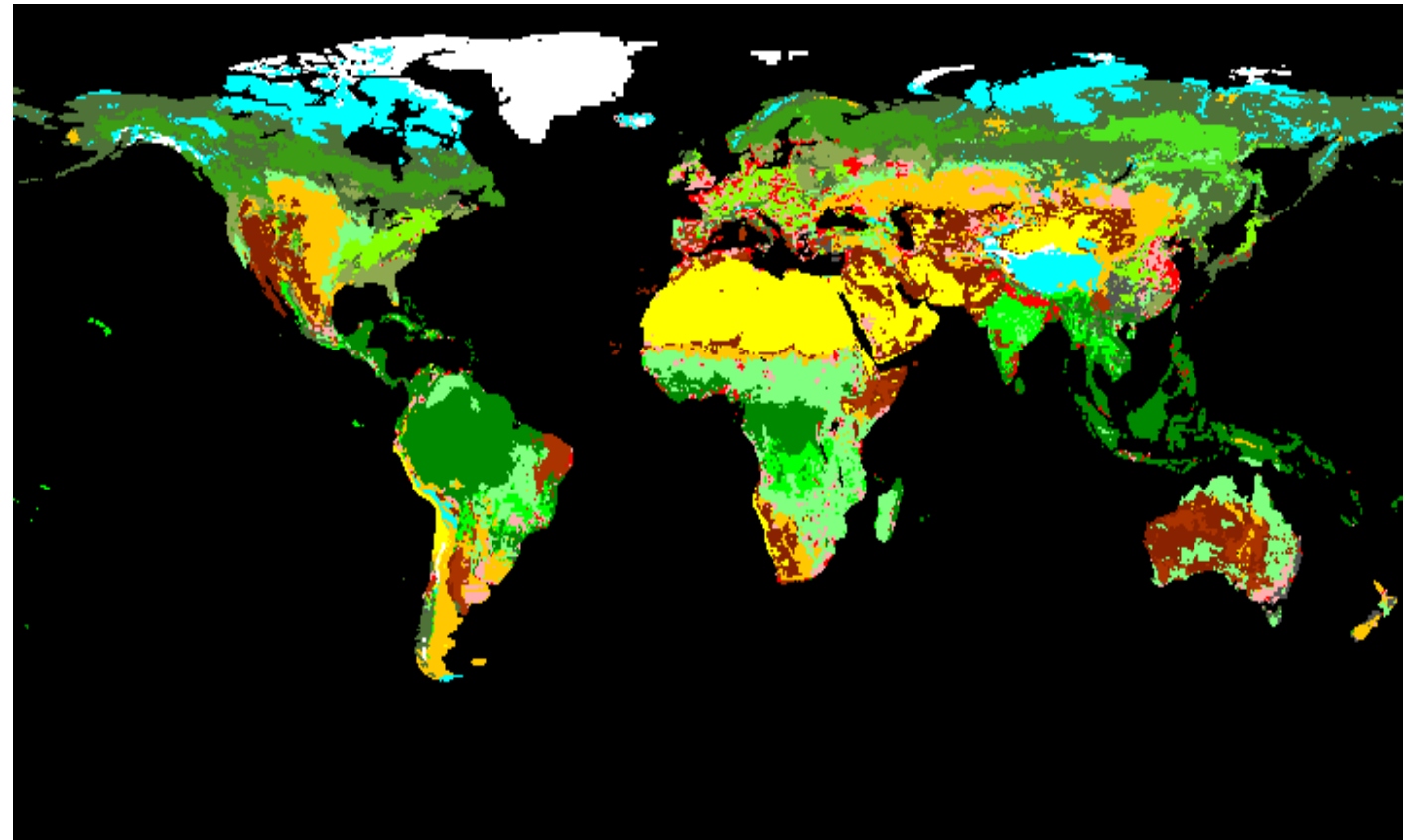


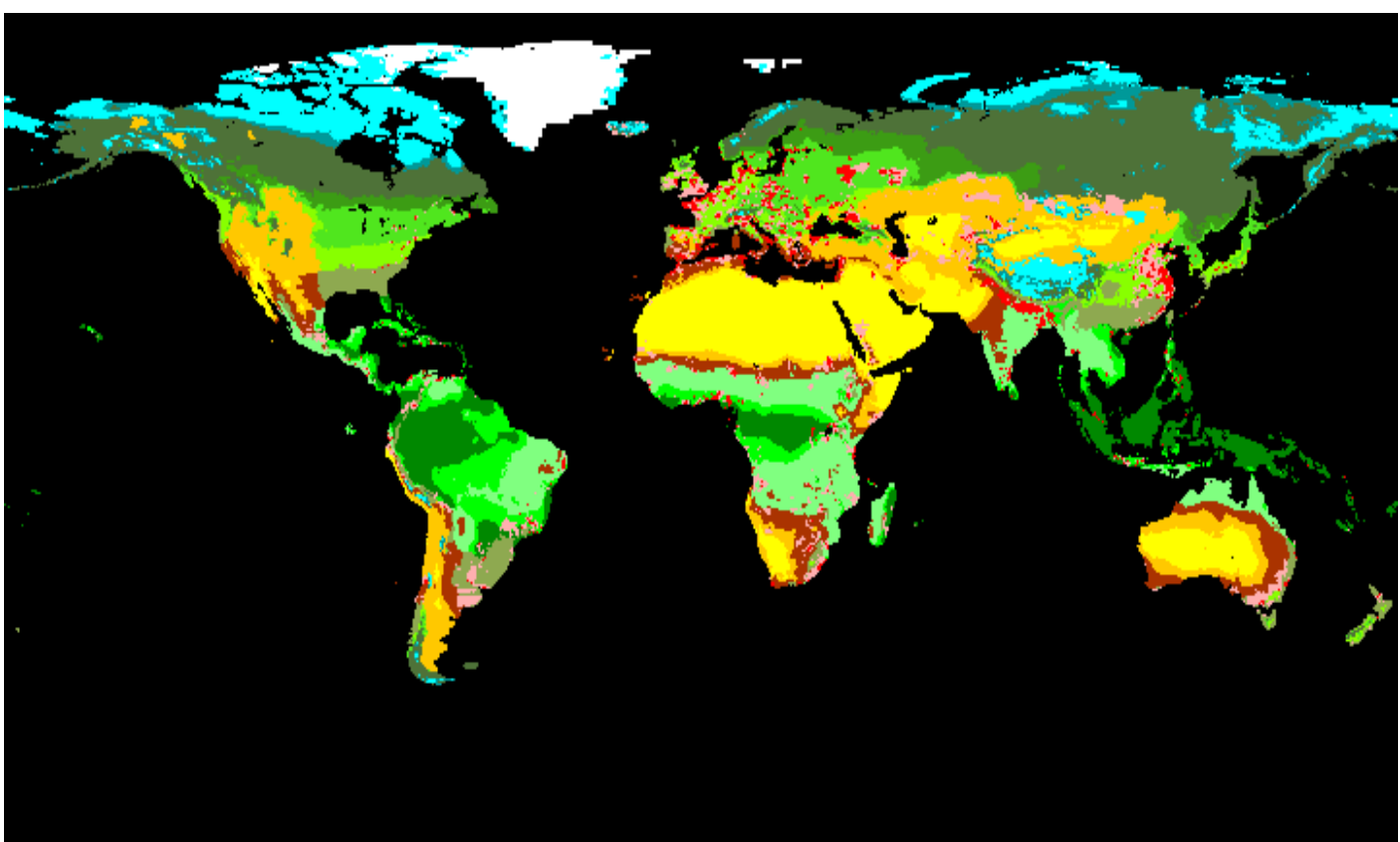


## 2. Contributions from Land Use Change Emissions

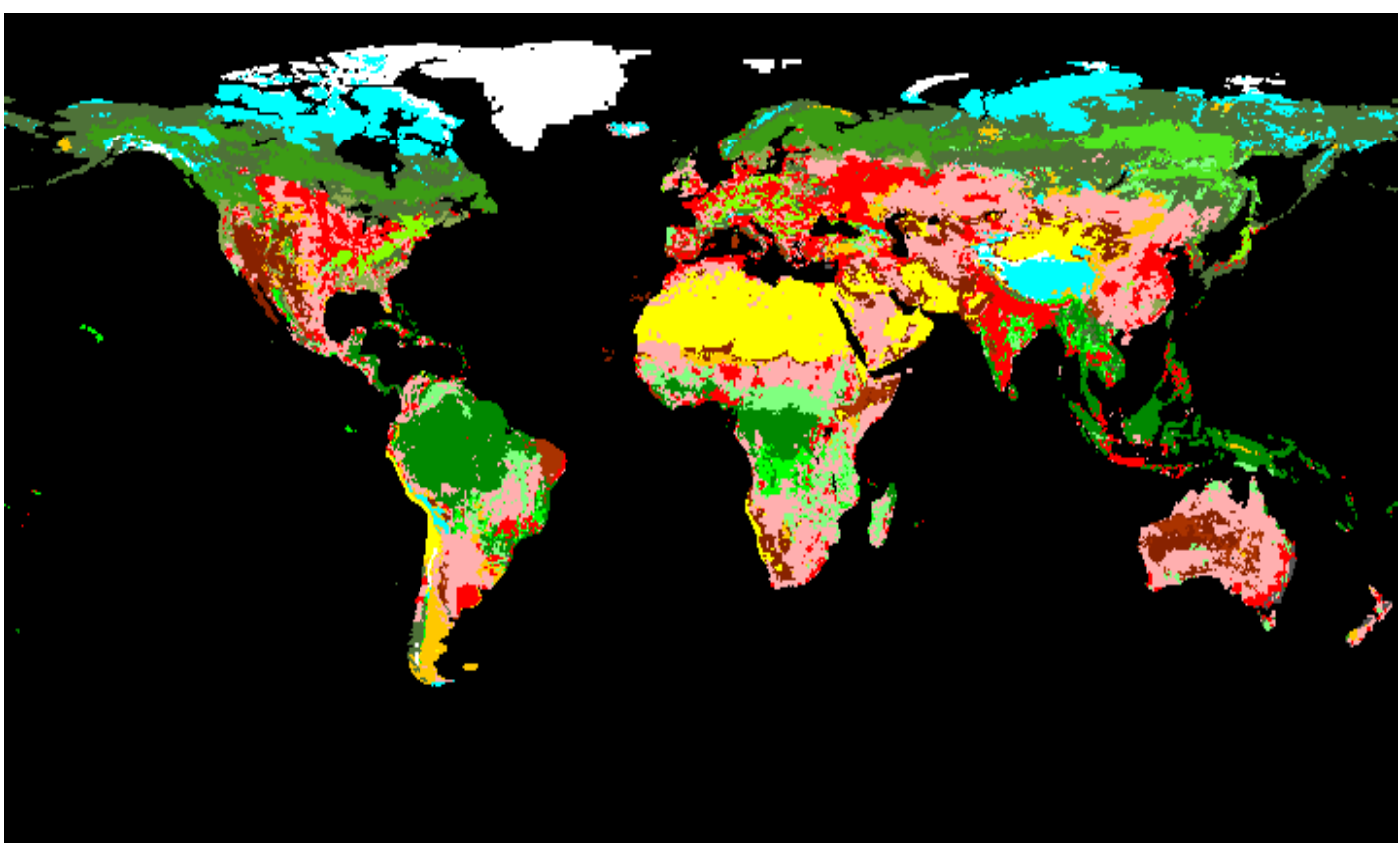
This poster illustrates new calculations on historical national land-use-change emissions and their relative contribution to the global CO2 concentration and temperature rise, combining the IVIG Land-Use Change model coupled with the global carbon cycle, climate and relative attribution modules of the Java Climate Model (see poster #1).



