Title: The challenge of feeding the world while conserving half the planet

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Amidst widespread concerns about biodiversity loss, a single clear conservation message is engaging leading conservationists: the proposal to give half the surface of the Earth back to nature. Depending on the landscape conservation strategy, we find that globally 15-31% of cropland, 10-45% of pasture land, 23-25% of non-food calories, and 3-29% of food calories from crops could be lost if half of Earth's terrestrial ecoregions were given back to nature.

The Convention on Biological Diversity, signed by 196 parties, is the world's primary multi-lateral, legally binding, treaty for protection and sustainable use of the planet's biological resources. Through it, world leaders made a commitment to halt biodiversity loss by 2010, but failed¹. This led to the development of the Strategic Plan for Biodiversity 2011-2020, and twenty ambitious Aichi Biodiversity Targets². With less than two years to go, these complex and ambiguous targets to halt biodiversity loss by 2020 seem out of reach³.

Amidst these signs of likely failure, prominent conservation leaders are congregating around an even more ambitious goal to give half the surface of the Earth back to nature (<http://www.half-earthproject.org/>; <http://natureneedshalf.org/>). This proposal roughly equates with expanding the – yet to be achieved – Aichi Target 11, to conserve 17% of world's terrestrial and 10% of marine areas, by roughly 3 and 5 times, respectively. In doing so, the project claims the potential to conserve ~85% of existing species⁴, by moving towards a system of interconnected high quality habitats of sufficient scale locally, regionally and globally to support the persistence of natural populations⁵. The added value of Half-Earth is also in its branding: the idea is conceptually simple and visionary, creating a single banner under which other scattered conservation initiatives could operate. As an aspirational goal, it is a powerful message that could motivate and empower the public and local organizations to take positive action to protect the biosphere at the level needed for reducing biodiversity decline.

Yet, despite these benefits, the practical costs of Half Earth incurred through trade-offs with other land uses, and its impacts on already disadvantaged populations around the world, remain poorly understood^{6,7}. Possibly the greatest trade-off embedded in the Half Earth proposal is with agriculture: the dominant land use competing for space with other species on this planet and the nexus of multiple Sustainable Development Goals linked to human health and wellbeing, climate change, biodiversity loss and water security⁸. While relationships between food production and biodiversity conservation have been analyzed previously^{9,10}, the food production costs of Half Earth have yet to be assessed.

In this paper, we offer an initial assessment of the potential global trade-offs between devoting half a planet for nature and agricultural production. We do this by assessing Half Earth conservation strategies designed to maximize protection of key biodiversity areas and existing wild lands while minimizing crop calorie losses caused by displacing arable agriculture. We conduct analysis at the global, country, and ecoregion scales, giving half of the land within each geographic boundary at each scale back to nature (see Methods for further details of our ranked prioritization used in the analysis). We run this analysis for two drastically different conservation approaches: “Nature only landscapes”, in which conservation displaces all crop production in regional landscapes¹¹ (~8.4km x ~8.4km pixels), and “Shared landscapes”, in which conservation and crop production are allowed to coexist within each landscape (8.4km x ~8.4km pixel), in any possible spatial configuration (i.e. both intensive and extensive production are possible, see Ref¹² for details of the debate surrounding these extremes). This latter, “Shared landscapes” approach works at the subpixel level, and so allows for implementation of fine scale resolution conservation strategies that are not limited by the landscape size.

Our results demonstrate clear potential for trade-offs between Half Earth and agricultural production that are strongly mediated by the approach taken and the spatial scale of the land units used for conservation planning. Firstly, there is a strong negative effect of the spatial scale of conservation units, with trade-offs increasing across Global (n=1) vs. Country (n=182) or Ecoregion (n=775) scales. At the global level, under a “Nature only landscapes” strategy, we see ~12% of cropland, ~21% of pasture, ~10% of non-food (i.e. feed, biofuel and other) calories, and ~11% of food calories lost – numbers that increase to ~31% of cropland, ~45% of pasture, ~25% of non-food calories, and ~29% of food calories at the Ecoregion level (Fig 1). Second, there are massive differences in trade-offs between conservation approaches. Under “Shared landscapes”, where agricultural production and conservation are allowed to coexist, productivity costs are much lower, demanding ~15% of cropland, ~10% of pasture land, ~23% of non-food calories, and ~3% of food calories at the Ecoregion level (Fig 1). However, even under a “Shared landscapes” approach, if pasture is converted to conservation before cropland, and non-food calories are abandoned before food calories, losses of non-food calories remain high. Overall, reaching the Half-Earth target without calorie losses could be achieved in only about 14% of Earth’s ecoregions through a “Nature only” approach, while the “Shared” approach could achieve this across more than four times as many ecoregions (65%) (Supplementary Information Fig S1). Simply put, the trade-offs between agriculture and Half Earth will be much lower if landscapes are allowed to remain as mosaics of shared land uses, and will be much higher if large contiguous areas are given back, as may be required for the conservation of some species, such as mega-fauna.

There are also differences in the spatial distribution of Half Earth’s agricultural trade-offs, depending on the conservation approach (Figure 2; only ‘calorie losses’ shown). Notably, a Shared approach dramatically minimizes the extent of spatial trade-offs. Yet regardless of conservation approach, food calorie losses occur in many locations and countries with marked food insecurity. At the country scale, even a Shared approach results in substantial losses of food calories in both China (12%), and India (22%) – countries with the highest absolute numbers of undernourished people on the planet at 133.8M and 194.6M, respectively¹³. Under any strategy

other than Global, substantial calorific losses also occur locally in Africa and elsewhere in Asia (Figure 2).

As our analysis highlights, there are major political consequences for national food systems embedded within global strategies for achieving Half Earth conservation targets, if the goal of feeding the human world equitably is to be balanced with sharing the planet with other species. Even with current populations and energy demands, potentially massive calorie losses would need to be offset by massive increases in the intensity of food production (i.e. by closing yield gaps to achieve 45-70% increases in crop production¹⁴), reductions in food waste (i.e. by mitigating the ~24% of calories lost in global supply chains¹⁵) and/or dietary shifts away from animal products (i.e. by diverting the 36% of crop calories currently fed to animals toward direct human consumption¹⁶). However, all of these co-strategies are extremely challenging ambitions in themselves.

Demands of future human populations and losses of pasture-fed animal calories are not considered here, nor did we conduct an explicit spatial prioritization for maximizing coverage of species ranges or connectivity (which may prioritize more productive lands than given back in our analysis), so our findings should be seen as conservative with respect to Half Earth's potential negative impacts on agriculture. That said, land use conversion from agriculture to conservation (e.g. either from pasture or cropland), would produce significant co-benefits too, such as gains in woody perennial vegetation cover and carbon sequestration, including up to a 40% increase in tropical deciduous forest cover globally, and a 36% increase in temperate deciduous forests, no doubt helping to meet climate targets while providing other socially valuable benefits of nature conservation (Supplementary Information Fig S2)¹⁷.

While our analysis has focused almost exclusively on agricultural production, the practical challenges of achieving Half Earth are many, and go far beyond the metrics discussed here. For example, a key concern is potential worsening of land tenure insecurity and increasing land prices, which together with loss of food security and sovereignty, may further impoverish or displace rural peoples¹⁸. These impacts, if not carefully managed, may lead to losses in conservation effectiveness over the long-term. Another important question concerns possible agricultural intensification in the other half of the planet under future population and economic growth¹⁹, and how different species and taxonomic groups might respond to this. Finally, while conservation spending (e.g. by governments, trust funds, donors) has proven effective where allocated²⁰, economic costings for global conservation priority areas are too narrow in scope, and the ecological, political, sociocultural, economic and business models needed to sustain a global conservation project of such scale and ambition over decades and into the deep future have yet to be developed.

We show that any discussion of Half-Earth needs to explicitly evaluate the local, regional, and global consequences of displacing land from agriculture and its consequences for food security. The trade-offs between nature and agriculture are potentially large, but depend strongly on the strategies used to achieve Half-Earth, highlighting the possible strengths of shared landscape approaches to expanding conservation with lower tradeoffs for agricultural production. However, we find no clear pathway to give half our planet to nature at a scale that maintains ecosystem connectivity and still feed the world, without at least some nations or subpopulations losing out.

Under this context, protection of existing vulnerable, malnourished, and food insecure populations is a key priority, and prerequisite, for humans and nature to coexist into the future.

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Contributions:

ZM, EE, and NR designed the analysis. ZM compiled the data and conducted the analysis. ZM wrote the paper with input from EE and NR.

Competing interests:

The authors declare no competing interests.

Figure legends (Main text):

Figure 1. Feeding the world under a global deal for nature. Scenarios were computed using a simple land allocation algorithm operating at global (green), country (blue), and ecoregion (red) scales, each allocating 50% of the planet back to nature. All agricultural area was given back in order of least agricultural productivity, based on the caloric content of 41 major crop plants. The allocation in each scenario was ordered by: (1) existing protected areas, (2) key biodiversity areas, (3) non-agricultural lands (i.e. forests, wetlands, shrublands, grasslands, ice-covered areas), (4) pasture lands, (5) non-food producing croplands (e.g. feed, biofuel, other) (6), food producing croplands (e.g. calories for food crops), and (6) urban areas. Under a “Nature only landscapes” approach we allocated land back to nature on a pixel-by-pixel basis, representing a sharp division between conservation and agriculture at the landscape scale, whereas under a “Shared landscapes” approach we allocated land back to nature on an areal basis, allowing the area within pixels to be shared between conservation and agricultural land uses. All analysis was run at a pixel size of 8.4km x 8.4km.”

