TECHNICAL DOCUMENTATION: AFRICA CARBON REMOVAL PROJECT

Contents

Section A. Continental Analysis

Purpose of the model

This model aims to show the environmental and economic potential of natural climate solutions (NCS) in Africa.[1] To this end, we provide estimates of the potential for CO_2e avoidance and removal, economic value creation and job creation and livelihood improvement for 13 different NCS methods and 12 pricing scenarios. Data is based on theoretical potential of carbon mitigation if a set of actions were taken, and thus, given lags associated with carbon mitigation projects, can be understood as as a projection of the annual opportunity achievable at some point between 2030 and 2050. Our analysis draws heavily on the excellent analysis led by the teams at Nature4Climate, we encourage readers interested in this area to peruse their website here. While based on widely cited academic research (cf. 'List of references for Section A' for a full list of citations), estimates presented in our model are highly directional and are not in themselves meant as academic contributions.

The goal of this work is to demonstrate that NCS present a significant economic opportunity for all of Africa, as well as a means for Africa to help tackle the global climate crisis. We deliberately project job creation *potential* in an ambitious policy scenario, rather than forecasting actual job creation by 2030 in a business-as-usual scenario.

Structure of the model

The model contains three substantial calculation steps, with most effort devoted to calculating the job creation potential of the examined NCS pathways.

Step 1: CO_2e mitigation / removal potential at different price points

The model employs data shared by the developers of the Natural Climate Solutions World Atlas (Nature4Climate. 2021a), which aggregates academic research into the country-specific CO_2e potential of nature-based climate interventions. This data is in turn heavily based on a 2017 paper on Natural Climate Solutions (Griscom et al. 2017) but complemented with various other research.

The research we cite analysed all land area globally for its CO_2e mitigation potential from various NCS pathways, while accounting for food and biodiversity security. From this the authors derive a maximum feasible amount of CO_2e that could be mitigated in every country on earth, which is then further sub-categorised in percentages that can be mitigated cost-effectively at different levels (see below). An example of how this would work for one intervention pathway – reforestation – is shown in Box 1 below. Please refer to this methodology paper (Nature4Climate. 2021b) for further detail on the Natural Climate Solutions World Atlas data.

[1] We focused on natural climate solutions as opposed to engineered climate solutions as the former had better data availability for the African continent and are more mature. That said, we plan to expand our analysis to engineered carbon dioxide removal methods in future iterations of this tool (see 'Limitations and plans for future iterations' below).

Box 1: Illustrative methodology note for the reforestation intervention pathway[2]

For reforestation, Griscom et al use a 1km^2 resolution map from the Atlas of Forest Landscape Restoration Opportunities (FLRO) to identify areas with <25% tree cover, as suitable for reforestation. This is limited to areas ecologically appropriate for forests, and the authors exclude afforestation, defined as conversion of native non-forest cover types (i.e. grassland, savanna, and transitional areas with forest) to forest. Boreal biomes were excluded from the analysis, due to albedo effects. All existing cropland areas were excluded, due to food security safeguards, and impervious surfaces were excluded. Projected business-as-usual forest gains through 2030 were deducted. Griscom et al also subtracted the maximum mitigation potential of "Optimal Grazing Intensity" and "Legumes in Grazing Pastures" pathways where co-occurring with our Reforestation potential map, to avoid double-counting. The remaining areas accounted for in the maximum estimate include existing grazing lands (where reforesting them is in line with food security in an agricultural intensification and planetary diet change scenario), and other non-forest cover types, within forest ecoregions.

The resulting area is multiplied with a per-km^2 value of carbon sequestration potential by area from a paper by Cook-Patton et al. (2020). That paper uses 13,112 georeferenced measurements of carbon accumulation from reforested areas. This is then combined with 66 environmental covariate layers to create a global, one-kilometre-resolution map of potential aboveground carbon accumulation rates for the first 30 years of natural forest regrowth. The result of the available area for reforestation and the granular estimates of carbon accumulation potential results in the maximum feasible tCO2e potential stated for this pathway.

In total, we studied 13 NCS intervention pathways for their potential. These pathways range from ecosystem protection and restoration to agricultural interventions, and are specified in terms of their CO_2 equivalent (CO_2e) capture / emission avoidance potential. Table 1 lists these interventions alongside their projected global potential.

