COMMENTS ON THE GEF STAR ALLOCATION ALGORITHM AND SUGGESTIONS FOR ALTERNATIVES

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For additional information on the project, see http://vitalsigns.org/gef-ldmp.

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CURRENT GLOBAL BENEFITS INDEX ALGORITHM

The current algorithm for the Global Benefits Index (GBI) is as follows:

Allocation = 0.2*area affected by land degradation + 0.2*vulnerable population + 0.6*share of country being drylands

AREA AFFECTED

The area affected by land degradation is crucial for allocation of resources. The only scientifically justifiable method to assess this is through time series of remotely sensed data. The pioneering study by Bai et al. (Bai et al. 2008) laid the foundation for a useful proxy for land degradation (and improvement). Trends of vegetation indices (various combinations of visible and near-infrared reflectance) provide an unbiased proxy for vegetation productivity, where a negative trend is a proxy for land degradation and a positive trend for land improvement. Different vegetation indices have been evaluated for the purpose of assessing land degradation, and NDVI turns out to be the preferred (Tucker III and Pinzon 2017; Yengoh et al. 2015), and also the most widely used vegetation index (Tucker et al. 2005).

The most important weakness of the data used in the previous GEF STAR algorithm was the coarse resolution and poor spatial sampling of the NOAA AVHRR dataset, an 8 km grid but representing a larger and fuzzy sampling area. This has improved enormously since 2000 and the launch of the MODIS series of sensing systems, with a spatial resolution of 1000 m or higher. Using linear trend of NDVI since 2000 is probably the most appropriate proxy for vegetation productivity, and hence the best proxy of land degradation.

The previous dataset used for the GEF STAR had used a particular algorithm, based on rain use efficiency (RUE), to filter out trends caused by climatic variations. Whether to use such filtering mechanism or not depends on what definition of land degradation is used. If the definition includes climatic factors as possible causes of degradation, the NDVI trend should not be filtered using RUE. If the definition excludes climatic variations as a cause of land degradation, the NDVI data should use some method for disentangling the influence of climate and land use processes. Even if such methods have been suggested, it is still an area in need of further research.

VULNERABLE POPULATION

The current GEF STAR algorithm used the percentage of a country's total population that is living in rural areas as a proxy for population vulnerable to degradation. This is a problematic proxy for at least three reasons.

- The data used to calculate this is inconsistent. It used the national definitions of rural areas, which vary substantially from country to country (Dasgupta et al. 2014, pp 618-619).
- With increasing urbanisation more and more people live in peri-urban areas which are notoriously misrepresented by national statistics (Revi et al. 2014, p. 541)
- The proportion of the population living in rural areas may not be the best proxy because it does not say much about livelihoods.

Vulnerable population is a very complex matter which can hardly be captured by a single indicator. We assume that land degradation is first and foremost related to agriculture (including pastoralism and transhumance) – both regarding causes of land degradation and in terms of impacts on society and economic activities (Foley et al. 2011; Clay 2013). We also assume that people who are poor are more vulnerable to the effects of land degradation (von Braun et al. 2013). To capture the vulnerability of people we, therefore, suggest two variables. Structurally agriculture is also very important to low-income countries and to capture this we suggest a third variable.

- V1: the proportion of population engaged in agriculture;
- V2: the proportion of rural people living below the national power line.
- V3: the proportion of GDP generated by agriculture.

SHARE OF COUNTRY BEING DRYLANDS

This variable, defined in the current GEF STAR algorithm as the proportion of the total area of each country falling into the three classes of aridity index (arid, semi-arid and sub-humid), is scientifically unjustified. Recent research has challenged the conventional wisdom that land degradation is particularly a problem of drylands (Tian et al. 2017; Brandt et al. 2016; Ahlström et al. 2015; Fensholt et al. 2012; Fensholt et al. 2013; Bai et al. 2015). If there are political or other reasons for treating countries with a big proportion of drylands differently, this is better done by categorizing the countries in different priority groups within which the GEF STAR algorithm could be used.

RELEVANCE TO UNCCD

In its capacity as the financial mechanism of the UNCCD, the GEF should also contribute to achievement of the UNCCD objectives. It is therefore of interest to compare the proposed variables of the GBI with the UNCCD progress indicators adopted by its Conference of Parties (Decision 22/COP.11):

UNCCD progress indicators for national reporting
Strategic objective 1: To improve the living conditions of affected populations
SO1-1: Trends in population living below the relative poverty line and/or income inequality in affected areas
SO1-2: Trends in access to safe drinking water in affected areas
Strategic objective 2: To improve the condition of affected ecosystems
SO2-1: Trends in land cover
SO2-2: Trends in land productivity or functioning of the land
Strategic objective 3: To generate global benefits through effective implementation of the UNCCD
SO3-1: Trends in carbon stocks above and below ground
SO3-2: Trends in abundance and distribution of selected species

We conclude that the improved GBI is also a better reflection of SO1-1, as poor people in rural areas are generally dependent on natural resources for their livelihoods and are engaged in some form of agriculture for their sustenance. With the use of new and improved NDVI datasets, it is also a better proxy for SO2-2.

SUGGESTION FOR A NEW ALGORITHM

As a first attempt, we suggest equal weights for the four variables, but this should be subject to further research to ensure the most appropriate set of variables.

Allocation = 0.25 * proportion of country affected by land degradation

+ 0.25 * proportion of population engaged in agriculture

+ 0.25 * proportion of rural people living below the national poverty line

+ 0.25 * proportion of GDP generated by agriculture

Data for these variables are continuously updated by international agencies, such as the World Bank and ILO.