Figure 2. Mapping calorie losses under each Half-Earth Scenario. Pixels show the summed caloric losses (from non-food and food crop calories) in each pixel on the planet under three different scales of analysis (global, country, ecoregion) and two different conservation approaches (Nature only landscapes vs. Shared landscapes). Even under a Shared landscapes approach, giving back half of every country or ecoregion on the planet leads to significant losses in geographic locations of major food insecurity concerns (i.e. India, China, Indonesia, W. Africa, Madagascar). Land allocations were made by minimizing calorie losses to show the lowest possible caloric costs to Half-Earth under current production, but we do not mean to advocate that farmers working on marginal lands should be compromised first, as this would likely be deleterious to food security for populations with limited access to farming technology and inputs, or access to land with good growing conditions.

Figure legends (Methods):

Figure 3. Flow-diagram for the analysis.

Methods:

To assess the trade-offs between Half Earth and agricultural production at three scales (Global, Country, Ecoregion), and with two conservation strategies (i.e. “Nature only landscapes” vs. “Shared landscapes” approaches), we compiled 8 spatial datasets: cropland and pasture area²¹; MODIS land cover²²; calorie production for the world’s 41 major crop plants¹⁶; the world database of protected areas²³; Key Biodiversity Areas²⁴; Ecoregion boundaries⁵; country boundaries²⁵, and Potential Natural Vegetation²⁶. All datasets were rasterized, projected to Eckert IV’s equal area at a spatial resolution of ~8.4km x ~8.4 km (the most accurate scale for reproduction of global sums for data set Ref¹⁶), and set to a common extent. We focused on Ecoregions because Half Earth targets have already been deemed achievable or attained in ~49% of the Earth’s 846 terrestrial Ecoregions⁵ by previous authors, and who argue that maintaining these geographic boundaries is critical for maintaining global conservation planning, as opposed to focusing conservation exclusively on global biodiversity importance maps which would disproportionately bias the tropics (e.g. Ref¹⁹).

Our analysis involved additional processing as follows. First, we created a new land class variable merging the above datasets from Refs²¹⁻²⁴. To do this we used Refs²³⁻²⁴ to define cells containing ‘protected areas’ and ‘key biodiversity areas’. Following this we used Ref²¹ to define cells containing ‘cropland’, ‘pasture’, or ‘cropland-pasture’, and then for the remaining cells used the numeric identifiers in Ref²² to represent ‘water’ (ID:0), non-agricultural land (IDs: 1:9, 11, 15:16), and ‘urban’ (ID:13). We then ranked all pixels for this new land class variable in the following order: protected areas > key biodiversity areas > non-agricultural lands (forests, wetlands, shrublands, savannahs, grasslands, snow-ice-barren), agricultural lands (pasture>cropland-pasture>cropland) and urban, and then ordered each pixel within each rank in order of increasing calorific production based on data from Ref¹⁶. Finally, we estimated the proportion of each pixel that was occupied by non agricultural land, land producing non-food crop calories (feed, biofuel and other), and land producing food crop calories (i.e. for direct human consumption) by using fractional cropland area coverage of Ref²¹ and proportional allocation to each calorie class using Ref¹⁶. We then adjusted the total calorie ranking, to allow for differences in the rank order of non-food calories and food crop calories within a given pixel. All water pixels were set to NAs so as to focus on only terrestrial Half Earth.

We simulated agricultural losses (cropland area, pasture area, feed/biofuel/other calories and food calories), under Half Earth with the two different conservation approaches and at the three different geographic scales. We assessed agricultural losses, by identifying the proportion of pasture land, cropland, and calories included in the pixels summing to 50% of the total area (“Nature only landscapes” approach), or sub-pixel areas summing to 50% of the total area (“Shared landscapes” approach) within each of the focal geographic boundaries (Global, Country, Ecoregion) included in the analysis. Under the “Shared landscapes” approach we maintained a priority ranking as: protected areas > key biodiversity areas > non-agricultural area>non-food calorie (feed/biofuel/other) producing land & pasture land> food calorie

producing land > urban, so that we prioritized giving back land area producing non-food calories and pasture lands before food calorie producing croplands. All analysis was done in R 3.4.2²⁷. A flow diagram with an overview of this analysis is given below (Fig 3).

Data availability

Additional analyses and a full set R code to reproduce the results is supplied in Supplementary Information. The data used in this study are either publically available, or available from third parties on request but not distributable by the authors. Full details of each data set, download links, and points of contact for third parties are given in the Supplementary Information.

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Nature only landscapes

Shared landscapes

Percent agricultural loss

Crop land

Pasture land

Crop feed,
biofuel, other
calories

Crop food
calories

Percent of earth given back

Nature only landscapes

Shared landscapes

Global

Country

Ecoregion

**Total crop
calorie
loss (kcal)**

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1 Supplementary Notes

1.1 Reproducibility

We use the **R** packages `knitr` and `checkpoint` [25, 8]. The package `knitr` facilitates producing a dynamic document that contains all the steps required to analyze the data. `checkpoint()` will install all packages versions for you that we used in our analysis to avoid result discrepancies that may arise from software differences. Thus the reader is provided with all the code to fully reproduce the analysis, and adapt or repurpose it for another analyses.

```
library("checkpoint")
checkpoint(snapshotDate = "2018-03-01")
```

For the analysis in this document we will be using the `raster` [13], `rgdal` [5], `ggplot2` [22], `plyr` [20], `sp` [14], `R.matlab` [3], `rworldmap` [17], `car` [11], `maptools` [6], `reshape2` [21], `gridExtra` [1], `amd`, `cowplot` [23], and, `data.table` [10] packages.

```
packages<-c("raster", "rgdal", "ggplot2", "plyr", "sp",
            "R.matlab", "rworldmap", "car", "maptools",
            "knitr", "reshape2", "gridExtra", "cowplot", "data.table")
lapply(packages, require, character=TRUE)
gpclibPermit()
```

1.2 Aims of this document

The aim of this document is to provide the code to reproduce the analysis presented in Mehrabi, Ellis and Ramankutty 2018 entitled “The challenge of feeding the world while conserving half the planet”. Half-Earth is a recent proposal to devote half the surface of the Earth to nature. (<http://www.half-earthproject.org/>; <http://natureneedshalf.org/>). The underlying rationale for Half-Earth derives from scaling relationships between habitat area and species numbers which imply that conserving half of Earth’s habitat area would save 85% of existing species on the planet [24]. The practical costs of Half-Earth incurred through trade-offs with other land uses, such as agriculture, and its impacts on already disadvantaged populations around the world still remain poorly understood [2]. This analysis aims to help fill this research gap.

The nuts and bolts of this analysis is a simple thought experiment constructed to better understand some of the broad trade-offs between agriculture and Half-Earth proposal. The document is structured into two sections, in section [2] we process the data, in section [3] we conduct the thought experiment, create the plots used in the figure in the main text of the manuscript, and conduct some additional analysis, and finally in section [4] we plot the Supplementary Figures. For brevity the code in section [2] is not evaluated in this document.

2 Supplementary Methods A

2.1 Data preparation overview

To assess the trade-offs between Half-Earth and agriculture we compiled 8 spatial datasets. Details of each and the currently live urls and points of contact for data set acquisition are listed below. In some cases these data are not available for us to redistribute, and so those wishing to reproduce this analysis are recommended to approach the persons responsible, and back-date to the dates of acquisition listed below.

1. Global Cropland and Pasture Area [16], retrieved online from www.earthstat.org , on December 13th 2017.
2. MODIS land cover [12], retrieved online from <http://glcf.umd.edu/data/lc/>, on December 17th 2017.
3. Calorie production for the worlds 41 major crop plants, [7] retrieved directly from the original authors, available from Minnesota Insitute on the Environment (jsgerber@umn.edu)
4. The World Database of Protected Areas, [19], retrieved online from <https://www.protectedplanet.net/>, on December 13th 2017.
5. Key Biodiversity Areas 2017 [4] retrieved via FTP link from Gill Bunting at Bird Life International (Gill.Bunting@birdlife.org) on Nov 6th 2017.
6. Ecoregion boundaries, [9], retrieved online from <https://storage.googleapis.com/teow2016/Ecoregions2017.zip>, on April 2017
7. Country boundaries [17], retrieved internally in R.
8. Potential Natural Vegetation, [15], retrieved online from on April 30th 2018, from www.earthstat.org.

All datasets were rasterized, projected to Eckert IVs equal area at a spatial resolution of 8.4km x 8.4 km (the most accurate scale for reproduction of global sums for data set [7], and set to a common extent). This section explains that processing.