Table 1: Considered interventions, incl. maximum feasible CO_2e potential and area extent

Type	*Intervention*	*Intervention type (CO_2e removal or avoidance)*	*Maximum global feasible CO_2e potential (in million tCO_2e / yr)*	*Average global CO_2e potential per hectare (tCO_2e / ha / yr)*
Land Ecosyste	Reforestation	Removal	10,124	15.2

[2] Based on methodology notes in appendix document to Griscom et al. 2017

	Avoided Forest Conversion	Avoidance	3,603	404.5
	Natural Forest Management	Removal	1,470	0.8
	Avoided Grassland Conversion	Avoidance	116	68.3
Aquatic Ecosystems	Coastal Wetland Restoration	Removal	841	23.5
	Peatland Restoration	Removal	815	17.6
	Avoided Peatland Impacts	Avoidance	754	977.1
	Avoided Coastal Wetland Impacts	Avoidance	304	1,289.2
Agriculture	Biochar[3]	Removal	1,102	0.6
	Trees in Agriculture Lands	Removal	1,040	1.4
	Rice management	Avoidance	265	1.6
	Optimal Grazing Intensity	Removal	148	0.2
	Legumes in Grazing Pastures	Removal	147	2.1

The data we use provides estimates on CO_2e potential for different interventions at carbon prices of US$ 10 / ton of CO_2 equivalent (tCO_2e) and US$ 100 / tCO_2e. This data also comes from Griscom et al. (2017), and builds on marginal abatement cost (MAC) curves work cited and conducted by the authors. To give greater granularity to the online tool that we developed in cooperation with Earthrise Media, our model estimates CO_2e potential at 12 price points in US$ 10 increments from US$ 10 / tCO_2e to $US 120 / t$CO_2$e.[4] To derive CO_2e potential at these different levels, we assume a linear progression of CO_2 potential between the provided US$10 and US$ 100 estimates, and beyond that to US$ 120 / tCO_2e.

[3] The supporting information to Griscom et al. (2017) quantified the maximum feasible area extent in hectares all interventions listed in Table 1, except biochar, where Griscom et al just state that the maximum feasible area extent is all global cropland. As such, we used data from the US Geological Survey to come up with the total area of global cropland (1.874 billion hectares).

[4] We expand beyond Griscom et al's US$ 100 maximum up to US$ 120, as what Griscom et al. (2017) predict to be feasible for all interventions at US$ 100 is still below the biological potential for these interventions. As such, we do not overshoot the maximum biological potential in any of our intervention pathways.

Step 2: NCS Revenue at different price points

Leading on from Step 1, we also calculate potential NCS revenue at country-level for different interventions and at the varying price points outlined in Step 1. To do that, we multiply the estimates of CO_2e potential arrived at in Step 1 with the corresponding carbon prices to get to a total revenue for different interventions in different carbon price scenarios.

Step 3: NCS job creation potential

At the core of our model is a calculation of how many NCS jobs (in full-time equivalents – FTEs) would be required to manage the area needed for various NCS interventions. To do this, we first get the area required to realise the CO_2e potential of different NCS interventions across African countries and different CO_2e price points.

The nature4climate.org provides estimates of global land requirements for the 13 NCS paths we selected for analysis. Combined with estimates of the maximum feasible CO_2e potential from different interventions, we calculated a ratio of tCO_2e / ha / yr. To do this, we relied on Griscom et al's methodology, which has tCO_2e/ ha estimates. While we are confident that this has resulted in useful estimates, we plan to work closely with the authors of nature4climate.org to strengthen these estimates in future iterations of this tool. This applies most to the 'Natural Forest Management' intervention pathway, which has seen significant tCO_2e per year revisions in more recent estimates in some countries.

We apply these ratios to data computed in Step 1, on the CO_2e potential of all interventions at price points from US$ 10-120 for all African countries, to calculate a required area in-country to remove a certain CO_2e amount. This is illustrated in examples in Table 2 below.

