, et al., 2021) or biorefinary reporposing for sugar production (Throup, et al., 2020). Finally, it may be possible that a lower caloric intake than the WHO recommendations is possible (WHO, 2012), so more clarity is required in the caloric input necessary to sustain human life to calculate the mass of leaf biomass that needs to be available in all scenarios.

## Conclusions

This study successfully applied a new approach for mapping available green leaf biomass and corresponding forest classes, and their spatial relationship to the global distribution of underweight people. It was able to find the forest classes most likely to offer proximate access to the world's hungry to use for alternative food from leaf concentrate. These forest classes are moist deciduous tropical forests, dry tropical forests and tropical rainforests. These results will be useful for developing a targeted list of tree species to conduct leaf toxicity analysis on in future studies, in order to develop leaves as an alternative food source for both current malnutrition as well as severe catastrophic scenarios.

**Conflicts of interest:** The authors declare that there is no conflict of interest.

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