2.2 Rasterizing

2.2.1 Ecoregions

First we read in the ecoregion data, rasterize it, and write to file.

```
Dinn<-shapefile("halfearthdata/Ecoregion2017_Erle/Ecoregions2017.shp")
raster.Dinn<-raster(resolution = 0.0833282)
extent(raster.Dinn) <- extent(Dinn)
Dinn$ECO_NAME<-as.factor(Dinn$ECO_NAME)
Dinn.raster <- rasterize(as(Dinn, "SpatialPolygons"), raster.Dinn, field = Dinn@data[, "ECO_NAME"], fun="first")
getwd()
Dinn.rast <- writeRaster(Dinn.raster, "halfearthdata/processed/Dinnrast.tif", format="GTiff", overwrite=TRUE)
```

2.2.2 KBA

Then we read in the KBA data, rasterize it, and write to file.

```
KBA<-shapefile("KBAsGlobal_2017_1a/Global_KBA_poly.shp")
raster.KBA<-raster(res = c(0.0833282,0.0833282))
extent(raster.KBA) <- extent(KBA)
KBA.raster <- rasterize(as(KBA, "SpatialPolygons"), raster.KBA, field = KBA@data[, "SITRECID"], fun="first")
kbavals<-values(KBA) #set non KBA values to NA
kbavals2<-ifelse(kbavals>0,1,NA)
KBA2<-KBA
values(KBA2)<-kbavals2
KBA.rast<- writeRaster(KBA2, "halfearthdata/processed/KBArast.tif", format="GTiff", overwrite=TRUE)
```

2.2.3 Crop calories

Then we read in the global crop calorie data, and write to file. These data are supplied as .mat files.

```
Cass.total<-readMat("halfearthdata/Emily_data/Cassidy Crop Allocation and Delivery/GlobalTotalkcal.mat")
rasterD <-raster(ncol=4320, nrow=2160)
values(rasterD)<-c(Cass.total$GlobalTotalkcal)
kcal.41<-rasterD
plot(kcal.41)
kcal.rast<- writeRaster(kcal.41, "halfearthdata/processed/kcalrast.tif", format="GTiff", overwrite=TRUE)
```

We also retrieve the calorie delivery fraction data from Cassidy et al. A unit of 1 identifies that all kcal produced are delivered as food, whereas a unit of <1 identifies that some proportion of calories are fed to animals from that pixel.

```
Cass.food<-readMat("halfearthdata/Emily_data/Cassidy Crop Allocation and Delivery/GlobalFoodkcal.mat")
rasterD <-raster(ncol=4320, nrow=2160)
# Cass.food$GlobalFoodkcal[is.na(Cass.food$GlobalFoodkcal)] <- 0 #replace NA with zero
values(rasterD)<-c(Cass.food$GlobalFoodkcal)
kcal.food<-rasterD
kcal.food<- writeRaster(kcal.food, "halfearthdata/processed/kcal.food.tif", format="GTiff", overwrite=TRUE)
```

2.2.4 WDPA

Here we read in the world protected area data. This data was first imported into QGIS [18], to simplify the geometry with the default tolerance. It was then rasterized it in QGIS, to reduce processing time in R. We set non-WDPA values in this raster to NA, and write the result to file.

```
WDPA<-raster("halfearthdata/WDPA_Oct2017/WDPA.tif")
str(WDPA)
wdpavals<-values(WDPA)#set non WDPA values to NA
wdpavals2<-ifelse(wdpavals>0,1,NA)
WDPA2<-WDPA
values(WDPA2)<-wdpavals2
WDPA.rast<- writeRaster(WDPA2, "halfearthdata/processed/WDPArast.tif", format="GTiff", overwrite=TRUE)
```

2.2.5 Countries

Finally we make a raster of the world country data from the `rworldmap` package.

```
world<-getMap(resolution='low')
raster.world<-raster(res = c(0.0833282,0.0833282))
extent(raster.world) <- extent(world)
world.raster <- rasterize(as(world, "SpatialPolygons"), raster.world, field = world@data[, "ADMIN"], fun="first")
world.rast<- writeRaster(world.raster, "halfearthdata/processed/worldrast.tif", format="GTiff", overwrite=TRUE)
```

2.3 Additional processing

2.3.1 Read data

Here we read in the data for additional processing. We read in the processed data sets outlined above, as well as two others. These include the MODIS LC data set as an indication of land cover, and potential natural vegetation.

```
KBA<-raster("halfearthdata/processed/KBARast.tif")
CA<-raster("halfearthdata/CroplandPastureArea2000_Geotiff/cropland2000_area.tif")
PA<-raster("halfearthdata/CroplandPastureArea2000_Geotiff/pasture2000_area.tif")
Dinn<-raster("halfearthdata/processed/Dinnrast.tif")
kcal<-raster("halfearthdata/processed/kcalrast.tif")
kcal.food<-raster("halfearthdata/processed/kcal.food.tif")
WDPA<-raster("halfearthdata/processed/WDPArast.tif")
world<-raster("halfearthdata/processed/worldrast.tif")
LC<-raster("halfearthdata/MODIS_GLCF/LC_hd_global_2012.tif")
PNV<-raster("halfearthdata/potveg_geotiff/potentialvegetation_geotiff/potentialvegetation.tif")
```

2.3.2 Convert to equal area

Here we project everything to be equal area (set to 8439m x 8439m, as this is with the best match for the kcal data, it is within 0.001%). We use two methods of interpolation, bilinear for continuous data and nearest neighbour for categorical data.

```
rast.list.ngb<-list(Dinn,KBA, WDPa, LC, world, PNV)
rast.list.bil<-list(kcal,CA,PA, kcal.food)

rast.list.ngb.eq<-lapply(rast.list.ngb, function(x)
  projectRaster(x, res=c(8439, 8439),
    crs="+proj=eck4 +datum=WGS84 +ellps=WGS84 +towgs84=0,0,0",method="ngb", over = T))

rast.list.bil.eq<-lapply(rast.list.bil, function(x)
  projectRaster(x, res=c(8439, 8439),
    crs="+proj=eck4 +datum=WGS84 +ellps=WGS84 +towgs84=0,0,0",method="bilinear", over = TRUE))

rast.list<-c(rast.list.ngb.eq, rast.list.bil.eq) #combine data
names(rast.list)<-c("Dinn", "KBA", "WDPa", "LC", "world", "PNV", "kcal", "CA", "PA", "kcal.food")
```

Now we double check that the sum of the original crop calorie data is equivalent to the equal area representation. We find these are very close to each other, and so the equal area conversion is reasonable in aggregate for this variable.

```
sum(values(rast.list.bil.eq[[1]]), na.rm = T) #check kcal values
sum(values(kcal), na.rm = T)
```

2.3.3 Back corrections

No reprojection of geospatial data is perfect. In some cases it can lead to nonsensical outputs. A good example of this is shown here with cropland and pasture data, where the sum of the original lat-long data on proportions of cropland and pasture in a cell is never greater than zero, but where for the derived products the summed area can exceed one. This is logically impossible in reality, but is an artifact created through the reprojection.

```
plot(CA+PA) #original lat long
plot(rast.list$PA+rast.list$CA) #eck 4 version
```

The details of the net differences between the aggregate sums of equal area projected and lat-long version are given below. As we can see reprojection reduced the global area of cropland by 2% and increased it for pasture by 1%.

```
cell.area=8439*8439 #area of grid cell
sum(values(rast.list$CA)*cell.area, na.rm=T)/sum(values(CA)*cell.area, na.rm=T)
sum(values(rast.list$PA)*cell.area, na.rm=T)/sum(values(PA)*cell.area, na.rm=T)
```

It is difficult to deal with these two issues easily in one fell swoop. It is possible to calibrate using the original data sources pretty easily. This is done in the chunk of code below for continuous data. But this does not deal with the nonsensical output of having proportional coverage in pixels greater than one.

```
values(rast.list$CA)<-(values(rast.list$CA)/sum(values(rast.list$CA),na.rm=T))*sum(values(CA), na.rm=T) #CA
values(rast.list$PA)<-(values(rast.list$PA)/sum(values(rast.list$PA),na.rm=T))*sum(values(PA), na.rm=T) #PA
values(rast.list$kcal)<-(values(rast.list$kcal)/sum(values(rast.list$kcal),na.rm=T))*sum(values(kcal), na.rm=T) #food kcal
values(rast.list$kcal.food)<-(values(rast.list$kcal.food)/
  sum(values(rast.list$kcal.food),na.rm=T))*sum(values(kcal.food), na.rm=T) #kcal
```

One work around, is to ensure that no sum of proportional areas in pixels exceeds one. We do this below, and preferentially reduce pasture areas within each pixel. A more exact approach, would be to write a spatial re-allocation algorithm that deals with both of these issues together. However, for the purposes of this thought experiment, and for the specific results we provide, the approach taken here seems reasonable. Indeed, as we can see from below, not only have we now achieved sensible plot values, but we still have maintained our pasture aggregate sums to a high degree – with our reprojected pasture areas being only 0.02% less than the original lat long file. By focusing only on pasture in correcting for proportional coverage, the aggregate sums of all other continuous variables is maintained.

```
values(rast.list$PA)<-ifelse(values(rast.list$PA)+values(rast.list$CA)>1,1-values(rast.list$CA), values(rast.list$PA))
plot(rast.list$PA+rast.list$CA)
sum(values(rast.list$PA)*cell.area, na.rm=T)/sum(values(PA)*cell.area, na.rm=T)
```

2.3.4 Set extents

Next we need to trim the extents. We can see from the plots below, and in the README for the MODIS LC data, that the LC data does not include Antarctica. In fact it only covers southern latitudes to -64 degrees.

```
par(mfrow = c(1,1))
lapply(rast.list, function(x) plot(x, main=names(x))) #check
```

Therefore, we need to expand the LC data to include the area that will house Antarctica. We draw from the country data which includes a boundary for Antarctica. As explained by Prof. Rob Hijmans in his manual for the package (<http://rspatial.org/spatial/rst/8-rastermanip.html>), the extend function fills NA's in rows that are added. We couple this with the crop function to maintain equal extents across all datasets, then apply the setExtent function to ensure that rounding is exactly the same across the files.

```
ex1<-extent(rast.list$Dinn)
rast.list.ex<-lapply(rast.list, function(x) extend(x, ex1)) #extend
rast.list.c<-lapply(rast.list.ex, function(x) crop(x, ex1)) #then crop
rast.list.et<-lapply(rast.list.c, function(x) setExtent(x, ex1, keepres=TRUE)) #then force extent to be the same
```

2.3.5 Create stack

With the data all with the same resolution, extent and equal area CRS, we can now create a stack of all the layers.

```
rast.all<-stack(rast.list.et)
```

Now let's check the plots again.

```
plot(rast.all) #check
```

2.4 Land class variable

2.4.1 Cropland and pasture

We now need to make a common land class variable that merges cropland and pasture area data and MODIS LC data. We will use the Ramankutty et al. identifiers for cropland and pasture data.