Table 2: Example calculations of required area for different intervention scenarios

Country	*Intervention*	*Price point (US$)*	*CO_2e potential ($MtCO_2$e)*	*tCO_2e / ha*	*Required area (Mha)*
Cote d'Ivoire	Reforestation	$20	5.2	15.2	0.34
Uganda	Peatland Restoration	$50	4.6	17.6	0.26

As a next step we use published data on job requirements for different NCS methods per hectare, heavily leaning on a paper co-published by WWF and ILO (Lieuw-Kie-Song et al. 2020; Edwards et al. 2013). The jobs numbers we use are full-time equivalents, so might not all be individual full-time jobs, but would add up to full-time equivalents of our stated figures. Equally, a majority of these jobs in any one year would likely be temporary jobs (esp. for ecosystem restoration pathways), but they and the more longer-term ecosystem management jobs we model have the potential to multiply through economies and significantly stimulate economic growth. A deeper understanding of these effects (both the temporary nature and the 'multiplier' effect on economic growth and job creation) can help refine the estimates and understand their effect over time. We welcome partnerships to achieve this. Table 3 provides an outline of likely work activities and job types for some illustrative interventions.

Table 3: Overview of work activities, job types and job spillovers for selected interventions[5]

Intervention pathway	**Notes and more detailed work activities**	**Types of Jobs**	**Opportunities and job spillovers**
Reforestation	Land preparation, nurseries, planting trees and shrubs, monitoring & reporting, watering/ protecting seedlings, landscape management, law enforcement	Environmental science jobs (forester), farmers, lawyers, administrative positions	Can allow for part- time employment/ supplementary income for rural workers, spillovers into increasing jobs in forestry and timber
Peatland restoration	Structures/measures to reduce soil erosion, allow for groundwater recharge, rehabilitating native vegetation, stakeholder engagement & inclusion	Urban planners, Environmental science jobs (hydrologists), construction workers	Can allow for part- time employment/ supplementary income for rural workers
Natural forest management	Collection of wood and NTFP, stakeholder engagement & inclusion, law enforcement, monitoring & reporting, indigenous & technical knowledge transfer, ecotourism	Administrative positions	Sustainable timber harvesting and other forest products. Improved ecosystem services, timber, NTFP, jobs in processing of forest products, ecotourism
Trees in agriculture land	Ploughing, sowing, composting, watering, raising livestock, tree planting, raised beds for agriculture, landscape planning, monitoring & reporting,indigenous & technical knowledge transfer, among many others	Farmers, pastoralists, agronomists, environmental science jobs	Can lead to higher incomes for farmer, as well as increased labour demand in agriculture and agro processing

[5] Adapted from Lieuw-Kie-Song et al. 2020

Intervention pathway	Notes and more detailed work activities	Types of Jobs	Opportunities and job spillovers
Mangrove restoration	Ecosystems monitoring & reporting, tree planting, law enforcement, indigenous & technical knowledge transfer, ecotourism	Environmental science jobs, landscape planners, administrative positions, rangers, tourist guides	Increased productivity of fishermen, increased employment and fishing and related processing, increase employment in tourism (diving), reduced job and income losses from flooding
Avoided forest / grassland / peatland / mangrove conversion	Management and education, monitoring & reporting, stakeholder involvement and inclusivity, indigenous & technical knowledge transfer, ecotourism	Rangers, managers and educators, community liaison officers, environmental science jobs, tourist guides	Important employment spillovers for tourism sector

By applying the job multipliers described above to the area required for different interventions in different countries and at different price points, we arrive at an estimate of the job creation potential of our examined interventions in different scenarios. See Table 4 for an illustration.

Table 4: Example calculations of required jobs for different intervention scenarios

Country	*Intervention*	*Price point (US$)*	*Required area (Mha)*	*Jobs (FTE) required / ha*	*Jobs potential (FTE)*
Cote d'Ivoire	Reforestation	$20	0.34	0.75	~255,000
Uganda	Peatland Restoration	$50	0.26	2	~520,000

In addition, for five interventions we considered, no published data points for job requirements per hectare were available. These being agricultural interventions, we mostly looked at these interventions' potential to positively impact the livelihoods of African smallholder farmers rather than creating new jobs. For this we analysed which share of the required area for the intervention might be run by smallholders (using different assumptions for cropland vs grazing interventions). We then assumed, conservatively, that per smallholder farm an average of one livelihood would be impacted.

The resulting figures should not be understood as full-time equivalent jobs, but rather positively impacted livelihoods. Examples of this approach are outlined in Table 5.

Table 5: Example calculations of positively impacted livelihoods from data-scarce interventions

Country	*Intervention*	*Price point (US$)*	*Required area (Mha)*	*Smallholder-farmed area (Mha)*	*Number of smallholder farms*	*Positively impacted livelihoods*
Cote d'Ivoire	Rice Management	$20	0.17	0.13	~132,000	~132,000
Uganda	Optimal Grazing Intensity	$50	0.61	0.49	~105,000	~105,000

Model output

This online tool presents the work outlined above at the country-level for African countries. Table 6 outlines the output variables available for the tool, underlying data sources, and reasons for inclusion.