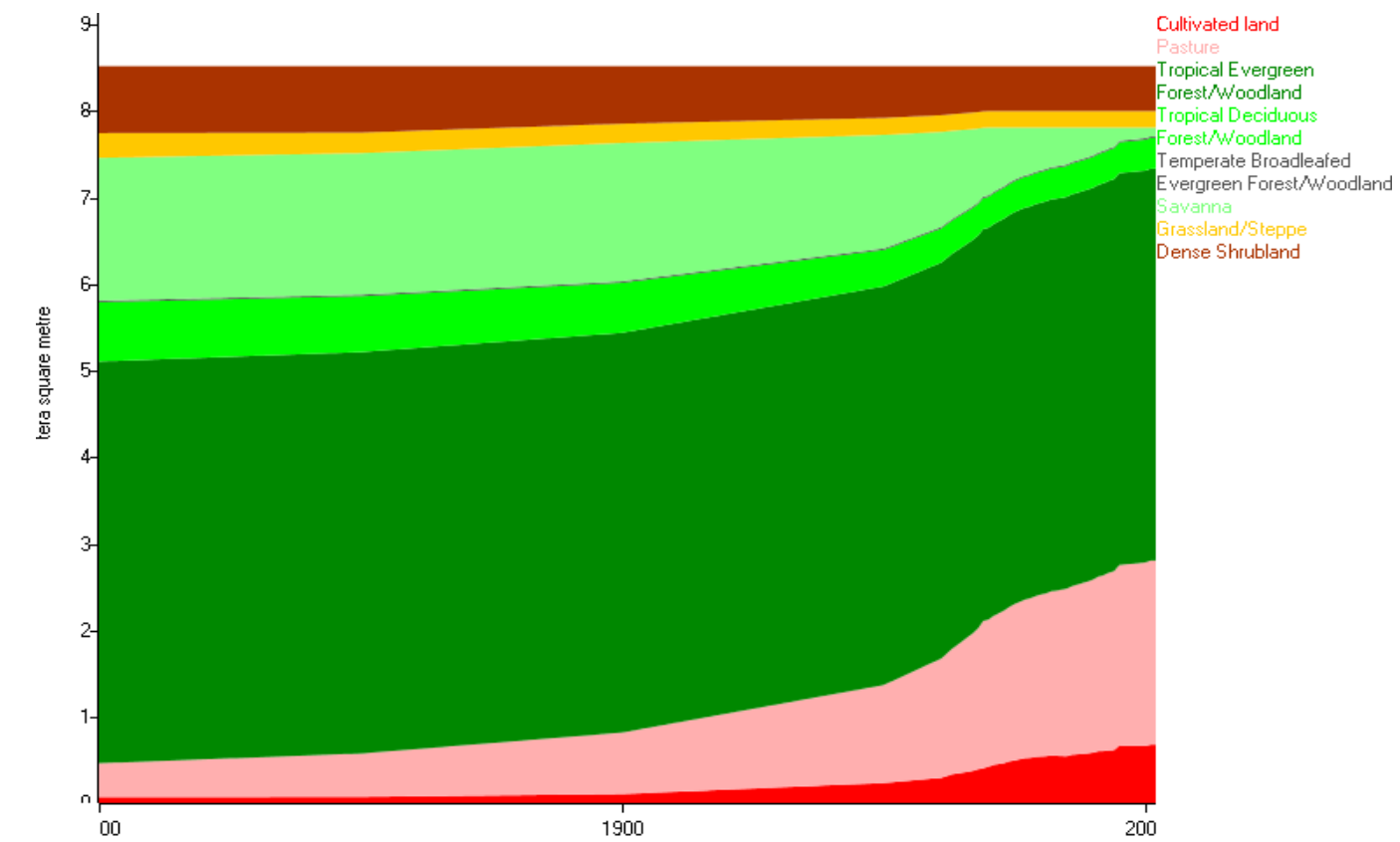
Biome classification "B", 1700 (Ramankutty and Foley)



Biome classification "A", 1700 (Haxeltine and Prentice)



Land use on biome classification "B" in 1990



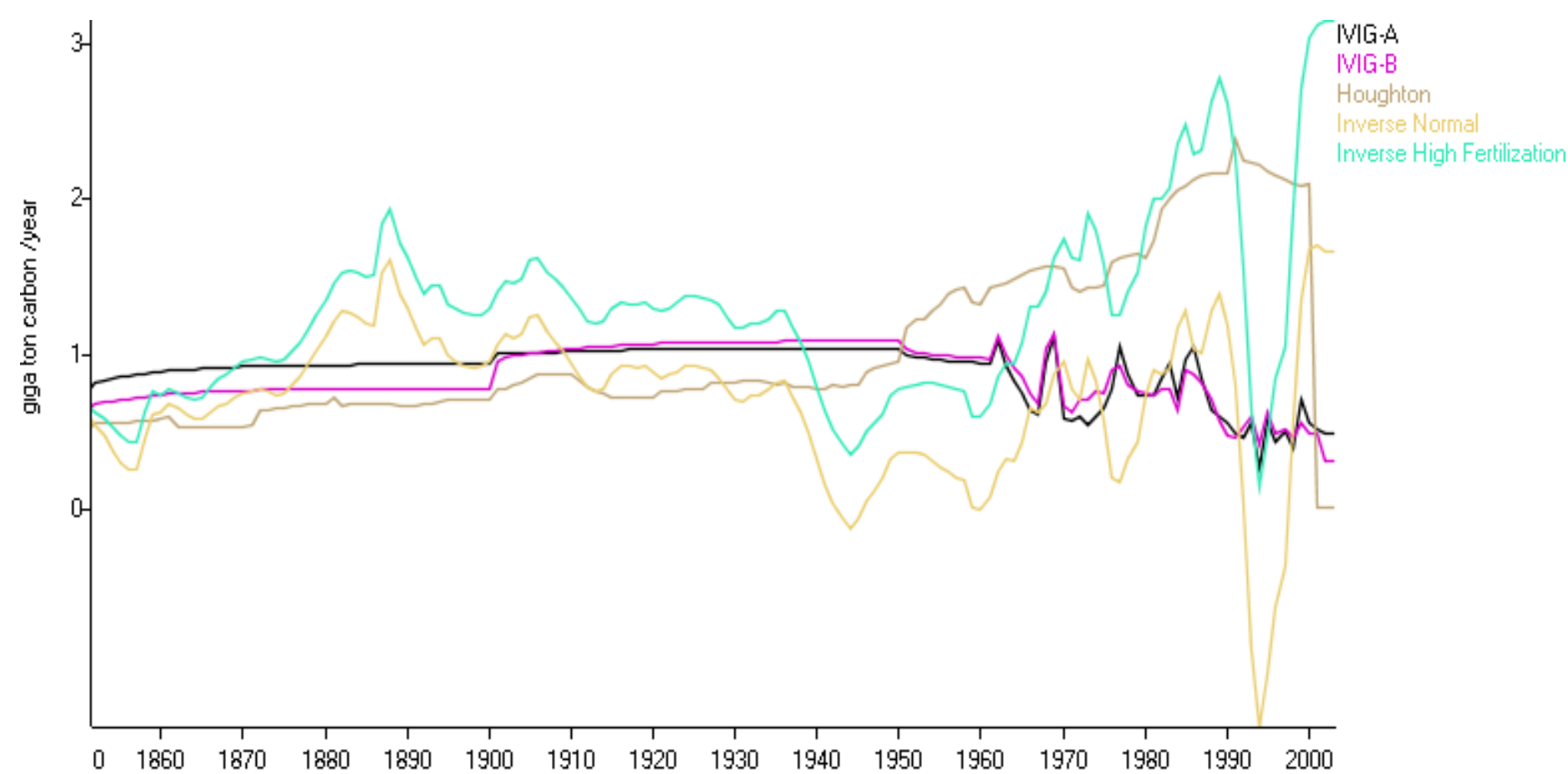
Example: IVIG model Biome areas for Brazil