We create a numeric code for each cropland, pasture and cropland-pasture mix and add this to the land class variable. For cropland we assign 18, for the pasture-cropland mix we assign 17, and for pasture we assign 19.

```
newclass<-ifelse(values(rast.all$CA) > 0 & values(rast.all$PA) > 0, 17,
  ifelse(values(rast.all$CA) > 0 & values(rast.all$PA) %in% c(0,NA), 18,
    ifelse(values(rast.all$PA) > 0 & values(rast.all$CA) %in% c(0,NA), 19,
      values(rast.all$LC))))
summary(as.factor(newclass)) #check
```

2.4.2 Antarctica

We need to specify Antarctica in the LC data. Antarctica is identified under an id of 9 in the country data. We therefore designate Antarctica an id of 15, to correspond to the id for "Rock and Ice" in the README given to accompany the LC file. We then check this by plotting, it looks good. We then add this to the newclass variable. [We add this in here because doing it before defining cropland, mixed and pasture pixels, would lead to it being lost due to NAs in CA and PA data sets].


```
values(rast.all$LC)<-ifelse(values(rast.all$world)==9, 15, values(rast.all$LC))
plot(rast.all$LC) #check Antarctica has been added
newclass<-ifelse(values(rast.all$LC)==15, 15, newclass) #add to newclass
```

2.4.3 WDPa and KBA

We then assign numeric values for the WDPa and KBA areas: 20, and 21 respectively. These may include agricultural production, but we will give these areas top priority in any Half-Earth Scenario for conservation. We keep the ocean as zero.

```
newclass<-ifelse(is.na(values(rast.all$KBA))|values(rast.all$LC)==0, newclass, 21)
newclass<-ifelse(is.na(values(rast.all$WDPa))|values(rast.all$LC)==0, newclass, 20)
```

2.4.4 Urban

We also maintain urban areas with agricultural production as urban.

```
newclass<-ifelse(values(rast.all$LC)==13, 13, newclass)
```

2.4.5 Add new LC

We then create a new layer in the stack for the new land class variable

```
rast.all$newclass<-rast.all$LC
values(rast.all$newclass)<-as.numeric(newclass)
summary(values(rast.all$newclass)) #check
```

And then join the data into a single data frame.

```
data.all<-data.frame(coordinates(rast.all), values(rast.all))
summary(as.factor(data.all$newclass))
```

2.4.6 Rank land classes

Finally we recode and rank the land cover variables into a more limited number of classes. The rank represents the order in which we will give back individual pixels (“nature only landscape approach”), or area within pixels (“Shared landscape approach”). All agricultural areas are given back in order of least productivity. We define agricultural productivity based on calories gained from 41 major arable crops. The ranking for this hypothetical deal with nature is given below. The order of this ranking is not supposed to be definitive, but simply to highlight broad scale the trade-offs between Half-Earth and agricultural production. We assign water to be NA.

1. World protected areas
2. Key Biodiversity Areas
3. Non-agricultural lands (Forests, Wetlands, Shrublands and savannas, Grasslands, Snow, Ice, Barren)
4. Agricultural lands (Pasture)
5. Agricultural lands (Mixed)
6. Agricultural lands (Cropland)
7. Urban

```
data.all$rank<-recode(data.all$newclass,
" c('0')= NA;
  c('1','2','3','4','5','6','7','8','9','10','11','12','14','15','16') = '3';
  c('13')= '7';
  c('17')= '6';
  c('18')= '5';
  c('19')= '4';
  c('20')= '1';
  c('21')= '2'
")
summary(as.factor(data.all$rank)) #check
```

2.4.7 Rank by calories

We then need to compute the calories in each pixel. We compute this in a similar step-wise process to the areas, for non crop productive locations (i.e. a value of zero), and for crop areas [split into non-food calories, i.e. feed and bio fuel and other, and food calories].

```
data.all$kcals.noag<-(0) #zero kcal for all non-ag areas
data.all$kcals.nonfood<- data.all$kcals-data.all$kcals.food
data.all$kcals.prop<-data.all$kcals.food/data.all$kcals
head(subset(data.all, kcals.prop>0))
```

We then join the calories column with the rank column. This orders the agricultural productivity, and other variables by the calories, but keeps the ranking of the land use classes. We generate three different calorie rankings, one for food, and one for non-food calories, and one for all sources of calories; marking them by different orders of magnitude.

```
data.all$rank.all<-(data.all$kcals/max(data.all$kcals, na.rm=T)+data.all$rank)
data.all$rank.nonfood<-(data.all$kcals.nonfood/max(data.all$kcals.nonfood, na.rm=T)+data.all$rank)+10
data.all$rank.food<-(data.all$kcals.food/max(data.all$kcals.food, na.rm=T)+data.all$rank)+100
head(data.all[which(data.all$kcals>0),])
```

2.4.8 Compute areal coverage

Next we compute the non-agricultural area in each grid cell, and the area allocated to non food calories (feed, bio fuels, other) vs. food calorie production. First we check to see if there are any cases with calorie data where our cropland area product is 0. There are a few cases here, but they only represent a very small amount of global kcal. This is an extremely minor part of the data, and likely results from processing error.

```
sub<-subset(data.all, kcals>0 & (CA==0))
#cells with kcal but no crop f. area data
sum(sub$kcals, na.rm=T)/sum(data.all$kcals, na.rm=T) #
```

Then we define the variables that we will need for later analysis, and sanity check these against those reported in Ramankutty et al. 2008. We also compute the non-crop area, feed/bio fuel/other area, and food area within each pixel in each ranked class. We disaggregate non-food vs food areas using the calorie fraction data, on the assumption that areal allocation is equal per unit of calories for a given pixel.

```
area<-cell.area*nrow(subset(data.all, !is.na(rank))) #terrestrial area
ice.free<- area- (cell.area*nrow(subset(data.all, LC==15))) #ice -free terrestrial area
crop.area<-data.all$CA*cell.area #crop area
pasture.area<-data.all$PA*cell.area #crop area
crop.area[is.na(crop.area)] <- 0 #remove NAs
pasture.area[is.na(pasture.area)] <- 0 #remove NAs
non.ag<-ifelse(!is.na(data.all$rank), cell.area-crop.area-pasture.area, NA) #non.ag
food.area<-crop.area*data.all$kcals.prop #food area
feed.area<-crop.area-food.area #feed/biofuel area
food.area[is.na(food.area)] <- 0 #remove NAs
feed.area[is.na(feed.area)] <- 0 #remove NAs
non.ag[is.na(other.ca.area)] <- 0 #remove NAs
sum(crop.area, na.rm=T)/ice.free #sanity checks, should be ~12%,
```

```
sum(pasture.area, na.rm=T)/ice.free #sanity checks, should be ~22%,
sum(crop.area,pasture.area, na.rm=T)/ice.free #sanity checks, should be ~34%,
sum(non.ag,crop.area,pasture.area, na.rm=T)/area
```

We then assign the relevant area calculations to the data frame. For all land classes except urban, first we give back non-agricultural area, then non-food (feed, bio fuel, and other) crop area alongside pasture area, then finally agricultural areas producing food calories. For urban locations we reverse the grouping – first we give back non-food (feed, bio fuel, other) agricultural area, then food crop areas and finally, non-agricultural areas. Notably, we simply embed this reversion for urban pixels in the data, to account for logic of high priority for avoiding encroaching on urban settlements, but it is not reflected in the variable names.

```
data.all$food.area<- ifelse(data.all$rank==5,food.area+non.ag, food.area)
data.all$feed.area<-feed.area+pasture.area
data.all$non.ag<-ifelse(data.all$rank==5,0, non.ag)
sum(crop.area, pasture.area, na.rm=T)/ice.free #sanity check
sum(data.all$non.ag,data.all$feed.area,data.all$food.area, na.rm=T)/area #sanity check
sum(non.ag, crop.area,pasture.area, na.rm=T)/area #sanity check
data.all$past.area<-pasture.area #add in pasture area for later
```

2.4.9 Add in Country ids

During processing we lost the country identifiers, so here we add that back in now, both in ADMIN names, and ISO3's.

```
world<-getMap(resolution='low')
lookup<-as.data.frame(cbind(as.character(world@data[, 'ISO3']),world@data[, 'ADMIN'],as.character(world@data[, 'ADMIN'])))
matched<-lookup[match(data.all$world, lookup$V2), ]
data.all$country<-matched[[1]]
data.all$ISO3<-matched[[3]]
```

Finally we save the processed data as an RDS file.

```
saveRDS(data.all, "halfearthdata/processed/data.all.new.rds")
```

3 Supplementary Methods B

3.1 Analysis overview

In this section we conduct the analysis underlying the results presented in the manuscript. To simulate crop calorie losses under Half-Earth, we gave back pixels (i.e. “nature only landscapes”), or area in pixels (“shared landscapes”), on the planet in sequence of the rank and increasing calorie production, at global (no boundary), country (boundaries set by countries), and ecoregion (boundaries set by Ecoregions) scales. We assess losses at 50% land re-allocation under each scenario.