Table 6: Output variables for the online tool

Output Variable	*Description*	*Reason for inclusion*	*Source*
CO_2e potential	Countries' combined CO_2e mitigation and removal potential in tCO_2e	To give a sense of scale of the absolute potential of African NCS in the global fight against climate change	Various. Cf. 'List of references for Section A'
CO_2e potential per km^2	Countries' combined CO_2e mitigation and removal potential in tCO_2e per km^2 of land area	To give a sense of the relative potential of different African countries, independent of their absolute size	Griscom et al. 2017; Worldbank Open Data Portal. 2020a
Total NCS revenue	Countries' potential revenue from selling CO_2e credits at a selected carbon price	To highlight the economic opportunity from internationally sold NCS carbon credits	Griscom et al. 2017

NCS Revenue as % of GDP	Countries' potential revenue from selling CO_2e credits relative to current GDP	To provide a sense of scale of the potential of NCS as an economic sector relative to other economic sectors	Griscom et al. 2017; Worldbank Open Data Portal. 2020b
NCS jobs	Countries' job creation potential from the NCS sector	To highlight the socioeconomic potential from NCS as a means to drive the development of Africa	Lieuw-Kie-Song et al. 2020; Edwards et al. 2013; Griscom et al. 2017
NCS jobs per working age pop	Countries' job creation potential from the NCS sector relative to the working age population	To establish a sense of scale of the job creation opportunity from NCS	Lieuw-Kie-Song et al. 2020; Edwards et al. 2013 Griscom et al. 2017; Worldbank Open Data Portal. 2020c

Limitations and plans for future iterations

The assumptions pointed out above, as well as a number of other assumptions used in this model are at a 'best guess' level of accuracy. Having an estimate for the potential for Africa at COP26 is helpful to shape discussions and help stakeholders understand the opportunity the continent provides, even if available data has inherent limitations. As we continue to expand and refine this tool, these are the model inputs into our model that we would like to refine in future iterations:

- **Inclusion of engineered climate solutions.** We focused the initial iteration of this tool on natural climate solutions as these had the best data availability for African countries among published literature we reviewed. That said, we plan to include assessments of the potential for engineered CDR in future iterations of this tool.
- **Cost levels.** In future, we would like to estimate costs for different interventions in different countries, rather than just estimating available supply levels at different price points. The current cost data is based on largely US and European historical data. Key cost drivers will be different in many African countries – it is likely that many important cost drivers are lower thus making a greater proportion of the potential viable at similar price points. Moreover, costs are likely to evolve as interventions mature – currently, our cost data do not reflect this. Using more granular cost data, we would like to further build out our model to provide basic investor information, e.g., expected ROI per tCO_2e in a given country and scenario, etc.
- **Job creation potential per hectare.** In future, we would like to collect more, ground-truthed data on the job creation potential of NCS interventions in different countries, and

provide more information on job types (e.g., permanent vs temporary, skilled vs unskilled, etc.). We would also like to be able to better account for variation within our intervention pathways, e.g., accounting for how job creation from reforestation differs between ecological zones. Currently our model applies flat multipliers to the hectarage for each intervention, sometimes using less than ideal proxies as best estimates.

- **Learning curve in job creation.** Currently we use data on job creation potential that are based on historical data. It is likely that as these interventions become more mainstream and as industries around these interventions grow in African countries, interventions may become less labour-intensive and more value-adding, likely creating less, but better-paid and more permanent jobs. We would like to reflect this as we model out jobs potential to 2050.
- **Carbon price differentials.** It seems likely that in future, different interventions will have different price points per tCO2e mitigated. We currently apply a flat carbon price, but chances are that in future (as is currently the case) carbon removal will have a higher price point than carbon emission avoidance. We hope to build more pricing granularity into our model, ideally pricing all intervention pathways differently
- **Cost curve inputs** at better granularity for different interventions at different price points are another feature we would like to refine. The model currently assumes a linear progression of % of the maximum feasible carbon potential becoming available as prices rise from US$ 10 to US$ 120, when in truth supply would likely respond to price changes more dynamically
- **% of farmland that is managed by smallholder farmers** in different countries (currently only estimated at continent-level due to lack of accessible data)
- **Average farm size** for smallholder farmers and pastoralists (currently only estimated at continent-level)

For any further technical questions about the work underlying this tool, please contact Scott Hosking who led this modelling exercise at scott.hosking@dalberg.com.