### Biome Changes

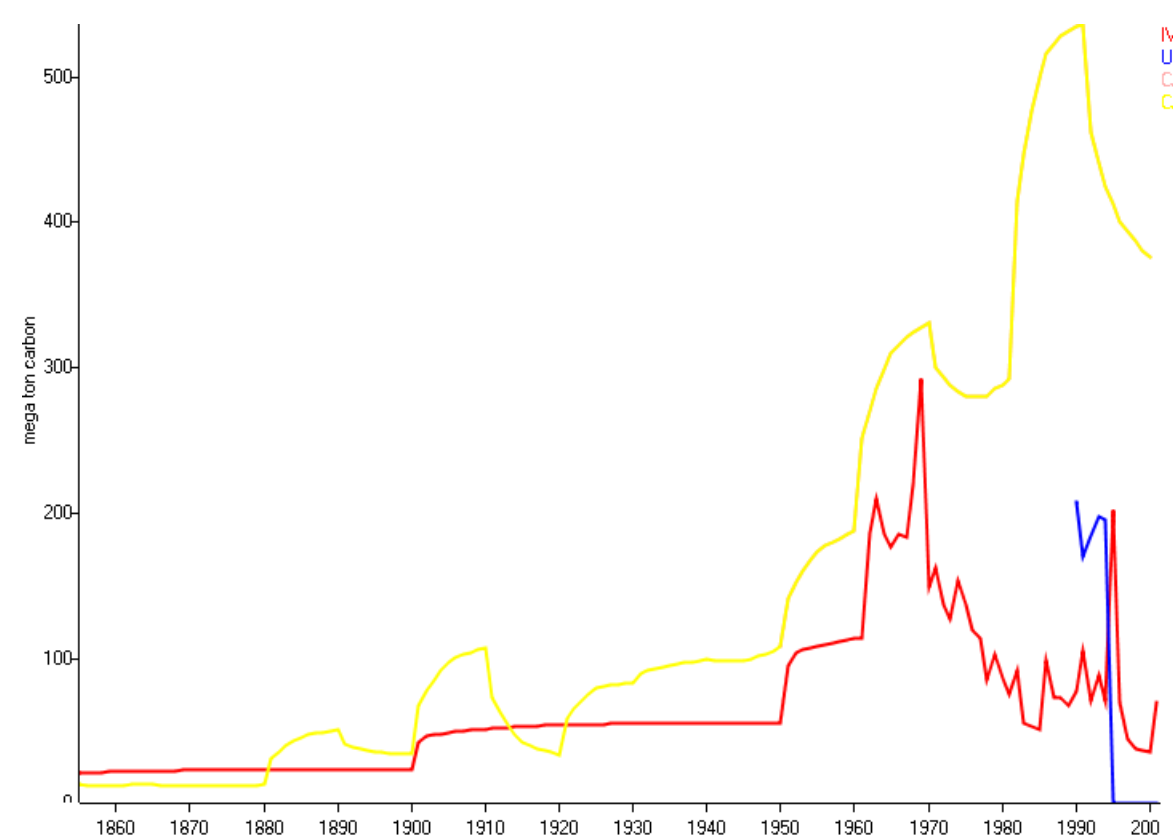
Two biome classification models have been compared to estimate the conversion of natural biome to pasture and cropland. The land use change estimates are based on data from HYDE database from Kees Klein Goldewijk, combined with national data from FAO after 1961

### LUC emissions -different sources

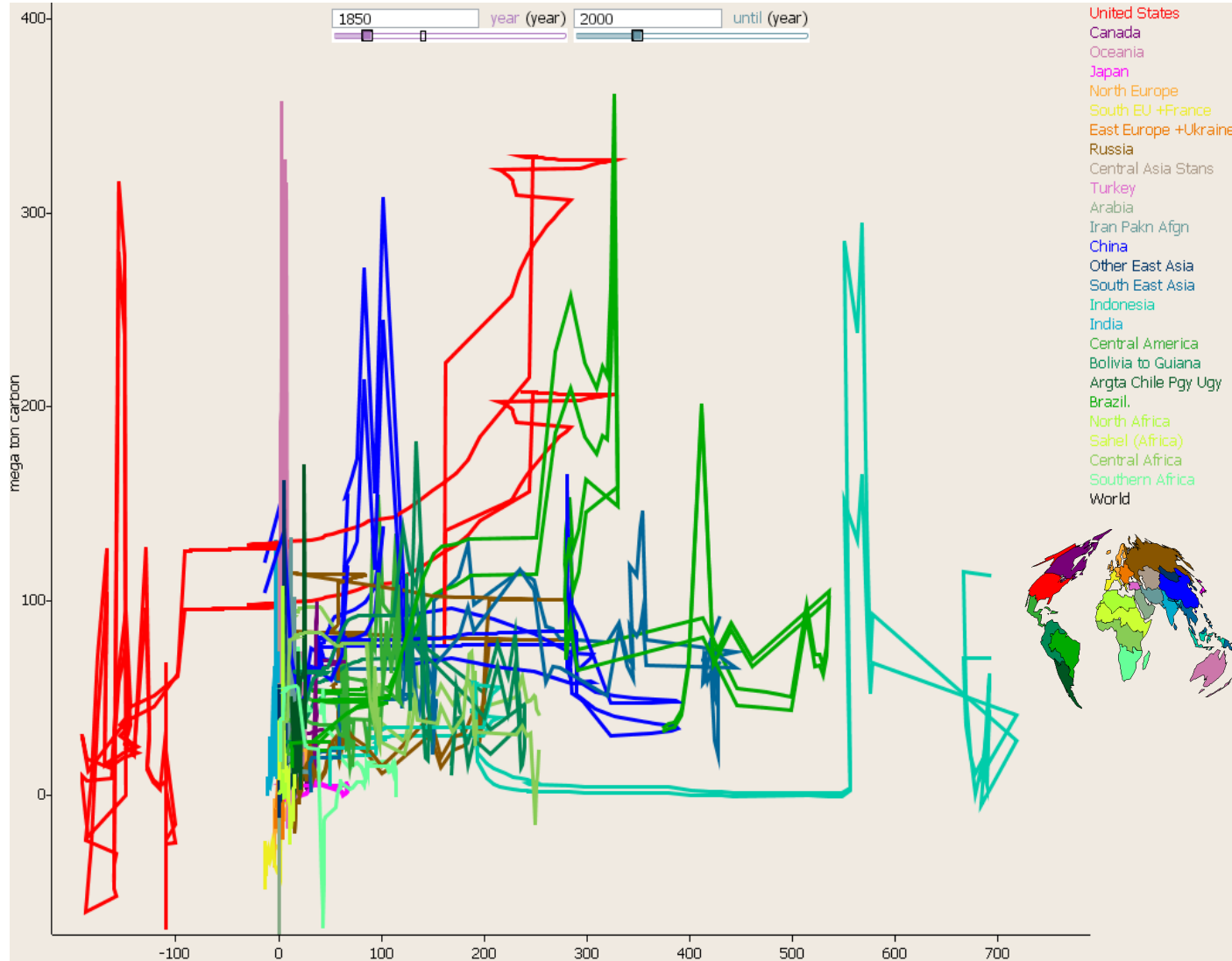
The plot below compares global Land Use Change Emissions derived from IVIG model with the two biome classifications (A/B), from Houghton dataset, and from two inverse calculations using JCM carbon-cycle model (one mid-range, the other with high carbon-fertilisation).



