Methodological Note – Potential Unrealised Carbon Across the Great Green Wall

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Step 1 – Identifying Source for Maximum Potential Biomass

The scale of the Great Green Wall (GGW) presents significant challenges in accurately assessing its carbon sequestration potential, even at high resolution. The GGW spans over 8,000 kilometres across the Sahel region of Africa, covering multiple countries, ecosystems, and land-use types. The variability in soil types, vegetation, climate conditions, and human activities across this expanse makes it difficult to perform detailed, location-specific analysis on a large scale. In this study, the primary source utilized was the work by Walker et al. (2022), titled "The global potential for increased storage of Carbon on land." This paper serves as the foundational reference for assessing the potential for enhanced carbon storage across various terrestrial ecosystems globally. More specifically, the paper combines global forest inventories with satellite and spaceborne Light Detection and Ranging (LiDAR) through Global Ecosystem Dynamics Investigation (GEDI) to predict potential biomass according to bioclimatic variables in future climate scenarios via random forest machine learning algorithm, with known per-pixel uncertainty and a 500m grid resolution. The analysis leverages the insights, data, and methodologies presented by Walker et al. to understand the unrealized carbon sequestration potential in different land-use types, including forests, grasslands, and agricultural areas.

The estimations provided by Walker et al. were validated against Tree Aid datasets to ensure validity. While the estimates of potential unrealised biomass were not verifiable due to being theoretical, the paper also provides a raster of the Current biomass in Mg ha^{-1}. Therefore, we were able to compare these per-hectare measurements to forest inventories conducted in Tree Aid project sites, which went on to become a VCM project. We found that Walker has underestimated current biomass, compared to Tree Aid measurements. Due to the nature of the estimations of potential unrealised biomass, we can conclude that the Walker dataset is accurate within a very conservative range of estimations, and derived analyses from this dataset will not lead to overestimations of potential unrealised Carbon. This source's rigorous scientific approach forms the backbone of the current analysis, ensuring that the findings are grounded in robust, peer-reviewed research.

Step 2 – Estimating/ Calculating Maximum Potential Biomass

The Walker et al. dataset used is "constrained" before the analysis, meaning that it was specifically filtered to exclude areas that are integral to human habitation. This approach is essential to ensure that the analysis focuses on areas where carbon sequestration potential can be realized without conflicting with essential human activities, such as residential areas, infrastructure, agricultural lands that are critical for food production and livelihoods[1]. By masking out areas integral to human habitation, our analysis targeted regions where large-scale afforestation, reforestation, or other ecological restoration activities could be successfully implemented. These might include degraded lands, forests with low current carbon storage, or other ecosystems that can be restored without significant socio-economic trade-offs. The resulting product is a raster dataset[2] showing global unrealised potential Carbon in tonnes, for Aboveground Carbon, Belowground Carbon, and Soil Organic Carbon.

The next stage of data processing is to convert the resolution to per hectare estimates. This fives a more granular understanding of carbon sequestration potential, which is particularly useful for detailed land management planning, policy-making, and local-scale interventions. Per hectare estimates allow for easier comparison between different regions or land-use types, as they standardize the data to a common unit of area.

The original data has a resolution of 500m according to standard Moderate Resolution Imaging Spectroradiometer (MODIS) grid cells. After clarification with the author, the conclusion is that values assigned to 500m pixels are equal to the *average* per-hectare value within that pixel. Therefore, to achieve the sum of the per hectare values within that pixel, the values given must be multiplied by the difference between 500m pixels and one-hectare pixels (24.46). In the final stage of data processing, the values were converted from tonnes of Carbon (C) into tonnes of CO_2 equivalent (tCO_2e) to align with terminology and standards best suited for Voluntary Carbon Market (VCM) analysis. This conversion is critical for making the data relevant and comparable in the context of carbon markets, where CO_2e is the standard unit used to represent greenhouse gas emissions and sequestration. The conversion from carbon (C) to CO_2e is based on the ratio of their molecular weights:

$$tCO_2 = tC \times \frac{44}{12}$$

Where:

tCO_2 is tonnes of Carbon Dioxide Equivalent

tC is tonnes of Carbon

44/12 is the difference between the molecular weight of CO_2 (44), and the molecular weight of Carbon (12). 44/12 is equal to 3.6667.