List of references for Section A

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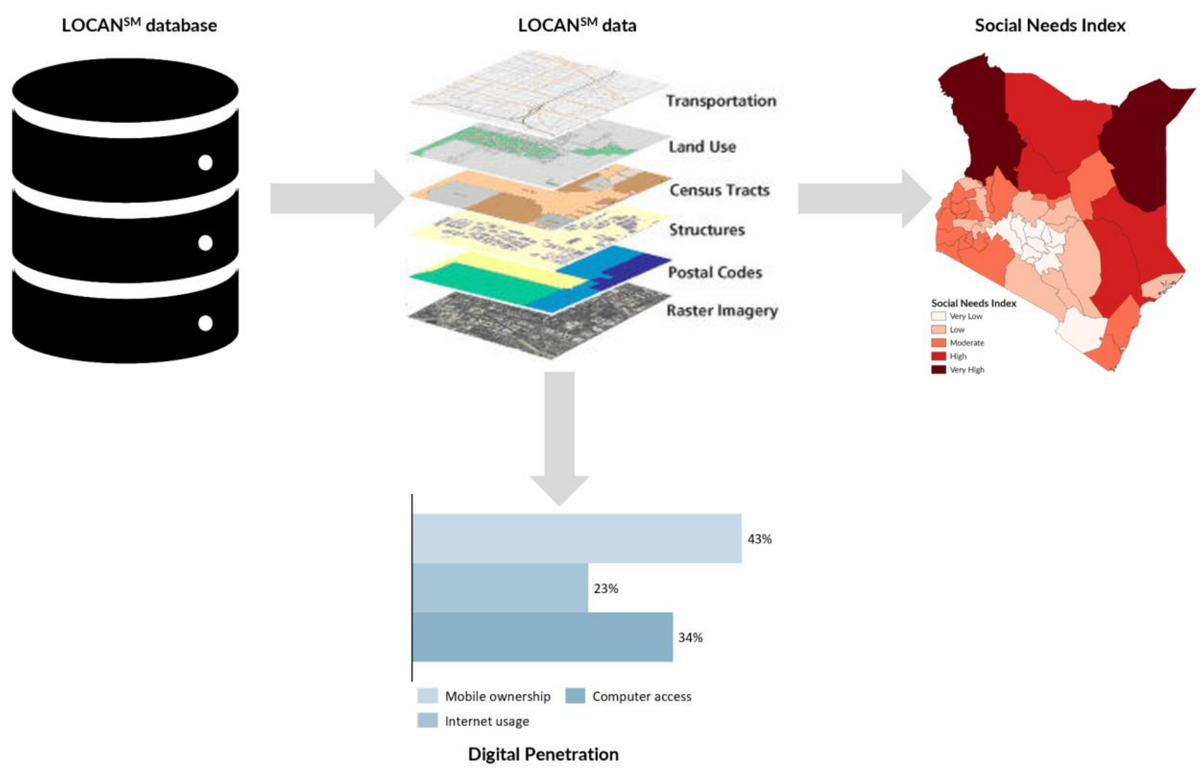
Section B. Country/Subnational Analysis-Dalberg Research

Location analytics is the process or the ability to gain insight from the location or geographic component of business data. Dalberg Research's Location Analytics (LOCAN^{SM}) is a powerful tool to answer all questions, where geographic context matters. After 4 years of development, we present a most comprehensive and dynamic geo-spatial research database. LOCAN^{SM} provides:

- Locations of shops, hotels, restaurants, banks, ATMs, pharmacies, hospitals, schools, agro-dealers, businesses and many more.
- Detailed demographic information covering the entire population
- Powerful self-developed indices to understand a country at a glance, e.g. our economic strength index LOCAN^{SM} -ESI
- A comprehensive map of infrastructure including road, air, energy, water
- Land cover analysis based on satellite imagery reaching from the present back to the year 2010

Dalberg Research leveraged its spatial capabilities and tools to perform locational analysis at the subnational level to provide actionable insights using our database, in-house derived indices and knowledge on publicly available geospatial data repositories.