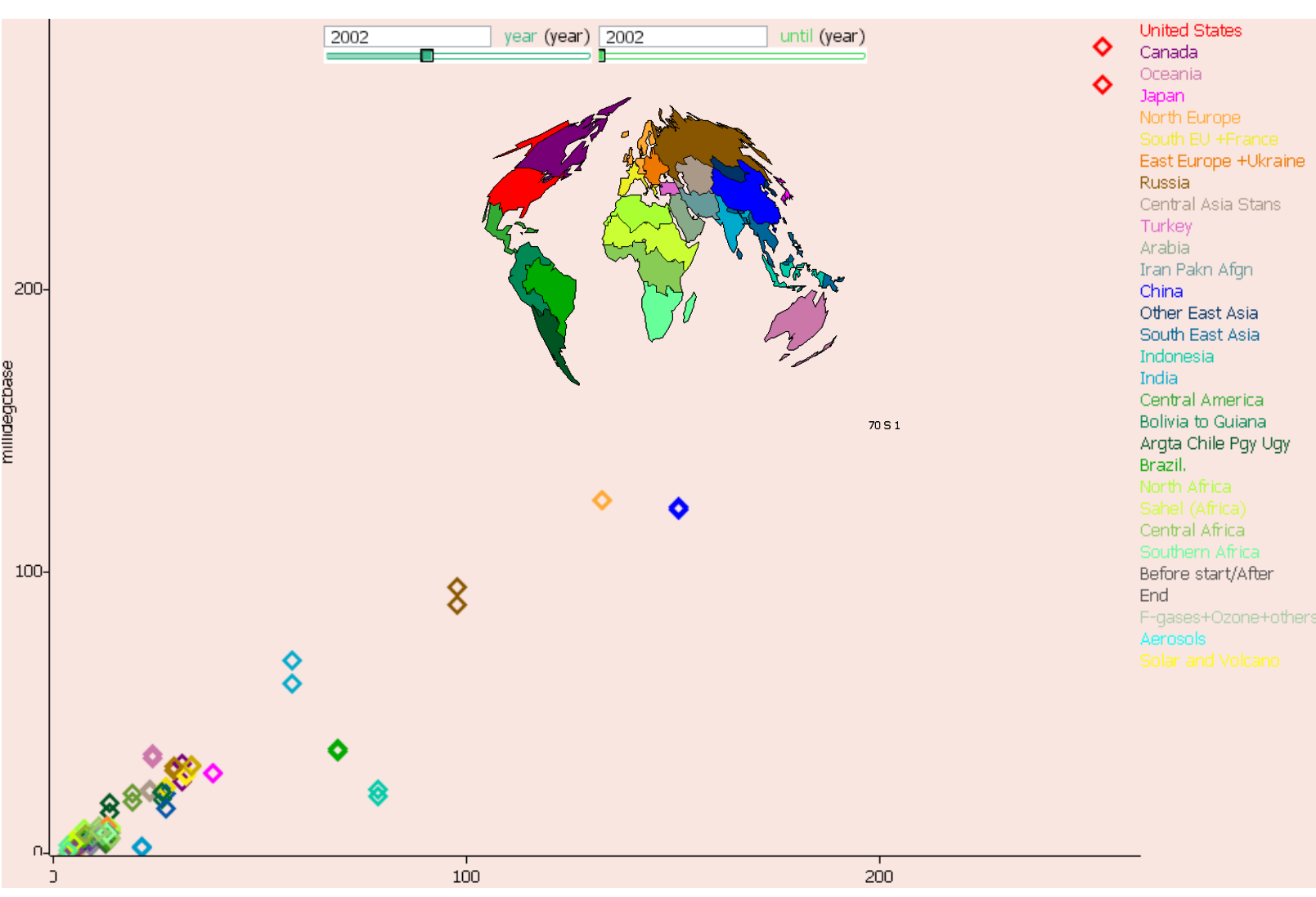
An example for one country, Brazil: Land use change emissions from different datasets: IVIG (red), CAIT derived from Houghton (yellow), and UNFCCC (blue).



### Comparing regional results from different methods



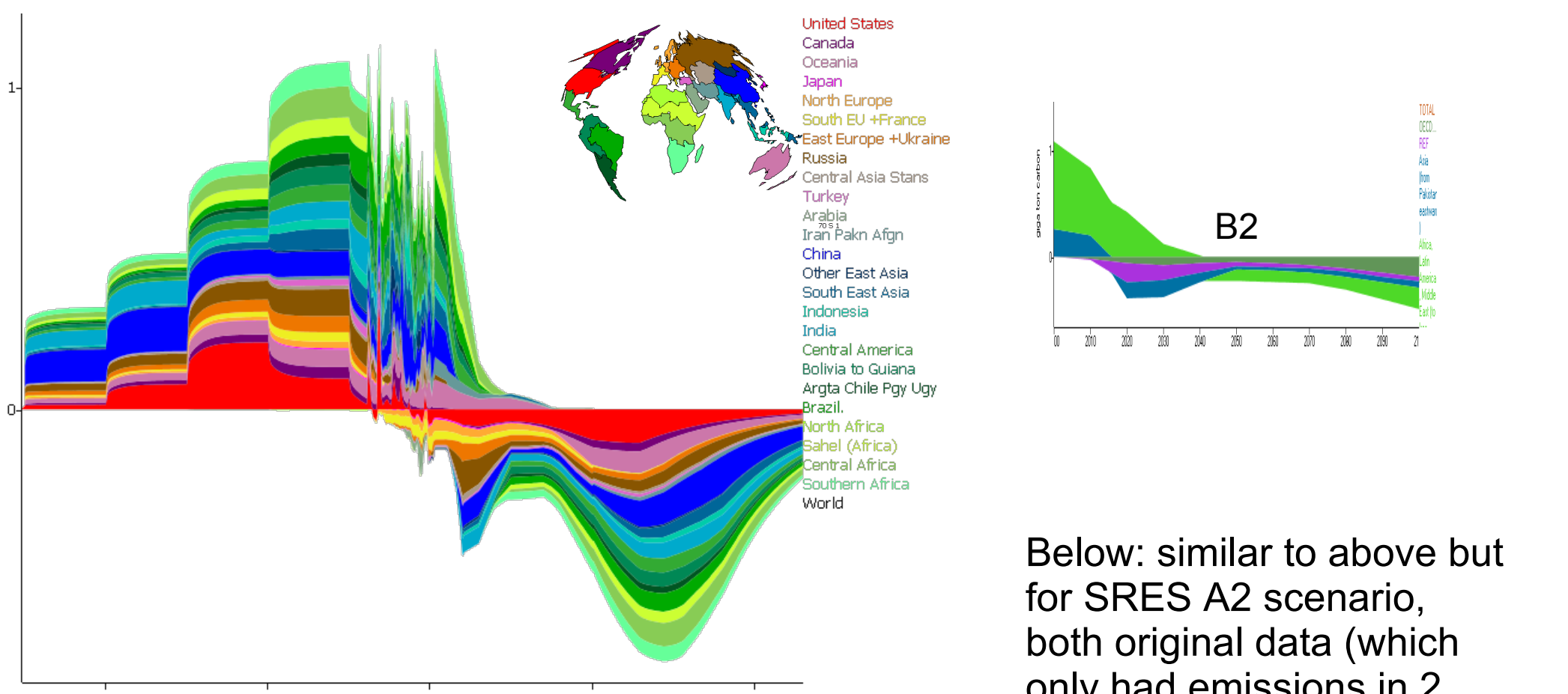
Regional Land Use Change Emissions: Comparing data from Houghton (X) vs IVIG A&B (Y), evolution from 1850 to 2000. Houghton gives much higher emissions for certain regions, particularly Indonesia (cyan), also Brazil and other East Asia, whilst IVIG emissions are higher in US and Oceania in some time -periods.