By summing the converted values of areas where carbon sequestration potential can be realized within the entire landmass of the 11 countries of the GGW other than tropical monsoon zones as defined by Koppen-Geiger climatic zones[3], the following summary table is produced. The total unrealised potential equates to **34.47 billion tCO2e**. For detail per country see ***Table 1*** in the appendix:

[1] N. Ramankutty, A. T. Evan, C. Monfreda, J. A. Foley, Global Agricultural Lands: Pastures, 2000 (2010).
[2] In a raster format, the data is stored as a grid of cells or pixels, with each cell holding a specific value that represents information about that location on the Earth's surface.
[3] Beck et al. (2023) *Koppen-Geiger maps for 1901-2099 based on constrained CMIP6 projections*. Scientific Data 10, 724, doi:10.1038/s41597-023–02549-6.

Carbon Pool	Unrealised Potential (billion tCO_2e)
Aboveground	**17.92**
Belowground	**4.86**
Soil Organic	**11.69**
Total	**34.47**

Step 3 – Introducing Dynamic World Dataset

While the initial analysis has revealed extensive Carbon sequestration potential across the Great Green Wall, the focal point of the paper covers the Voluntary Carbon Market (VCM), and therefore must consider standards' limitations for "*eligible land'*.

Verra's VCS VM0047 methodology, titled "Methodology for Afforestation, Reforestation and Revegetation (ARR) of Degraded Lands," specifies that for land to be eligible for tree planting projects, such as under ARR, it must be classified as either 'stable forest' or 'non-forest'. This involves assessing the land's historical use, current condition, future prospects and its suitability for carbon sequestration activities. In the context of this study, below are the definitions used for "stable forest" and "stable non-forest":

> *<u>Stable Forest Land</u>*
>
> *Stable forest land refers to forest areas that are degraded, underutilized, or at risk of further degradation but are unlikely to face changes like conversion to agriculture or development. These areas are not functioning at their full ecological potential, often showing signs of decline such as reduced tree density or biodiversity. The purpose of projects on such land is to restore the forest, enhancing its carbon sequestration capacity, with the expectation that the land will remain forested and not be subject to deforestation or other land-use changes.*
>
> *<u>Stable Non-Forest Land</u>*
>
> *Stable non-forest land refers to areas that have not been classified as forest for at least 10 years and are often degraded, abandoned, or underutilized. These lands are suitable for afforestation or reforestation projects aimed at transforming land use and enhancing carbon sequestration. The land must have a clear history of non-forest use, and be unlikely to face future changes, such as development or agricultural conversion, that could disrupt the project's objectives. For instance, this could be agricultural land that has been abandoned due to soil degradation, or degraded savanna that are no longer suitable for grazing.*

Extrapolating this to all land uses, it becomes useful to demonstrate VCM-aligned Carbon sequestration potential within the Great Green Wall. For this purpose, Google and the World Resources Institute's 'Dynamic World'[4] dataset was utilised[5]. The dataset is based on imagery from the European Space Agency's Sentinel-2 satellites, which provide multispectral data that is ideal for distinguishing different land cover types. Google's advanced machine learning algorithms are used to

[4] Brown, C.F., Brumby, S.P., Guzder-Williams, B. *et al.* Dynamic World, Near real-time global 10 m land use land cover mapping. *Sci Data* **9**, 251 (2022). https://doi.org/10.1038/s41597-022-01307-4

[5] The 'Dynamic World' dataset is an innovative, high-resolution global land cover dataset that leverages satellite imagery and machine learning to provide near-real-time data on land use and land cover changes. This dataset is particularly valuable for environmental monitoring, land management, conservation efforts, and research on global ecosystems.

analyse the satellite imagery and classify land cover types. These models have been trained on a large dataset of labelled images and combined with field measurements ensure high accuracy in land cover classification at a 10m resolution. The dataset covers the entire globe, offering consistent and comparable data across different regions and ecosystems. Using this dataset also solves the issue of scale, as while individual machine learning algorithms per country per bioclimatic strata would have lower uncertainty due to hyperlocal parameterisation, this would be some undertaking. The dataset spans June 2015 to current 2024 – which does not quite cover the typical 10-year look-back period employed in Carbon projects, but strongly establishes whether a land use is under stable classification.

By taking files from two full years 2016 and 2022, and subtracting them, all classes that display no change are considered stable, and their individual land classifications extracted. The total area estimated amounts to **~24 million hectares** across the GGW. This allowed for Carbon sequestration estimates from the previous step to be analysed according to principles common in the VCM, finding a potential unrealised Carbon storage of **1.8 billion tCO_2e**.