FIGURE 1: LOCAN^{SM} FLOWCHART



Subnational analysis was carried out on six African countries (Kenya, Nigeria, Senegal, Ethiopia, Rwanda and Malawi) to show the variation within countries that contribute to the overall picture. These analyses were based on data availability:

Based on the different data granularity, the analysis focused on the administration level 1 for Kenya, Nigeria, Ethiopia, and Senegal, while for Malawi and Rwanda, it focused on administration level 2.

The variables were used to determine:

- The economic feasibility of setting carbon removal technologies in all subnational areas. Areas highly feasible would be considered for carbon removal activities
- Social Needs Index to capture the socioeconomic status and livelihood opportunities available to individuals within a given geography
- General profile information to provide us with the demographic, biophysical and economic details of the area

These datasets were sourced from various online repositories and were mainly census or survey datasets and satellite images provided at a global /African scale with a varying spatial (100m to 1km) and temporal (1997 - 2021) resolution.

Tool Variable list

A table highlighting relevant attributes of the data used to assess carbon removal feasibility, generate the Social Needs Index and the location profiles.

TABLE 7: VARIABLE LIST FOR THE TOOL

Variable	Dataset	Country	Spatial Resolution/ Data Level	Year	Source
Socio-economic status	Economic Strength Index (ESI)	Kenya	County	2015 - 2016	Kenya National Data Archive, 2015 – 2016, Dalberg analysis.
		Nigeria	State	2018	The Demographic and Health Survey, 2018, Dalberg analysis.
		Senegal	Region	2019	The Demographic and Health Survey, 2019, Dalberg analysis.

		Ethiopia	State	2019	The Demographic and Health Survey, 2019, Dalberg analysis.
		Malawi	District	2017	The Demographic and Health Survey, 2017, Dalberg analysis.
		Rwanda	District	2020	National Institute of Statistics Rwanda, 2020, Dalberg analysis.
Economic activity	Nighttime Lights VIIRS Day/Night	Kenya Nigeria Senegal Ethiopia Malawi Rwanda	Grid (1km by 1km)	2016	Earth Observation Group, National Oceanic and Atmospheric Administration (NOAA)
Average precipitation	Precipitation (monthly)	Kenya Nigeria Senegal Ethiopia Malawi Rwanda	Grid (5km by 5km)	2020	Food and Agriculture Organisation of the United Nation
Unemployment rate	Population and household census/ Demographic	Kenya	Sub-county	2019	Kenya National Bureau of Statistics (KNBS), 2019

	and Health Survey	Nigeria	State	2018	The Demographic and Health Survey, 2018
		Senegal	Region	2015	National Agency for Statistics and Demography, Senegal, 2015
		Ethiopia	State	2019	The Demographic and Health Survey, 2019
		Malawi	District	2018	National Statistics Office, 2018
		Rwanda	District	2019 - 2020	National Institute of Statistics Rwanda, 2019 - 2020
Digital penetration (mobile phone ownership/computer access/internet usage	Population and household census/ Demographic and Health Survey	Kenya	Sub-county	2019	Kenya National Bureau of Statistics (KNBS), 2019
		Nigeria	State	2018	The Demographic and Health Survey, 2018
		Senegal	Region	2015	The Demographic and Health Survey, 2015
		Ethiopia	State	2019	The Demographic and Health Survey, 2019
		Malawi	District	2018	National Statistics Office, 2018
		Rwanda	District	2020	National Institute of Statistics Rwanda, 2020

Population density	Gridded Population Count	Kenya Nigeria Senegal Ethiopia Malawi Rwanda	Grid (1km by 1km)	2020	WorldPop, 2020
Rural/urban settlement	Global Human Settlement Growth	Kenya Nigeria Senegal Ethiopia Malawi Rwanda	Grid (1km by 1km)	2015	European Commission, 2015
Primary/secondary/tertiary education	Population and household census/ Demographic and Health Survey	Kenya	Sub-county	2019	Kenya National Bureau of Statistics (KNBS), 2018
		Nigeria	State	2018	The Demographic and Health Survey, 2018
		Senegal	Region	2019	The Demographic and Health Survey, 2019
		Ethiopia	State	2019	The Demographic and Health Survey, 2019
		Malawi	District	2018	National Statistics Office, 2018

