Methods

Datasets

Plant Functional Traits datasets and publications

I retrieved the PFT estimates of interest from Bloom *et al* (2015) and Butler *et al.* (2017) scientific publications (Appendix A). The raw mean and uncertainty PFT estimates from Bloom *et al.* (2015) relate to Leaf Carbon Mean Area (gC/m^2). This data can be downloaded from datashare.is.ed.ac.uk/handle/10283/875. Those from Butler *et al.* (2017) relate to Specific Leaf Area (m^2/kg). Both datasets are gridded at 1° x 1° spatial resolution (360x180) and present only one time dimension. I used the dataset from Bloom *et al.* (2015) as the benchmark to which I compared the other dataset, from Butler *et al.* (2017).

Other datasets and databases

I used the Ecoregions17 database to retrieve the spatial extents of the 14 major biomes across the world (fig.2). The dataset is available to download from ecoregions2017.appspot.com/. I used *rworldmap* package from R, to obtain the spatial extents of the 6 continents. I also used historical climate data (i.e. mean temperature and annual precipitation), averaged for the years 1970-2000 at 10 minutes spatial resolution (~340 km^2), from WorldClim database (Appendix A). These datasets can be downloaded from worldclim.org/data/worldclim21.html (BIO01 and BIO12).

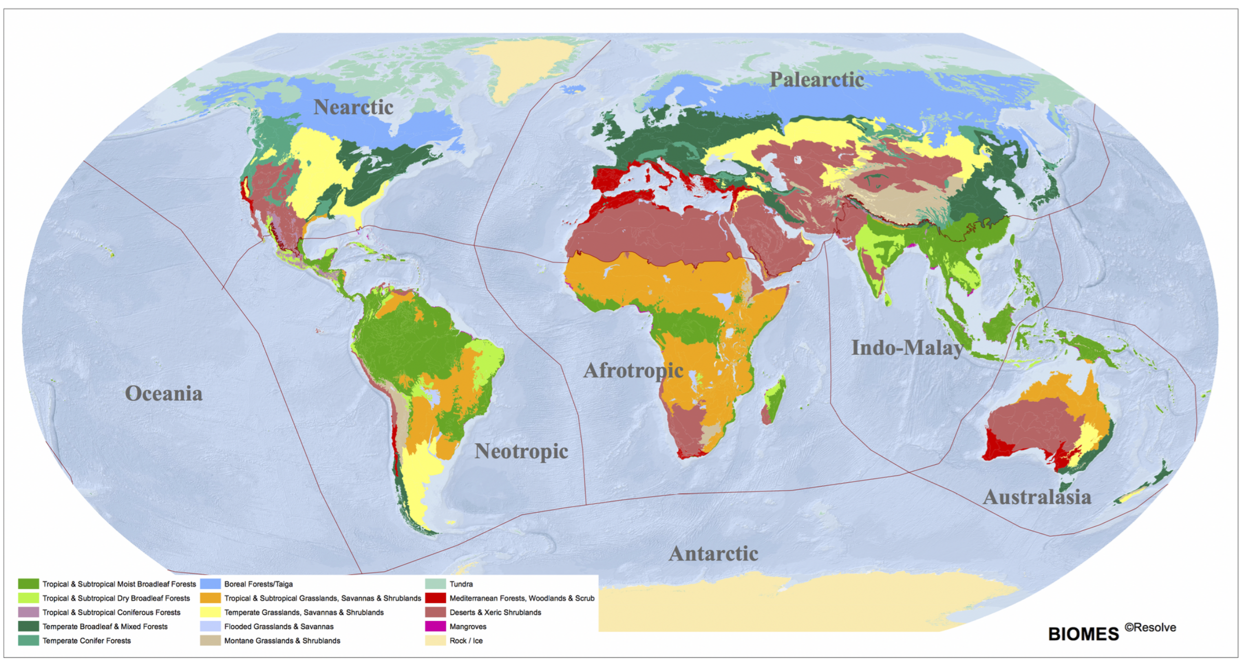

Figure 1: 14 major biomes as retrieved from Supplementary Materials by Dinerstein et al. (2017)