3.2 Read data

First we read in data.

```
data.all<-readRDS("halfearthdata/processed/data.all.new.rds")
```

Let’s double check the number of countries and ecoregions.

```
geocount<-c(length(unique(data.all$Dinn)),length(unique(data.all$IS03)))
geocount
[1] 821 231
```

Because we want consistency in the number of cells, and area, given back under each scenario, and because each of the polygon boundaries for the ecoregions, countries and the land cover datasets are not exactly the same, we ensure NAs across the datasets are consistent. In addition we remove the NAs in the land cover data which represent water bodies, so we are working only on the terrestrial land surface area from here on in.

```
data.all<-subset(data.all, !is.na(Dinn) & !is.na(country) & !is.na(rank))
```

Now let’s check how many countries and ecoregions we are working with now.

```
subgeocount<-c(length(unique(data.all$Dinn)),length(unique(data.all$IS03)))
subgeocount
[1] 775 182
```

3.3 Run scenarios

We then write out a loop to compute the half-earth scenario for each geographical scale of analysis. All the processing is included as one chunk of code here, but is hopefully laid out in a logical way that can be refactored if needed in future. It takes the following inputs:

1. geog = column name with the geographic identifier (i.e. indicating scale of analysis)
2. data= dataset (i.e. data.all)
3. scen = character label for the scenario being run

And then creates a list output of length 4. The first and second elements are the output for the “nature only landscapes” approach to Half-Earth. The third and fourth are the outputs for the “shared landscapes” approach. The first, and third, elements include all original variables in the data.all data.frame, alongside a range of new ones. As outlined below, these list elements and the new variables in them can be used to identify the exact pixels given back under any Half-Earth scenario (it includes a variable called below.mid with 1’s to identify these cells), and for summarizing kcal losses by ecoregion and country. The second and fourth elements of this list are dataframes with the following three columns summarizing losses under each scenario:

1. perc.world = cumulative sum of terrestrial land area given back
2. kcal = kcal cumulative of the kcal lost in cells given back
3. perc.kcal = cumulative sum of the percent of kcal given back

Each of the lists for each scale of analysis are saved to their own RDS file. Before we run this analysis we first call a function for computing cumulative sums while ignoring NAs. We also re-call the cell area.

```
cum.na <- function(x) { #cumulative sum, ignore NA function
x[which(is.na(x))] <- 0
return(cumsum(x))}
cell.area <- 8439*8439 #define cell area
```

And now we run the scenarios.

```
#####SETUP#####
geog.n<-list(1,as.factor(data.all$Dinn), as.factor(data.all$IS03))#geographic ids
scen<-c("global", "ecoregion", "country") #scenarios

geog.n<-list(1)#geographic ids
scen<-c("global") #scenarios

for(i in 1:length(geog.n)){

data<-data.all
geog<-geog.n[[i]]
dat.split<-split(data,geog) #split data

#####NATURE ONLY APPROACH#####
#ORDER CELLS BY RANK#
dat.split.s<-lapply(dat.split, function(x) x[order(x$rank.all),])

#IDENTIFY GRID CELLS TO GIVE BACK#
dat.split.s<-dat.split.s[lapply(dat.split.s,nrow)>0] #remove locations with no data
dat.split.s<-lapply(dat.split.s, function(x) cbind(x, 1/nrow(x))) #assign numbers
dat.split.s<-lapply(dat.split.s, function(x) cbind(x, round(cumsum(x$1/nrow(x)`), digits=2))) #add in the cumulative percentag
names<-c(colnames(dat.split.s[[1]])[1:26], "id", "perc.area") #reset names
dat.split.s<-lapply(dat.split.s, setNames, names)
dat.split.s<-lapply(dat.split.s, function(x) cbind(x, ifelse(x$perc.area<0.51, 1,0)))
dat.split.all.short<-rbindlist(dat.split.s) #use rbindList, quicker

#COMPUTE THE PERCENT LOSSES BY AREA ACROSS GEOG UNITS#
dat.all.sum.short<-ddply(dat.split.all.short,"perc.area", summarize,
  kcal.sum=sum(kcal, na.rm=T),
  PA.sum=sum(PA*cell.area, na.rm=T),
  CA.sum=sum(CA*cell.area, na.rm=T),
  kcal.food.sum=sum(kcal.food, na.rm=T),
  kcal.feed.sum=sum(kcal.nonfood, na.rm=T)
) #summarize the kcal by percent area, take time
dat.all.sum.short$perc.kcal<-cumsum(dat.all.sum.short$kcal.sum)/max(cumsum(dat.all.sum.short$kcal.sum))
dat.all.sum.short$perc.CA<-cumsum(dat.all.sum.short$CA.sum)/max(cumsum(dat.all.sum.short$CA.sum))
dat.all.sum.short$perc.PA<-cumsum(dat.all.sum.short$PA.sum)/max(cumsum(dat.all.sum.short$PA.sum))
dat.all.sum.short$perc.kcal.non<-cumsum(dat.all.sum.short$kcal.feed.sum)/max(cumsum(dat.all.sum.short$kcal.feed.sum))
dat.all.sum.short$perc.kcal.food<-cumsum(dat.all.sum.short$kcal.food.sum)/max(cumsum(dat.all.sum.short$kcal.food.sum))
```

```
#####SHARED APPROACH#####
#MAKE DATA LONG#
vars<-setdiff(colnames((dat.split[[1]])), c("feed.area", "food.area", "non.ag"))
dat.split.l <-lapply(dat.split, function(x) melt(x, id.vars = c(vars), value.name="area", variable.name="Area.type"))
head(dat.split.l[[1]])
#DEFINE NEW RANK AND OUTCOME VARIABLES#
dat.split.l<-lapply(dat.split.l , function(x) cbind(x, ifelse(x$Area.type=="non.ag",
x$rank.all,ifelse(x$Area.type=="feed.area", x$rank.nonfood, x$rank.food)), #new rank column
ifelse(x$Area.type=="non.ag", 0,
ifelse(x$Area.type=="feed.area", x$kcal.nonfood, x$kcal.food)), #new kcal
ifelse(x$Area.type=="feed.area", x$kcal.nonfood,0), #new kcal.nonfood
ifelse(x$Area.type=="food.area", x$kcal.food,0), #new kcal. food
ifelse(x$Area.type=="non.ag", 0, x$CA*cell.area), #new CA column
ifelse(x$Area.type=="non.ag", 0,x$past.area))) #new PA column

names<-c(colnames(dat.split.l[[1]])[1:25], "rank.new",
"kcal.new", "kcal.new.feed", "kcal.new.food", "CA.n", "PA.n") #reset names
dat.split.l<-lapply(dat.split.l, setNames, names)

#ORDER CELLS BY NEW RANK#
dat.split.l<-lapply(dat.split.l, function(x) x[order(x$rank.new),])

#IDENTIFY GRID CELLS TO GIVE BACK#
dat.split.l<-lapply(dat.split.l , function(x) cbind(x,cum.na(x$area), #cumsum area
rep(nrow(x)*cell.area*(1/3), nrow(x)))) #total area
dat.split.l<-lapply(dat.split.l , function(x)
cbind(x, round(x$cum.na(x$area)/(x$rep(nrow(x) * cell.area * (1/3), nrow(x)))`), digits=2),
ifelse(x$cum.na(x$area)`<= (x$rep(nrow(x) * cell.area * (1/3), nrow(x)))`/2, 1, 0))) #area percent
names<-c(colnames(dat.split.l[[1]])[1:31], "cum.sum.area",
"tot.area", "perc.area", "below.med") #set names

dat.split.l<-lapply(dat.split.l, setNames, names)

dat.split.all<-rbindlist(dat.split.l) #use rbindList, quicker

#COMPUTE THE PERCENT LOSSES BY AREA ACROSS GEOG UNITS#
dat.all.sum<-ddply(dat.split.all,"perc.area", summarize,
kcal.sum=sum(kcal.new, na.rm=T),
PA.sum=sum(PA.n, na.rm=T),
CA.sum=sum(CA.n, na.rm=T),
kcal.food.sum=sum(kcal.new.food, na.rm=T),
kcal.feed.sum=sum(kcal.new.feed, na.rm=T)
) #summarize the kcal by percent area, take time
dat.all.sum$perc.kcal<-cumsum(dat.all.sum$kcal.sum)/max(cumsum(dat.all.sum$kcal.sum))
dat.all.sum$perc.CA<-cumsum(dat.all.sum$CA.sum)/max(cumsum(dat.all.sum$CA.sum))
dat.all.sum$perc.PA<-cumsum(dat.all.sum$PA.sum)/max(cumsum(dat.all.sum$PA.sum))
dat.all.sum$perc.kcal.non<-cumsum(dat.all.sum$kcal.feed.sum)/max(cumsum(dat.all.sum$kcal.feed.sum))
dat.all.sum$perc.kcal.food<-cumsum(dat.all.sum$kcal.food.sum)/max(cumsum(dat.all.sum$kcal.food.sum))

#####SAVE RESULT#####
return<- list(dat.split.all.short, dat.all.sum.short, dat.split.all, dat.all.sum)
path<-paste("halfearthdata/processed/",scen[i],"processed.rds", sep="")
saveRDS(return, path)
}
```