Step 4 – Final interpretation of combined datasets including recommended interventions

After identifying areas within the GGW that are classified as under stable land use the next step was to overlay the stable land use map with the Walker et al. (2022) dataset and perform a spatial intersection to identify the areas within the GGW that both meet the stability criteria and are covered by the Walker et al. data. This step filters out any areas that are not classified as stable, focusing the analysis on regions with the highest potential for sustained carbon sequestration.

It is important to highlight that some limitations in applying Walker et al.'s Natural Climate Solution (NCS) recommendations when applied to the GGW were noted, particularly regarding the use of broad ecological classifications and thresholds that are not well parameterised to the GGW. First, the entirety of the African continent is grouped into a single "Tropical" ecoregion. When considering interventions in diverse dryland ecosystems like those within the GGW, it is important to consider the need for more region-specific parameters. Secondly, under Walker et al, to establish suitability for Forestry NCS a 'biotic threshold' (T_b) is set at the lower 5^{th} percentile of the current biomass across the region, for all cells with 26% tree canopy cover, at 20MgC ha^{-1}. This threshold is combined with a 'forestry threshold', separating closed and open forest systems and asserting that closed systems are designated high forestry potential, and open systems with low. Here the thresholds could be customized based on localized vegetation types and existing land use. For instance, savanna ecosystems, which are common in the Sahel, might require a lower canopy cover threshold, such as 10-15%, reflecting the natural sparse tree cover in these areas, and is more aligned with the typical national definition of forest. Thirdly, biomass thresholds should reflect the productivity of these ecosystems, potentially adjusting the carbon storage expectations to a lower, 'more realistic' range at baseline (e.g., 5-10 MgC ha-1).

Despite some of the above-mentioned drawbacks of Walker et al.'s NCS recommendations, from the data extracted, stable land classes between 2016-2022 were identified as *eligible for Voluntary Carbon programmes* and classified under: Trees, Grass, Flooded-Vegetation, Crops, Shrub & Scrub, Built, and Bare, as per ***Table 2*** in the appendix below.

Drawing on understanding of carbon markets, standards, and methodologies, Tree Aid's analysis assessed several carbon sequestration activities/ approaches across the various land types. The analysis concluded that areas dominated by 'Trees' would most effectively sequester carbon through the implementation of Improved Forest Management (IFM) and ARR interventions. These approaches are anticipated to enhance carbon storage in above-ground biomass (AGB), below-ground biomass (BGB), and soil organic carbon (SOC). Grassland areas would be prioritized for carbon sequestration under Improved Grassland Management (IGM). Flooded vegetation zones are recommended for mangrove restoration projects to optimize carbon sequestration. Agricultural lands would be managed using Improved Agricultural Land Management (IALM) techniques. Shrubland and scrubland ecosystems would be targeted for Assisted Natural Regeneration (ANR) within the ARR framework. Urban areas would benefit from Urban Forestry initiatives under ARR methodologies, and finally, bare land could be reclaimed and reforested using ARR strategies.

Despite the partially prescriptive nature of this classification, under the Walker methodology each of these stable land classes has potential for sequestration in Aboveground, Belowground, and Soil Organic Carbon. For this analysis classes and recommended interventions were targeted to be proposing minimal *land conversion*, particularly for grass, crop, and flooded ecosystems. This is because a key risk in Carbon project scaling across the continent of Africa is both the conversion of natural ecosystems, and the displacement of agricultural activities elsewhere which may exacerbate degradation in the new area.

Step 5 – Contextualising the Results

While analysing stable land use brings the potential Carbon storage into context in regard to the land eligible for Carbon projects across the Great Green Wall, it is useful to further break this down so as to aid communication of the scale of intervention that is needed. A paper that was useful in this further analysis was the University of Copenhagen collaboration with NASA in 2023[6] . The paper looks at analysis carried out of a series of high-resolution satellite imagery using an Artificial Neural Network (ANN) which was able to identify tree species and their characteristics according to their crown diameter and the shadow cast by the tree, bolstered with field data. This analysis was done across the Sub-Saharan Sahelian sub-tropical zone experiencing <1,000mm mean annual rainfall. The study identified 9.9 billion trees in this zone, with a total Carbon stock of 0.84(±19.8%) Pg C. This averages to 0.084 tonnes of Carbon per tree, or 0.03 tCO_2e. Extrapolating this to the results of our study across the Great Green Wall countries (Step 2), where the potential unrealised Carbon storage is equal to ~34billion tCO_2e, and assuming this storage was realised through tree planting, the effort would require ***111.3 billion*** trees to be planted across the 11 countries. If we carry out this extrapolation on our analysis on the 'eligible' land areas (Step 3), this equates to ***5.833 billion*** trees.