Comparison of contributions to temperature rise in 2002, depending on the land use emissions data: Houghton (X) vs IVIG A&B (Y). Attribution includes cumulative effect of fossil+landuse CO2, CH4 and N2O, calculated as described in poster #1. The uncertainty due to land use emissions varies by region, being especially large for Indonesia and Brazil, but also US.

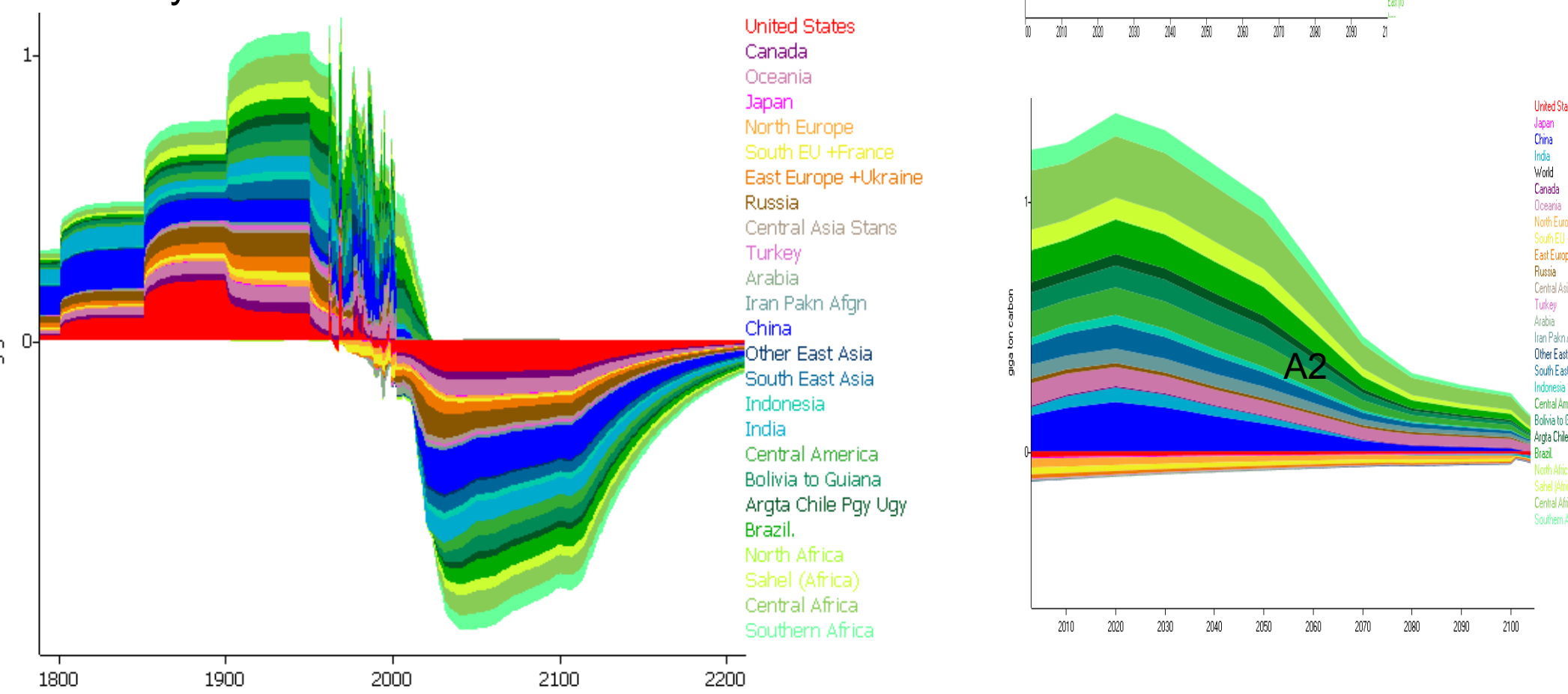
### Extension to Future Scenarios

It is important to consider the consistency of historical land-use-change emissions estimates with future scenarios of land-use-change, such as those from IPCC-SRES. The plot below shows the regional emissions from IVIG (B) model, combined with SRES B2 scenario. As SRES data are only provided for four regions from 2000 to 2100 (small plot right), a potential LUC sink factor based on cumulative historical emissions was used to interpolate from SRES to smaller regions, and to extrapolate beyond 2100. Note in particular the (dis)continuity at 2002 as we move from data to scenario.