3.4 Main Text Figures

First we read in the data processed in the previous subsection.

```
global<-readRDS("halfearthdata/processed/globalprocessed.rds")
ecoregion<-readRDS("halfearthdata/processed/ecoregionprocessed.rds")
country<-readRDS("halfearthdata/processed/countryprocessed.rds")
```

3.4.1 Figure 1

We then join all of the data together for plotting. Here we are interested in the results for both nature only landscapes and shared landscapes approaches, and comparing the summary results for each of these. To do this we, we need to call the second, and fourth elements of each of the lists read in above.

```
to.plot<-rbind(global[[2]], country[[2]], ecoregion[[2]],
               global[[4]], country[[4]], ecoregion[[4]])

to.plot$Scenario<-c(rep("Global.NatOnly", nrow(global[[2]])),
                    rep("Country.NatOnly", nrow(country[[2]])),
                    rep("Ecoregion.NatOnly", nrow(ecoregion[[2]])),
                    rep("Global.Shared", nrow(global[[4]])),
                    rep("Country.Shared", nrow(country[[4]])),
                    rep("Ecoregion.Shared", nrow(ecoregion[[4]])))

to.plot$Scenario1<-c(rep("Global", nrow(global[[2]])),
                     rep("Country", nrow(country[[2]])),
                     rep("Ecoregion", nrow(ecoregion[[2]])),
                     rep("Global", nrow(global[[4]])), rep("Country", nrow(country[[4]])),
                     rep("Ecoregion", nrow(ecoregion[[4]])))

to.plot$Scenario2<-c(rep("Nature Only", nrow(global[[2]])),
                     rep("Nature Only", nrow(country[[2]])),
                     rep("Nature Only", nrow(ecoregion[[2]])),
                     rep("Shared", nrow(global[[4]])),
                     rep("Shared", nrow(country[[4]])),
                     rep("Shared", nrow(ecoregion[[4]])))
```

Before we plot we print the aggregated losses for each scenario below. These are the main results reported in the manuscript.

```
to.plot.sub<-subset(to.plot,perc.area<0.501)
ddply(to.plot.sub, c("Scenario1", "Scenario2"), summarize,
      kcal.loss.feed=max(perc.kcal.non)*100,
      kcal.loss.food=max(perc.kcal.food)*100,
      CA.loss=max(perc.CA )*100,
      PA.loss=max(perc.PA )*100
      )
```

	Scenario1	Scenario2	kcal.loss.feed	kcal.loss.food	CA.loss	PA.loss
1	Country	Nature Only	15.7	22.09	21	37.4
2	Country	Shared	11.0	0.39	10	4.1
3	Ecoregion	Nature Only	24.5	28.80	31	45.4
4	Ecoregion	Shared	22.7	2.88	15	10.3
5	Global	Nature Only	9.7	11.24	12	21.1
6	Global	Shared	0.0	0.00	0	0.0

And then we make this summary data long for plotting, and make the variable names intelligible.

```
vars<-setdiff(colnames(to.plot), c("perc.kcal.food", "perc.kcal.non", "perc.PA","perc.CA"))
to.plot.l <- melt(to.plot, id.vars = c(vars), value.name="loss", variable.name="Loss.type") #make data long

to.plot.l$Loss.type<-recode(to.plot.l$Loss.type, #make var names intelligible
" c('perc.kcal.food')= 'D. Food kcal';
c('perc.kcal.non') = 'C. Feed, biofuel, and other kcal';
c('perc.PA')= 'B. Pasture land';
c('perc.CA')= 'A. Crop land'" )
```

We then plot out the different scenarios. These plots form the basis for figure 1 given in the main text of our manuscript.

```

ggplot(to.plot.1, aes(perc.area*100,loss*100, color=Scenario1))+
  geom_vline(xintercept=50, lty=2, colour="black")+
  geom_line()+
  scale_colour_manual(values = c("#56B4E9", "#E75E00", "#009E73", "gray"))+
  theme_bw()+
  theme(plot.background = element_blank(),
        panel.grid.major = element_blank(),
        panel.grid.minor = element_blank(),
        # strip.text.x = element_blank(),
        strip.background = element_rect(colour = "white", fill = "white"),
        legend.key = element_rect(fill = "white", colour = "white"))+
  ylab("Percent agricultural loss")+
  xlab("Percent of earth given back")+
  # ylab("")+
  # xlab("")+
  facet_wrap(~Loss.type*Scenario2, nrow=4, ncol=2) + theme(legend.position="none")

```

Figure 1: Feeding the world under a global deal for nature. The horizontal dashed line shows the Half-Earth line. Left side: Nature only landscapes, Right side: Shared landscapes. green= global, blue= country, red= ecoregion.

3.4.2 Figure 2

Here we map out the scenarios. First we need to identify which pixels were given back under each scenario, and the calories lost in each. We do this to visualize where the calorie trade-offs are locally. We isolate the data needed for plotting.

```
global.NatOnly<-subset(global[[1]], `ifelse(x$perc.area < 0.51, 1, 0)`==1)
country.NatOnly<- subset(country[[1]], `ifelse(x$perc.area < 0.51, 1, 0)`==1)
ecoregion.NatOnly<-subset(ecoregion[[1]], `ifelse(x$perc.area < 0.51, 1, 0)`==1)
global.Sharing<-subset(global[[3]], below.med==1)
country.Sharing<- subset(country[[3]], below.med==1)
ecoregion.Sharing<-subset(ecoregion[[3]], below.med==1)

kcal.max<-round(max(log10((global.NatOnly$kcals/1000)+1), na.rm=T), digits=1)
kcal.min<-round(min(log10((global.NatOnly$kcals/1000)+1), na.rm=T), digits=1)
```

Then we write a function to map the kcal lost for each scenario in each location given back. We choose a blue colour gradient to aid discernment of logged steps in the scale.

```
breaks=c(0:9)
map.scenarios<-function(data, kcal){
  df<-data.frame(data$x, data$y,kcal)
  dfr<- rasterFromXYZ(df) #Convert first two columns as lon-lat and third as value
  crs(dfr)<-"+proj=eck4 +datum=WGS84 +ellps=WGS84 +towgs84=0,0,0"
  values(dfr)<-log10((values(dfr)/1000)+1)
  colfunc <- colorRampPalette(c("gray95", "#edf8b1", "#c7e9b4", "#7fcdbb", "#41b6c4", "#1d91c0",
                                "#225ea8", "#253494", "#081d58", "black")) #set the color

  data(wrld_simpl) #get world map data
  wrld <- spTransform(wrld_simpl, crs(dfr))
  plot(wrld, col='light gray', border="transparent",lwd=0.2)
  plot(dfr, col=colfunc(10),add=TRUE, legend.width = 1, legend.shrink=0.5,
       legend.args=list(text=' loss (log10 kcal)' ,side=4,cex=0.8,line=2), breaks=breaks)
}
```

And then we plot all of these together. The result forms the basis of figure 2 in the main text of the manuscript.

```
par(mfrow = c(3,2),
    oma = c(0,0,0,0) ,
    mar = c(0,0,1,0))
map.scenarios(global.NatOnly, global.NatOnly$kcals)
map.scenarios(global.Sharing,global.Sharing$kcals.new)
map.scenarios(country.NatOnly,country.NatOnly$kcals)
map.scenarios(country.Sharing,country.Sharing$kcals.new)
map.scenarios(ecoregion.NatOnly,ecoregion.NatOnly$kcals)
map.scenarios(ecoregion.Sharing,ecoregion.Sharing$kcals.new)
```

Figure 2: Maps of calorie losses under each Half-Earth scenario. From top to bottom: global, country and ecoregion. Legends show kcal losses in $\log_{10}$ units. Left side: Nature only landscapes, Right side: Shared landscapes.