[6] Tucker et al., 2023. *Sub-continental-scale carbon stocks of individual trees in African drylands*. Nature. https://www.nature.com/articles/s41586-022-05653-6

<u>Appendix</u>

Table 1 - tCO_2e potential per country (Desert, Arid, Tropical Savannah) per Carbon pool

	tC 500m			tC per ha (*24.46)			TCO2e (*3.667)			
Country	Aboveground	Belowground	Soil	Aboveground	Belowground	Soil	**Aboveground**	**Belowground**	**Soil**	**Total**
Nigeria	77,623,196	20,137,863	39,518,335	1,898,663,374	492,572,129	966,618,474	6,962,398,593	1,806,261,997	3,544,589,945	12,313,250,535
Ethiopia	57,171,762	15,561,646	21,076,446	1,398,421,299	380,637,861	515,529,869	5,128,010,902	1,395,799,037	1,890,448,030	8,414,257,969
Mali	21,790,278	5,997,925	9,813,743	532,990,200	146,709,246	240,044,154	1,954,475,063	537,982,803	880,241,912	3,372,699,778
Burkina Faso	14,563,193	4,306,374	10,744,187	356,215,701	105,333,908	262,802,814	1,306,242,975	386,259,441	963,697,919	2,656,200,335
Senegal	10,834,614	3,028,776	7,465,540	265,014,658	74,083,861	182,607,108	971,808,752	271,665,518	669,620,267	1,913,094,537
Niger	638,310	201,717	17,488,775	15,613,063	4,933,998	427,775,437	57,253,101	18,092,970	1,568,652,526	1,643,998,596
Chad	10,022,821	2,825,221	4,077,505	245,158,202	69,104,906	99,735,772	898,995,125	253,407,689	365,731,077	1,518,133,892
Mauritania	173,396	54,480	15,667,789	4,241,266	1,332,581	383,234,119	15,552,723	4,886,574	1,405,319,514	1,425,758,811
Sudan	6,434,625.00	1,899,161	3,604,170	157,390,928	46,453,478	88,157,998	577,152,531	170,344,904	323,275,379	1,070,772,815
Eritrea	523,171	175,540	780,010	12,796,763	4,293,708	19,079,045	46,925,729	15,745,029	69,962,857	132,633,614
Djibouti	33,217	11,171	118,049	812,488	273,243	2,887,479	2,979,393	1,001,981	10,588,384	14,569,757
						Total Per pool	**17,921,794,887**	**4,861,447,942**	**11,692,127,809**	**34,475,370,638**

Table 2., Area (ha) per country identified as being under stable land use from 2016 to 2022.

	Land Classification (ha) in Stable Land Use (2016-2022) Eligible for Carbon							
	Trees (1)	Grass (2)	Flooded-Vegetation (3)	Crops (4)	Shrub and Scrub (5)	Built (6)	Bare (7)	**TOTAL (ha)**
Burkina Faso	1,050,912	20,450	8,531	321,940	2,093,389	92,110	781,119	4,368,451
Chad	363,369	40,086	18,411	215,381	815,332	897	287,407	1,740,883
Djibouti	-	-	-	2,838	3,211	47	10,702	16,798
Eritrea	1,143	152	-	9,448	70,327	76	55,088	136,234
Ethiopia	576,326	92,869	3,687	384,392	1,111,217	29,991	384,044	2,582,526
	-	-	-	-	-	-	-	
Mali	97,336	64,085	15,987	337,574	885,806	3,102	381,954	1,785,842
Mauritania	616	46	297	30,297	114,064	68	182,511	327,898
Niger	5,652	864	3,176	31,692	171,165	724	263,789	477,063
Nigeria	1,461,373	39,610	35,102	1,262,341	2,787,615	145,951	927,113	6,659,105
Senegal	81,215	292	1,047	74,810	505,555	2,752	306,718	972,390
Sudan	232,149	4,138	3,807	1,790,870	1,486,111	6,373	1,714,618	5,238,065
Total	**3,870,091**	**262,593**	**90,045**	**4,461,582**	**10,043,791**	**282,090**	**5,295,063**	**24,305,255**