Data manipulation

The state of PFT estimates at retrieval required standardisation in order to be compared. I converted LCMA (gC/m^2), from Bloom *et al.* (2015), to SLA (m^2/kg) [1]. I did so knowing that SLA is the inverse of LCMA, and that LCMA measures the carbon content within the leaf, thus representing 50% of the its dry-biomass equivalent *REF*. Unit conversion to m^2/kg was also necessary to ensure standardisation of the two PFT parameters. I executed all conversions with the Linux environment, though this can be done with any programming language at disposition. I carried out this calculation for both mean and uncertainty (standard deviation) estimates:

$$[1]\ \mathrm{SLA} = \frac{1}{\cdot 2 \times LCMA}$$

I carried out the greater portion of data visualisation and analysis with R programming language (code available in Appendix **letter?**. The most important packages used for observing the relationships between SLA datasets are the following:

- *ncdf4*, *sf*, *tiff* and *raster* for visualisation and manipulation of spatial data;
- *LSD* for creating heatscatters of the relationship between the two data distributions;
- *overlapping* for calculating the percentage overlap of the data distributions with one another.

I carried out the data observation and analysis at four different spatial extents: global, by latitudinal gradients, by biomes across the world and by biomes split further by continent. I decided to repeat the analysis at these different spatial extents, assuming that differences in overlap between SLA mean and stdev estimates would be more evident when limiting environmental and physical variability across the world. The splitting by latitude mainly takes into account the climatic differences observed from tropics to polar regions. I determined the range of the different climatic zones following convention, thus extracting tropics between 23.5°S and 23.5°N, sub-tropics between 23.5°S/N and 35°S/N, temperate between 35°S/N and 66.5°S/N and north pole between 66.5°N and 90°N. There were no data available for the south pole from Bloom *et al.* (2015) and Butler *et al.* (2017). I confined SLA datasets to the spatial extents of the 14 major biomes across the globe, using spatial polygons extracted from the Ecoregions17 database. Following, I carried out a further subdivision of the SLA data into biomes split by continent, using the *rworldmap* package from R to extract spatial polygons for the 6 continents. Lastly, I prepared the climate datasets from WorldClim by changing their original spatial resolution (0,1667° x 0,1667°) to match that of the SLA datasets (1° x 1°).

Visual analysis

In order to visualise the spatial distribution of the two SLA estimates, I first set them at the same scale with *raster* package. Following that, I produced density plots, and with the package *overlapping* I was able to calculate the percentage overlap of the data distributions. I then created stippling maps. Stippling maps represent one dataset as a baseline, and overlay on top those data points from the baseline that lie within the confidence intervals of the benchmark. I related the percentage overlap of the mean SLA estimates with the number of stipples present on the map, to visualise the spatial distributions of more closely related values between the two SLA datasets. I also created 2d scatterplots or heatscatters, depicting the correlation between the two datasets and the level of concentration of data points on the space. I repeated this visual analysis for all four spatial extents.

When testing the sensitivity of the datasets with climate data, I first plotted the spatial correlation between SLA estimates and climate data. I then created a 2d density graph, in order to test the overlap between SLA estimates in correlation with climate data. I calculated the percentage overlap between the two correlations again with *overlapping* package.

Statistical analysis

I tested the degree of overlap between mean and uncertainty estimates of the two SLA parameters by executing the following statistical analyses - R^2 [2] or coefficient of determination, Root Mean Square Error (RMSE) [3] and bias [4]. R^2 is a useful parameter for testing what proportion of variance from the dependent variable is predictable by the independent variable. I extracted the R^2 from simple linear regression models I ran, where I used SLA from Bloom *et al.* (2015) as the benchmark or independent variable and that from Butler *et al.* (2017) as the dependent variable. I considered only R^2 values from model results with a p-value that is less than 0.001.

$$[2]\ R^2 = \frac{\sum_{n=i}(y_i - \overline{y})^2}{\sum_{n=i}(y - \overline{y})^2}$$

I calculated RMSE to assess the average magnitude of the error when correlating Bloom *et al.*, again as benchmark, and Butler *et al.* (2017). RMSE was a more appropriate statistical parameter than Mean Absolute Error, as it gives higher weight to undesired large errors.

$$[3]\ \text{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}(y_i - x_i)^2}{n}}$$

Assuming that these SLA estimates are biased, being retrieved from different approaches, I retrieved the bias to estimate the average difference between SLA benchmark and the underlying SLA model. The result from the bias is an indicator of the quality of the methods for collecting and calculating the data.

$$[4]\ \text{Bias} = \frac{y - x}{n}$$