3.5 Country calorie losses

Here we report the countries with calorie losses under the two different conservation approaches at the ecoregion scale. We report countries with the top losses under the natures only landscapes approach below. Notably China and India show substantial calorie losses.

```
country.loss.hard<-ddply(ecoregion.NatOnly, c("country"), summarize, #global
                        kcal.loss=sum(kcal, na.rm=T))
head(country.loss.hard[order(-country.loss.hard$kcal.loss),])
```

	country	kcal.loss
31	CHN	4.9e+14
76	IND	4.5e+14
172	USA	3.1e+14
75	IDN	1.6e+14
115	MYS	7.5e+13
119	NGA	6.6e+13

We then compute the losses under a shared landscapes approach. While these reduce the losses for China and India by at least a half, the losses still remain high.

```
country.loss.soft<-ddply(ecoregion.Sharing, c("country"), summarize, #global
                        kcal.loss=sum(kcal.new, na.rm=T))
head(country.loss.soft[order(-country.loss.soft$kcal.loss),])
```

	country	kcal.loss
76	IND	2.1e+14
31	CHN	2.0e+14
172	USA	1.7e+14
75	IDN	9.3e+13
115	MYS	6.4e+13
119	NGA	5.1e+13

Next we compute the total calories produced in different countries. Below we show the top calorie producing nations.

```
country.kcal<-ddply(data.all, c("country"), summarize, #global
                    kcal=sum(kcal, na.rm=T))
head(country.kcal[order(-country.kcal$kcal),])
```

	country	kcal
32	CHN	1.7e+15
174	USA	1.4e+15
78	IND	1.0e+15
77	IDN	5.0e+14
24	BRA	4.8e+14
117	MYS	3.6e+14

And finally we join all of these data, to estimate the percent losses. We are particularly interested in the losses under the shared approach, which we report in the main text of the paper. We show the top losses in percent terms below.

```
kcal.count<-country.kcal[match(country.loss.soft$country, country.kcal$country), ]
country.loss.soft$perc.loss<-country.loss.soft$kcal.loss/ kcal.count$kcal
(country.loss.soft[order(-country.loss.soft$perc.loss),])[1:10,]
```

	country	kcal.loss	perc.loss
24	BRN	1.4e+10	0.30
61	GHA	8.8e+12	0.29
119	NGA	5.1e+13	0.27
130	PNG	1.4e+12	0.25
14	BEL	8.5e+11	0.24
96	LBR	4.3e+11	0.23
76	IND	2.1e+14	0.21
107	MKD	4.0e+11	0.20
154	SVN	3.0e+11	0.20
75	IDN	9.3e+13	0.19

3.5.1 Ecoregion coverage

In an earlier publication Dinerstein et al. [9] reported that Half-Earth has been already attained, or been deemed achievable, in 49% of the Earth's 846 terrestrial Ecoregions. Dinerstein et al. identified 98/846 (or 12%) had achieved more than half protected, and that 313/846 Ecoregions (or 37%) to have not achieved half protected, but to have enough “unaltered habitat” available to achieve it. They defined this unaltered habitat (also synonymously labelled as both “natural” in the main text, and “natural/semi-natural” in the Supplementary Methods) by a two-step procedure, first using satellite classified tree cover data to identify forests, and then defining remaining habitats according to anthropogenic biomes. However, in their analysis they did not quantitatively identify the trade-offs with agricultural production. Here we identify how many of the world's Ecoregions could achieve the 50% figure without a loss of calories, under both the nature only landscapes, and shared landscapes approaches. We find that for a nature only landscapes approach, Half-Earth can be achieved in 101 or the 775, or 14%, of Ecoregions used in this analysis without any loss of calories.

```
lossbyeco<-ddply(ecoregion.NatOnly, 'Dinn', summarize,
  loss=sum(kcal, ra.rm=T))
nrow(subset(lossbyeco, loss<10)) #number of ecoregions with no calorie loss

[1] 111

(nrow(lossbyeco[which(lossbyeco$loss<10),]))/nrow(lossbyeco) #percent of ecoregions

[1] 0.14
```

Interestingly, under a shared landscapes approach, we find that Half-Earth can be achieved in nearly five times more ecoregions without calorie losses (or 65%).

```
lossbyeco.s<-ddply(ecoregion.Sharing, 'Dinn', summarize,
  loss=sum(kcal.new, ra.rm=T))
nrow(subset(lossbyeco.s, loss<10)) #number of ecoregions with no calorie loss

[1] 501

(nrow(lossbyeco.s[which(lossbyeco.s$loss<10),]))/nrow(lossbyeco) #percent of ecoregions.

[1] 0.65
```

3.6 Co-benefits

To understand the co-benefits of a Half-Earth scenario, (e.g. such as climate mitigation potential) it is important to understand the gross change in vegetation that might result from such a plan. Here we show the how agriculturally productive land given back under each scale of analysis (country, ecoregion, and global), influences change in the coverage of potential vegetation. To do this we use the Potential Natural Vegetation (PNV) data set [15].

First we need to calculate PNV coverage in area without agricultural production – this represents a baseline. We will then calculate the PNV area inside agriculturally productive pixels given back under each Half-Earth scenario. The ratio of these two numbers is used to indicate the potential vegetation benefits of giving back agricultural land. It should be noted that the baseline estimates are consistent across scenarios, but are likely to overestimate PNV in current in non-agricultural lands because these lands are unlikely to be completely unaltered by human activity (and hence our estimates of PNV gains are likely to be conservative).

3.6.1 Nature only landscapes

First we get the number of cells for the baseline PNV, in non-agriculturally productive and non-urban land globally.

```
cell.area <-8439*8439 #define cell area
data.all$PNV.base<-ifelse(data.all$rank >=7, NA,data.all$PNV)

baseline<-ddply(data.all, 'PNV.base',
```

```

summarize,
n.cells= length(x),
ag.area= sum(CA*cell.area, PA*cell.area, na.rm=T),
area=length(x)*cell.area)

```

```
baseline$PNV.base<-baseline$area-baseline$ag.area #this is the baseline vegetation on the planet
```

Then we obtain the PNV in recovered agricultural land in each scenario.

```

world.no<-ddply(global.NatOnly, 'PNV',
  summarize,
  area= sum(CA*cell.area,PA*cell.area, na.rm = T),
  n.cells= length(x))

country.no<-ddply(country.NatOnly, 'PNV',
  summarize,
  area= sum(CA*cell.area,PA*cell.area, na.rm = T),
  n.cells= length(x))

ecoregion.no<- ddply(ecoregion.NatOnly, 'PNV',
  summarize,
  area= sum(CA*cell.area,PA*cell.area, na.rm = T),
  n.cells= length(x))

```

Finally we join all data together into a common data.frame. The Gain.prop column represents the proportional gain in cells for each PNV class for agriculturally productive land.

```

gain<-c(world.no$area/baseline$PNV.base,
  country.no$area/baseline$PNV.base,
  ecoregion.no$area/baseline$PNV.base)
scenario<-c(rep("Global", 16), rep("Country", 16), rep("Ecoregion", 16))
class<-rep(world.no$PNV, 3)
gain.df.no<-data.frame(gain, scenario, class)
colnames(gain.df.no)<-c("Gain.prop", "Scenario", "PNV.class")
gain.df.no<-(subset(gain.df.no, !is.na(PNV.class))) # remove NAs

```

We then write the code to plot the results.

```

NO<-ggplot(gain.df.no, aes( PNV.class,Gain.prop*100, colour=Scenario))+
# geom_point()+
  geom_hline(yintercept=c(25,50,75,100), lty=2, colour="black", lwd=0.1)+
  geom_line()+
  scale_colour_manual(values = c("#56B4E9", "#E75E00", "#009E73"))+
  theme_bw()+
  theme(plot.background = element_blank(),
    panel.grid.major = element_blank(),
    panel.grid.minor = element_blank(),
    strip.background = element_rect(colour = "white", fill = "white"))+
  theme(legend.position="none") +
  scale_x_continuous(breaks= 1:15, labels= c("1" = "Tropical Forest (E)", "2" = "Tropical Forest (D)",
    "3" = "Temp.Forest (BE)", "4" = "Temp.Forest (NE)",
    "5" = "Temp.Forest (D)", "6" = "Boreal.Forest (E)",
    "7" = "Boreal.Forest (D)", "8" = "Mixed Forest (E/D)",
    "9" = "Savanna", "10" = "Grassland/Steppe", "11" = "Dense Shrubland",
    "12" = "Open Shrubland", "13" = "Tundra", "14" = "Desert",
    "15" = "Polar"))+

  ylab("Change in area (%)")+
  xlab("")+
  coord_flip()

```

3.6.2 Shared landscapes

Now we repeat the analysis except for the sharing landscapes approach.

```

world.s<-ddply(global.Sharing, 'PNV',
  summarize,
  n.cells= length(x),
  area= sum(CA.n,PA.n, na.rm = T)

```

```

)
country.s<-ddply(country.Sharing, 'PNV',
  summarize,
  n.cells= length(x),
  area= sum(CA.n,PA.n, na.rm = T))

ecoregion.s<- ddply(ecoregion.Sharing, 'PNV',
  summarize,
  n.cells= length(x),
  area= sum(CA.n,PA.n, na.rm = T))

```

And join all data together into a common data.frame.

```

gain.s<-c(world.s$area/baseline$PNV.base,
  country.s$area/baseline$PNV.base,
  ecoregion.s$area/baseline$PNV.base)
scenario<-c(rep("Global", 16), rep("Country", 16), rep("Ecoregion", 16))
class<-rep(world.s$PNV, 3)
gain.df<-data.frame(gain.s, scenario, class)
colnames(gain.df)<-c("Gain.prop", "Scenario", "PNV.class")
gain.df.s<-(subset(gain.df, !is.na(PNV.class))) # remove NAs

```

Then we create the plot.

```

s<-ggplot(gain.df.s, aes( PNV.class,Gain.prop*100, colour=Scenario))+
  geom_hline(yintercept=c(25,50,75,100), lty=2, colour="black", lwd=0.1)+
  geom_line()+
  scale_colour_manual(values = c("#56B4E9", "#E75E00", "#009E73"))+
  theme_bw()+
  theme(plot.background = element_blank(),
    panel.grid.major = element_blank(),
    panel.grid.minor = element_blank(),
    strip.background = element_rect(colour = "white", fill = "white"))+
  theme(legend.position="none")+
  scale_x_continuous(breaks= 1:15, labels= c("1" = "", "2" = "",
    "3" = "", "4" = "", "5" = "", "6" = "",
    "7" = "", "8" = "", "9" = "", "10" = "",
    "11" = "", "12" = "", "13" = "", "14" = "",
    "15" = ""))+
  ylab("Change in area (%)")+
  xlab("")+
  coord_flip()