DATA SOURCES FOR CALCULATION

The proportion of country affected by land degradation:

The proportion of country affected by land degradation was estimated using statistically significant (p-value < 0.05) declines in annual integrals of NDVI using 250m resolution MODIS data for the period 2001-2015 (MOD13Q1 collection 6, figure 1). This data set has been identified as the most appropriate for this type of analysis, given its relatively fine spatial resolution and consistent calibration methods. The table attached summarizes the areas identified as experiencing significant increases, decreases, and no-changes in NDVI over the period. Areas covered by water and cities in 2015 were masked from the trend analysis.

The results from our preliminary analysis differ greatly from those reported by Bai et al. (2008) due to several reasons. First, the period analyzed is different, while Bai et al. (2008) assessed trends in changes in NDVI for 1981-2003, our period of analysis is 2001-2015 given that MODIS data became available in mid-2000. Even though longer time records are preferred for analyzing trends in NDVI, the improved spatial resolution greatly compensates for the loss in time coverage. Moreover, 2000-2015 is the baseline period suggested for several SDGs, including SDG 15.3.1 (land degradation neutrality), so the currently proposed period better aligns with other global monitoring strategies.

The second reason for the differences between the previous estimates and ours is related to the change in the data source. AVHRR has an 8-km pixel size (constructed by an average of four out of five 1.1km pixels along scan lines and one out of three scan lines) compared to the 250-m pixel of MODIS, which allows it to capture finer scale processes which would have been masked by the coarse aggregation of AVHRR. Also, different products are subject to different calibration and correction procedures. Even though great effort is continually devoted to harmonize datasets, uncertainty between them still exists.

Finally, there is a difference in methodology for filtering NDVI trends to identify what could potentially be a proxy for degradation. While Bai et al. (2008) filtered NDVI trends masking out areas with positive correlation between annual precipitation and NDVI and negative trends in rain use efficiency, we recommend against climatic filtering. Declines in primary productivity even when they are related to climatic events have the same negative effects in the provision of ecosystem services and for the sustainability of human livelihoods. For that reason, we only filtered trends by statistical significance (p-value <0.05), regardless of the possible causality of climate in driving those trends.

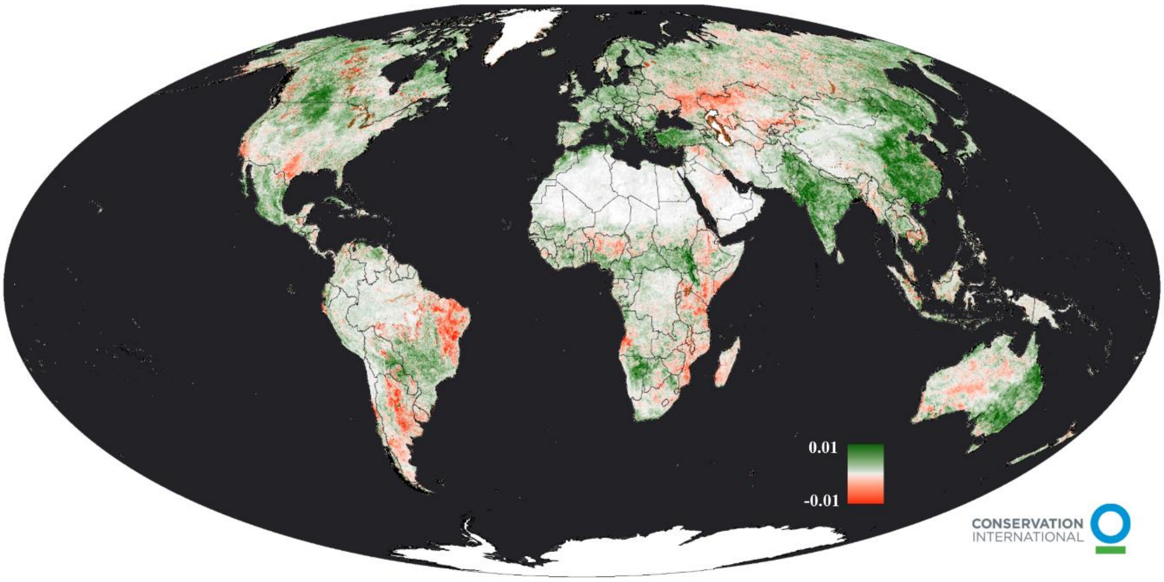

Figure 1: Linear trends in NDVI annual integrals for the period 2001-2015. Data source: MOD13Q1 collection 6. Values represent slope of the regression.

Proportion of population engaged in agriculture:

Available from the International Labour Organization: http://www.ilo.org/ilostat/faces/oracle/webcenter/portalapp/pagehierarchy/Page3.jspx?MBI_ID=33&_afrLoop=961778305544031&_afrWindowMode=0&_afrWindowId=1b2z66mlly_1#!%40%40%3F_afrWindowId%3D1b2z66mlly_1%26_afrLoop%3D961778305544031%26MBI_ID%3D33%26_afrWindowMode%3D0%26_adf.ctrl-state%3D1b2z66mlly_33

Proportion of rural population below national poverty line:

Available from the World Bank: http://wdi.worldbank.org/table/1.1#

Proportion of GDP generated by agriculture:

Available from the World Bank: http://wdi.worldbank.org/table/4.2

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