Below: similar to above but for SRES A2 scenario, both original data (which only had emissions in 2 regions) and our interpolation to 25 regions, only until 2100

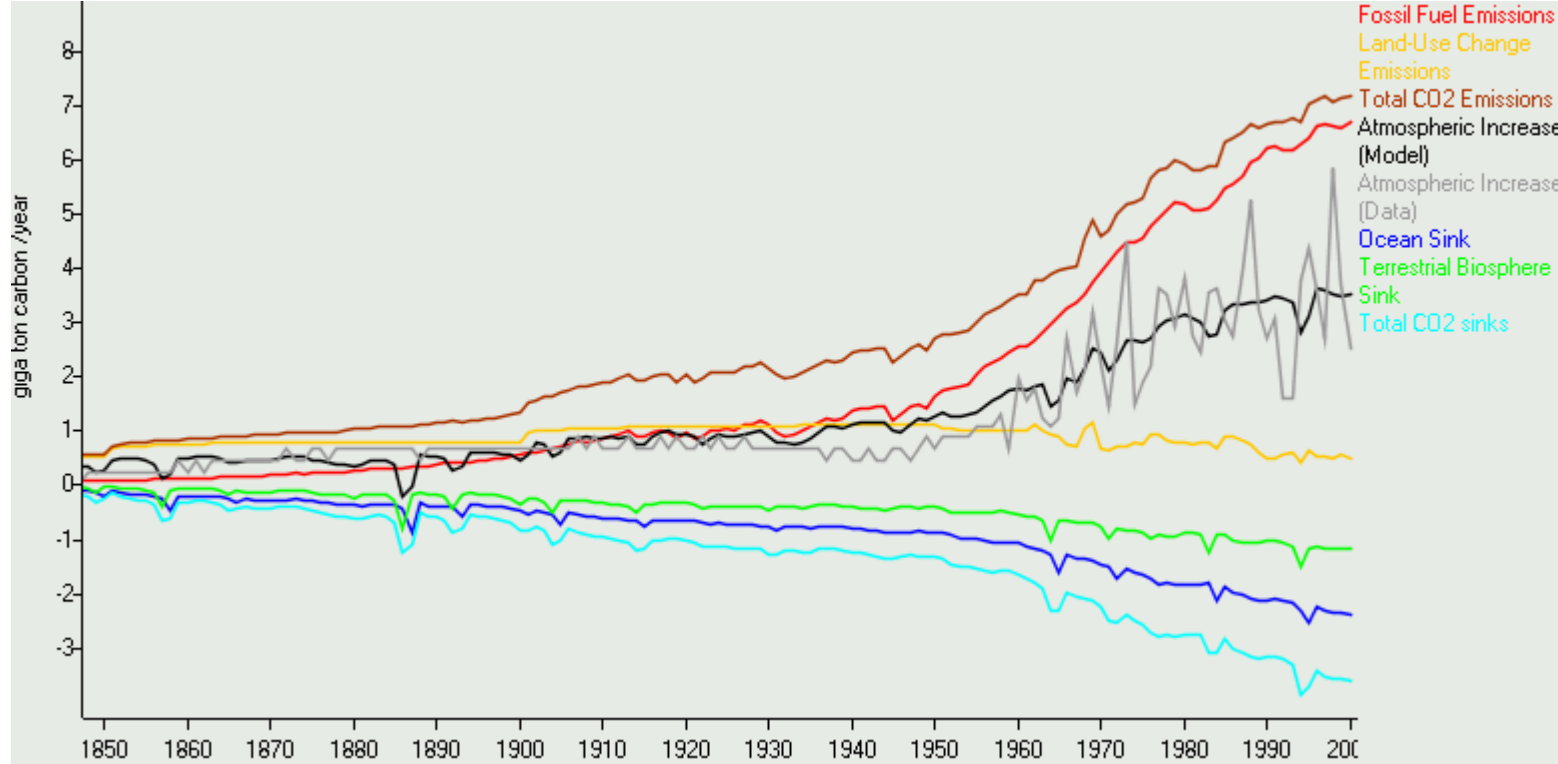
The plot below shows the same history, combined with a scenario aiming to stabilise global temperature rise at 2C above the preindustrial level (limit proposed by EU). In this case the potential sink factor is used to inform the balance of effort between increasing LUC sink and decreasing fossil emissions, for each region. Compared to the history, a large transformation is evidently needed.