```

We also print a table of the gains below which show the percent gain figures under each scenario.

```

all.gain<-data.frame(gain.df.no$Scenario, gain.df.no$PNV.class, gain.df.no$Gain.prop, gain.df.s$Gain.prop)
colnames(all.gain)<-c("Scenario", "PNV.class", "Nat.Only", "Shared")
all.gain$PNV.class<-recode(all.gain$PNV.class,
  " c('1')= 'Tropical Forest (E)';
  c('2')= 'Tropical Forest (D)';
  c('3')= 'Temp.Forest (BE)';
  c('4')= 'Temp.Forest (NE)';
  c('5')= 'Temp.Forest (D)';
  c('6')= 'Boreal.Forest (E)';
  c('7')= 'Boreal.Forest (D)';
  c('8')= 'Mixed Forest (E/D)';
  c('9')= 'Savanna';
  c('10')= 'Grassland/Steppe';
  c('11')= 'Dense Shrubland';
  c('12')= 'Open Shrubland';
  c('13')= 'Tundra';
  c('14')= 'Desert';
  c('15')= 'Polar'
  ")

```

all.gain

	Scenario	PNV.class	Nat.Only	Shared
1	Global	Tropical Forest (E)	0.0398	0.00000
2	Global	Tropical Forest (D)	0.1214	0.00000
3	Global	Temp.Forest (BE)	0.0717	0.00000
4	Global	Temp.Forest (NE)	0.0444	0.00000
5	Global	Temp.Forest (D)	0.1272	0.00000
6	Global	Boreal.Forest (E)	0.0068	0.00000
7	Global	Boreal.Forest (D)	0.0069	0.00000
8	Global	Mixed Forest (E/D)	0.0173	0.00000
9	Global	Savanna	0.1360	0.00000
10	Global	Grassland/Steppe	0.4150	0.00000
11	Global	Dense Shrubland	0.1262	0.00000
12	Global	Open Shrubland	0.2300	0.00000
13	Global	Tundra	0.0601	0.00000
14	Global	Desert	0.0295	0.00000
15	Global	Polar	0.0111	0.00000
16	Country	Tropical Forest (E)	0.0779	0.07106
17	Country	Tropical Forest (D)	0.2601	0.39317
18	Country	Temp.Forest (BE)	0.1016	0.01117
19	Country	Temp.Forest (NE)	0.0994	0.02191
20	Country	Temp.Forest (D)	0.2256	0.05298
21	Country	Boreal.Forest (E)	0.0098	0.00038
22	Country	Boreal.Forest (D)	0.0104	0.00217
23	Country	Mixed Forest (E/D)	0.0321	0.00625
24	Country	Savanna	0.2298	0.08504
25	Country	Grassland/Steppe	0.7275	0.22649
26	Country	Dense Shrubland	0.1989	0.06394
27	Country	Open Shrubland	0.4318	0.08320
28	Country	Tundra	0.1172	0.00374
29	Country	Desert	0.0388	0.00727
30	Country	Polar	0.0184	0.00319
31	Ecoregion	Tropical Forest (E)	0.0909	0.07585
32	Ecoregion	Tropical Forest (D)	0.4022	0.37771
33	Ecoregion	Temp.Forest (BE)	0.2689	0.11883
34	Ecoregion	Temp.Forest (NE)	0.1533	0.06645
35	Ecoregion	Temp.Forest (D)	0.3630	0.18358
36	Ecoregion	Boreal.Forest (E)	0.0103	0.00298
37	Ecoregion	Boreal.Forest (D)	0.0110	0.00420
38	Ecoregion	Mixed Forest (E/D)	0.0525	0.02820
39	Ecoregion	Savanna	0.3498	0.14244
40	Ecoregion	Grassland/Steppe	0.9416	0.65670
41	Ecoregion	Dense Shrubland	0.3280	0.19671
42	Ecoregion	Open Shrubland	0.4264	0.22300
43	Ecoregion	Tundra	0.0730	0.03195
44	Ecoregion	Desert	0.0359	0.00811
45	Ecoregion	Polar	0.0131	0.00297

4 Supplementary Figures

In this section we plot the supplementary figures that we do not present in the main text of the manuscript.

4.0.1 Supplementary Figure 1

First we plot the maps of binarized calorie losses by country under Half-Earth. Each plot shows Ecoregions in which Half-Earth can be achieved without loss of calories. Note that Antarctica and Greenland are listed as locations under a “Nature only landscapes” approach where loss of calories occurs. This is due to the fact these locations are listed under a common “Rock and ice” Ecoregion, along with other locations on the Earth, such as a few pixels in Northern India and Nepal, which are subject to calorie loss. Removing this “Rock and ice” Ecoregion from this analysis makes no difference to the percentage of losses for this approach (e.g. 101/775 vs 100/775).

```
map.ecoregion.loss<-function(data, lossby){
  data.all$Dinn.no<-ifelse(data.all$Dinn %in% c(subset(lossby, loss<10)$Dinn), 1,0 )
  dfloss<-data.frame(data.all$x, data.all$y,data.all$Dinn.no)
  dfloss<- rasterFromXYZ(dfloss) #Convert first two columns as lon-lat and third as value
  crs(dfloss)<-"+proj=eck4 +datum=WGS84 +ellps=WGS84 +towgs84=0,0,0"
  colfunc <- colorRampPalette(c("red", "light gray")) #set the color ramp
  data(wrld_simpl) #get world map data
  wrld <- spTransform(wrld_simpl, crs(dfloss))
  plot(wrld, col='light gray', border="transparent",lwd=0.2)
  plot(dfloss, col=colfunc(10), add=TRUE, legend=F)
}

par(mfrow = c(2,1),
    oma = c(0,0,0,0) ,
    mar = c(0,0,1,0))
map.ecoregion.loss(data.all, lossbyeco)
map.ecoregion.loss(data.all, lossbyeco.s)
```

Figure 3: Ecoregions where Half-Earth be achieved without a loss of calories. Gray= Ecoregions with no loss of calories, Red= Ecoregions with loss of calories. Top = Nature only landscapes. Bottom = Shared landscapes.

4.0.2 Supplementary Figure 2

Then we plot out the co-benefits of Half-Earth for recover of natural vegetation. As we see from below, the ecoregion based Half-Earth plan leads to large gains in grasslands and modest gains in tropical and temperate deciduous forests, and in savanna and shrublands.

```
plot_grid( NO,s, align =c("v", "h"), ncol = 2)
```

Figure 4: Recovery of natural vegetation from agriculture under each Half-Earth Scenario. The x axis shows the percent gains in areal coverage in potential natural vegetation attained by giving back least agriculturally productive lands. green= global, blue= country, red= ecoregion. E=evergreen, D=deciduous, N=needle, B=broadleaf. Left = Nature only landscapes. Right = Shared landscapes.

4.0.3 Supplementary Figure 3

And finally we plot out a flow diagram for the analysis, which we reference in the methods section of our paper.

Session information

```
sessionInfo()

R version 3.4.2 (2017-09-28)
Platform: x86_64-apple-darwin15.6.0 (64-bit)
Running under: macOS High Sierra 10.13.5

Matrix products: default
BLAS: /System/Library/Frameworks/Accelerate.framework/Versions/A/Frameworks/vecLib.framework/Versions/A/libBLAS.dylib
LAPACK: /System/Library/Frameworks/Accelerate.framework/Versions/A/Frameworks/vecLib.framework/Versions/A/libLAPACK.dylib

locale:
[1] en_CA.UTF-8/en_CA.UTF-8/en_CA.UTF-8/C/en_CA.UTF-8/en_CA.UTF-8

attached base packages:
[1] stats      graphics  grDevices  utils      datasets  methods   base

other attached packages:
[1] data.table_1.10.4-2 cowplot_0.8.0      gridExtra_2.3
[4] reshape2_1.4.3      maptools_0.9-2     car_2.1-6
[7] rworldmap_1.3-6     R.matlab_3.6.1     plyr_1.8.4
[10] ggplot2_2.2.1       rgdal_1.1-10       raster_2.6-7
[13] sp_1.2-7            checkpoint_0.4.1    knitr_1.17
[16] RevoUtils_10.0.6

loaded via a namespace (and not attached):
[1] Rcpp_0.12.13      nloptr_1.0.4      compiler_3.4.2
[4] highr_0.6         R.methodsS3_1.7.1 R.utils_2.5.0
[7] tools_3.4.2       lme4_1.1-14       dotCall64_0.9-04
[10] nlme_3.1-131      evaluate_0.10.1   tibble_1.3.4
[13] gtable_0.2.0      lattice_0.20-35   mgcv_1.8-22
[16] rlang_0.2.1       Matrix_1.2-11     parallel_3.4.2
[19] SparseM_1.77      spam_2.1-1        stringr_1.2.0
[22] MatrixModels_0.4-1 fields_9.0         maps_3.2.0
[25] grid_3.4.2        nnet_7.3-12       foreign_0.8-69
[28] minqa_1.2.4       magrittr_1.5      scales_0.5.0
[31] MASS_7.3-47       splines_3.4.2     pbkrtest_0.4-7
[34] colorspace_1.3-2  labeling_0.3       quantreg_5.33
[37] stringi_1.1.5     lazyeval_0.2.0    munsell_0.4.3
[40] R.oo_1.21.0
```

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