		Rwanda	District	2020	National Institute of Statistics Rwanda, 2020
Road density	Road network classification	Kenya	Line feature	2021	Kenya Rural Board
		Nigeria Senegal Ethiopia Malawi Rwanda			OpenStreetMap
Literacy rate	Population and household census/ Demographic and Health Survey	Kenya	Sub-county	2019	Kenya National Bureau of Statistics (KNBS)
		Nigeria	State	2018	The Demographic and Health Survey, 2018
		Senegal	Region	2019	The Demographic and Health Survey, 2019
		Ethiopia	State	2019	The Demographic and Health Survey, 2019
		Malawi	District	2018	National Statistics Office, 2018
		Rwanda	District	2020	National Institute of Statistics Rwanda, 2020
Domestic water sources	Population and household census/ Demographic	Kenya	Sub-county	2019	Kenya National Bureau of Statistics (KNBS)

	and Health Survey	Nigeria	State	2018	The Demographic and Health Survey, 2018
		Senegal	Region	2019	The Demographic and Health Survey, 2019
		Ethiopia	State	2019	The Demographic and Health Survey, 2019
		Malawi	District	2018	National Statistics Office, 2018
		Rwanda	District	2020	National Institute of Statistics Rwanda, 2020
Average temperature	Climate data	Kenya Nigeria Senegal Ethiopia Malawi Rwanda	Grid (20km by 20km)	1970 - 2000	Dalberg analysis.WorldClim, 1970 – 2000
Conflict areas	Political violence and protest data	Kenya Nigeria Senegal Ethiopia Malawi Rwanda	Point feature	2021	The Armed Conflict Location & Event Data Project

Carbon accumulation potential	Aboveground biomass carbon	Kenya Nigeria Senegal Ethiopia Malawi Rwanda	Grid(1km by 1km)	2020	Cook-Pattern,2020 Global Forest Watch,
Soil carbon content	Soil organic carbon content	Kenya Nigeria Senegal Ethiopia Malawi Rwanda	Grid(250m by 250m)	1950-2017	Open Land Map

Detailed variable descriptions

1. Feasibility

Feasibility captures the infrastructural, economic, and labour dynamics shaping the feasibility of carbon projects in each location. The following datasets were used as proxies for feasibility. Notably, whether 'low' or 'high' helps or hinders feasibility, will be different for different solutions. Therefore, we only show these drivers of feasibility without rolling them into a combined metric for overall feasibility. We look forward to working with implementers and experts to refine the use of these proxies – and add others where needed and possible.

Road density: This is the ratio of the road length to a specific geography. The sum of road length is divided by the area of the region. Road density highlights how accessible and connected a subnational area is. This is in understanding the degree of movement with the area, for example, the ease of distribution of raw materials or final products under the carbon removal exercise.

Population density: This is a measure of population per unit area in a given location. This was generated by estimating the ratio of the population to the subnational area in square kilometres. Understanding the population density of an area provides an idea of how much free land is available for carbon removal activities.

Digital penetration: This is the proportion of the population that has access to and uses digital devices and internet services. This variable takes into account mobile phone ownership, desktop computers/laptops/tablets access and internet usage. Digital penetration allows for communication and dissemination of information and may even speak to the digital literacy of the population– which is important to make some solutions viable.

Land cost: This was estimated using the socio-economic status (a proprietary index representing the economic well-being of a population, based on ownership of common household assets). Here we interpret a directly proportional relationship between socio-economic status and the cost of land. Understanding the cost of land indicates the degree of investment required for the project.

Economic activity: Nighttime light was used as a proxy for diverse economic activity. It highlights areas of varying night light intensity symbolising their level of economic activity. The higher the intensity the higher the level of economic activity. Areas with high economic activity are also likely to have a high population and therefore unsuitable for carbon sequestration activities.

2. Location Profile Variables

Location profiles were developed to provide overview information on specific sector characteristics to understand the key drivers of a given location. The variables used for the location profile include:

Carbon accumulation potential: This is a measure of biophysical carbon avoidance or the sequestration potential of different natural carbon solutions pathways. This data shows the annual rate of atmospheric carbon capture by forests in the form of above-ground biomass aggregated at either subnational or grid level.

Average temperature: This data was drawn from monthly climatic mean temperature data from 1970 to 2000. Temperature is a strong driver of tree growth. A clear understanding of the prevailing temperature conditions will advise on the tree species likely to thrive in a region for carbon removal activities.

Average precipitation: This is the average rainfall for the year 2020. The data was generated from monthly precipitation experienced in 2020. By estimating the average rainfall in a geographical area, it becomes easy to accurately identify the type of trees/ crops that can thrive in the area giving the maximum carbon removal potential.