## Constraining Uncertainty in Contribution of Land Use emissions using Measured Atmospheric CO2 Concentrations

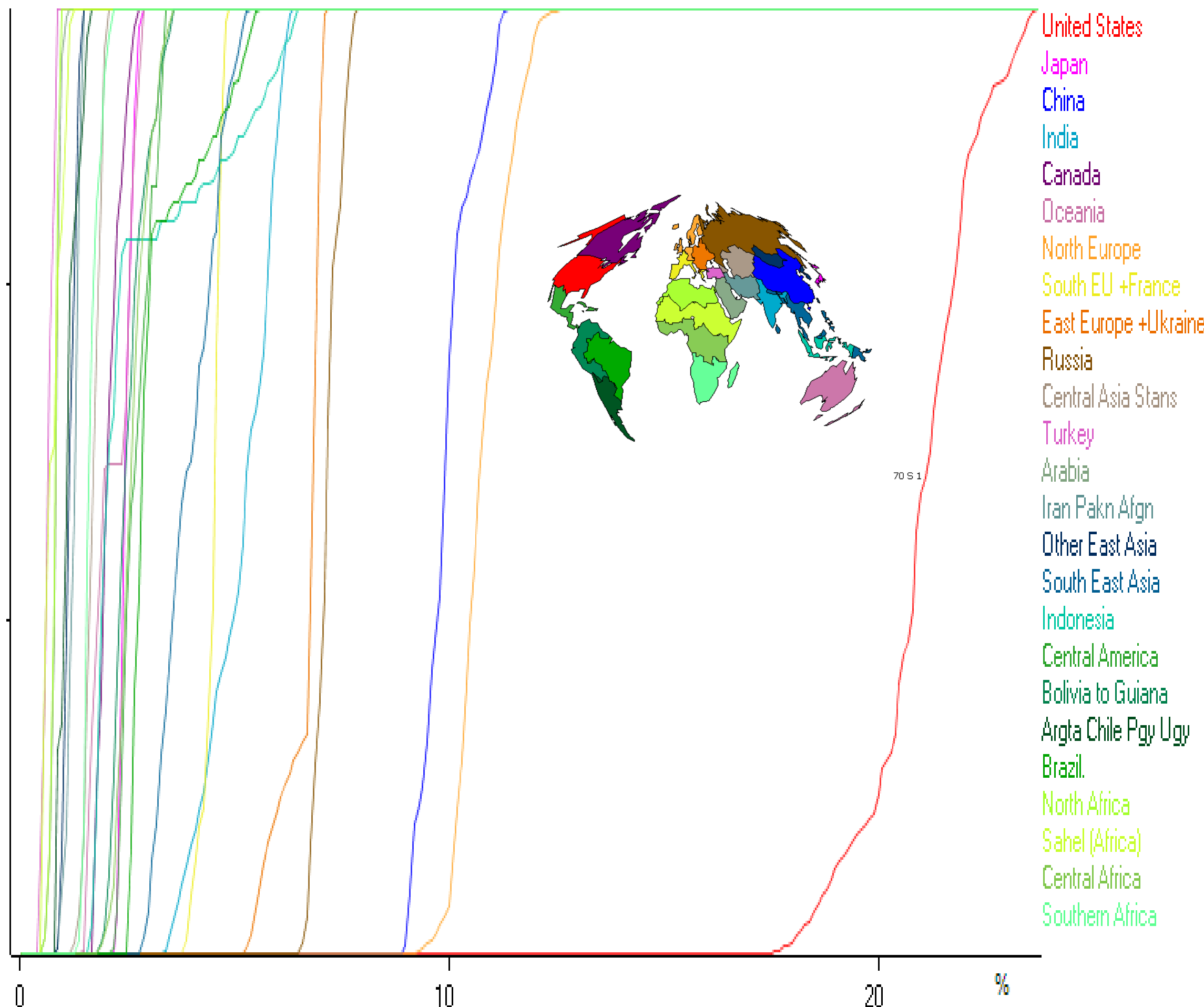
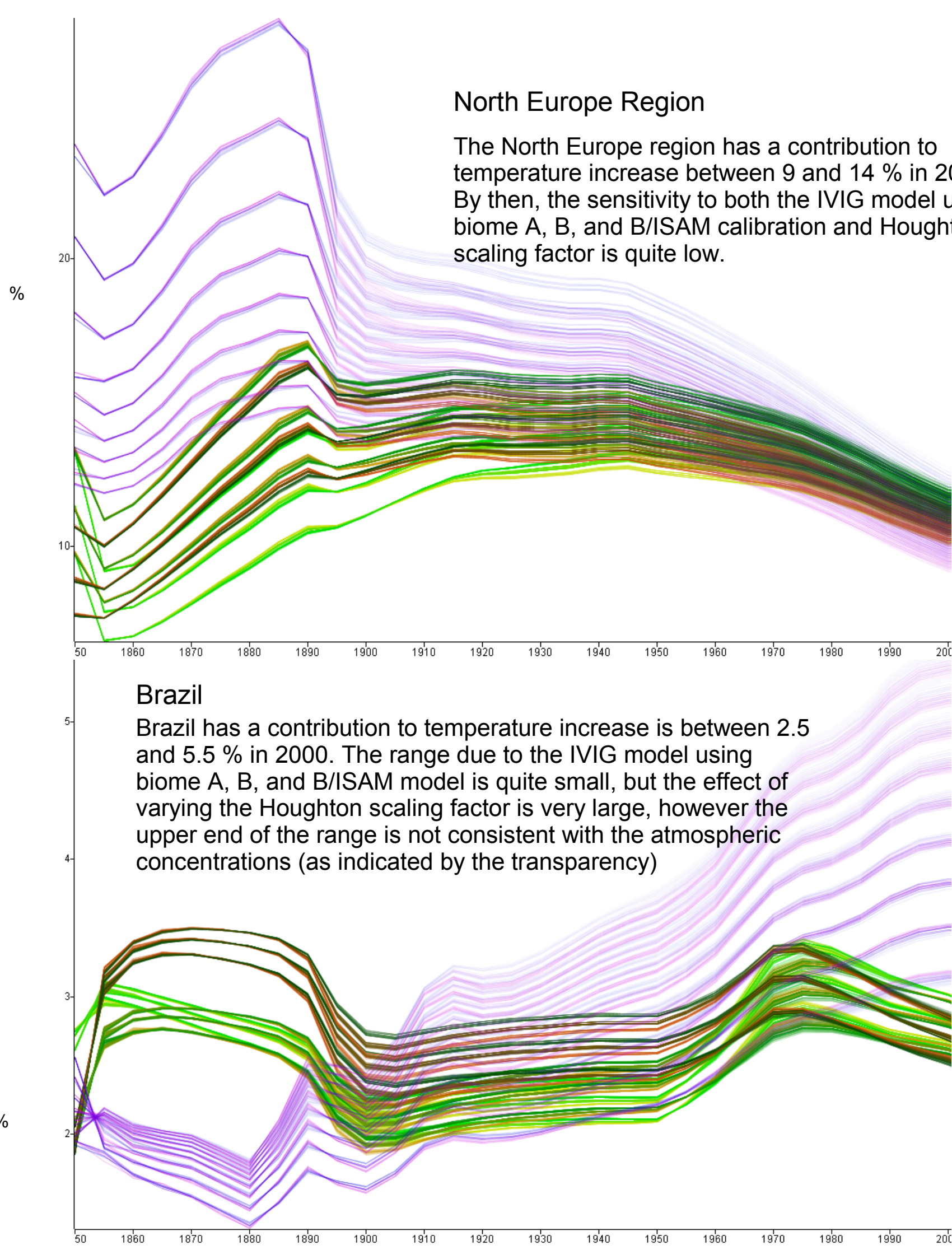
The uncertainty in the land use change emissions and hence their contribution to temperature increase may be constrained by coupling the land use emissions module with the carbon cycle and climate from JCM.

The plot below shows fluxes in the global carbon cycle. The grey curve shows the measured annual net increase of CO2 in the atmosphere. The black shows the same net increase, calculated as the sum of fossil (red) and land-use (yellow) emissions, minus ocean and terrestrial biosphere sinks (blue and green).



There is a large uncertainty in both the landuse emissions and in the modelled sinks, so we aim to find coherent sets of parameters in which the grey and black curves are consistent. However, there are also natural variability (e.g. due to fires) not included in the model, so we don't seek a perfect fit. Instead many parameters were varied in both the IVIG land use change emission model (agriculture carbon soil loss, pasture carbon loss, biome classification, and biome carbon content) and in the Bern carbon model parameters CO2 fertilization factor, the temperature-respiration feedback factor (Q10) and the ocean diffusivity factor. Each set of parameters was then given a weight inverse to the integrated absolute difference between the black and grey curves above. For comparison the Houghton landuse emissions data set was also incorporated as an alternative, scaled by an adjustable parameter.

Plots above right show some example results using the method. Each plot shows the relative contribution to temperature change, calculated as explained in poster #1, as a function of time. Blue lines are the combination with Houghton database scaled, the light green lines are from IVIG model with land use classification A, middle green lines are from IVIG model with land use classification B, and the dark green are from IVIG model with land use classification B with carbon content calibrated by ISAM model. The transparency of each curve illustrates the relative weight of each set derived from the fit to CO2 data.



Above: Cumulative frequency for relative contributions to temperature increase (%) due to emissions from CO2, CH4 and N2O 1850 to 2000 from 25 regions (map), combining methods introduced left and on poster #1. This illustrates that the uncertainty due mainly to land-use change is much greater for some regions (e.g. Indonesia, Brazil), than to others (e.g. Europe). This type of analysis of relative uncertainty may help to identify on which regions future study should focus. Note: the deviation at the top of the curves for Indonesia and Brazil is due largely to scaling Houghton data.