Soil organic carbon content: The amount of carbon in the soil represents the amount of carbon transferred from the atmosphere to the land via plants, plant residues and other organic components. Machine learning prediction was used to generate the soil organic carbon content. The data was based on the compilation of soil profiles and samples. Understanding the current levels of the soil organic carbon content allows for the quantification of the amount of carbon removed during the project phase.

Labour force population: This was generated based on the level of education of the population. People with tertiary education were considered as skilled labour whereas those with secondary and lower attainment education levels were considered unskilled labour. Identifying this labour force is key in providing cheap and available labour for this exercise.

Settlement type: Global Built-Settlement Growth data was used to provide information on rural or urban lands. This data was extracted at the grid level (1km by 1km) and is the population count for each settlement type which includes rural, urban, periurban and water. We identified these rural areas as of great potential for ample land available for carbon removal projects due to the less densely distributed populations.

Education levels: This data provided the highest level of education achieved by the population in a given region. We focused mainly on primary, secondary, and tertiary education levels. This variable was considered because it is likely to influence public participation in the carbon removal process.

Conflict areas: These were locations within subnational areas where political violence and protest events were experienced. This data helps in providing insights into areas where this risk needs to be considered explicitly because conflicts may interfere with the implementation of the carbon removal technologies.

3. Social Needs Index Variables

The Social Needs Index (SNI), which ranges from 0 to 100 is a measure capturing the socioeconomic status and livelihood opportunities available to individuals within a given geography. In calculating SNI, a set of weighted variables were normalised on a scale of 0 to 1 and summed up. The weights were assigned based on a theoretical hypothesis. Certain variables such as socioeconomic status were deemed as more important than others and therefore given a higher potential portion of the overall SNI score.

Areas scoring high on the 'social needs index' will benefit most, socio-economically, from the opportunities that CR removal technologies will offer. That said, implementers should also keep in mind that some of the constituent factors of this index have implications for program and intervention design.

The SNI was developed using five key variables:

Socio-economic status: This is an asset-based wealth index representing the economic well-being of a population, based on ownership of common household assets. The Economic Strength Index, (ESI), a proprietary LOCAN^{SM} dataset was used in determining the socio-economic status and was assigned a weight of 30%. The actual rate values range between 0 -100. Lower values of the socioeconomic status highlight areas in most need of diversification of the economy. Before weighting the values, an inverse was calculated resulting in lower ESI values being favoured in the calculation of the Social Needs Index .

The source of the dataset were survey datasets from the Demographic Health Survey(DHS) and population and housing census from the respective statistical bureaus in the deep dive countries.

Literacy rate: The use of literacy variables highlights areas where there is a need to train individuals and the community on the need to have carbon removal technologies to mitigate the negative effects of climate change. This will ensure that CR technologies are embraced and that the community benefits from the capacity building. Literacy rates also point to the potential of unskilled labour in an area. In calculating the SNI, the proportion of the population that are not literate (have no formal education) was used.

The data used ranges from between 2016 to 2019 and is at the subnational level. The sources are survey datasets from DHS and census tables and reports from the respective deep dive countries.

Unemployment rate: Refers to the proportion of the population that is unemployed. The unemployment variable is useful in determining areas where the population would benefit most from additional job opportunities arising from setting up carbon removal technologies.

Note: Unemployment was defined as persons in the labour force who are actively seeking work.

The time range of the dataset is between 2016 and 2019 and is at the subnational level. Sources are DHS and population and housing census from the respective statistical bureaus in the deep dive countries.

Digital penetration: This is the measure of access to digital information through a measure of mobile ownership, use of the internet, access to digital devices such as desktop computers and laptops. In calculating the SNI, the inverse of digital penetration was used and hence lower values were favoured in calculating the index. Areas with a high social needs index are less advanced in the digital space and would therefore benefit most from digital infrastructure set up to monitor carbon removal projects.

Mobile ownership, computer access/ownership and internet use datasets were derived from DHS and population and housing census from the respective statistical bureaus in the deep dive countries. They ranged from between 2016 and 2019.

Domestic water use: This dataset highlights the proportion of households using unimproved sources of drinking water i.e. ponds, dams/lakes, stream/river and springs. The dataset was used to identify areas where getting access to improved sources of drinking water is a challenge, as these would benefit from improved water infrastructure and hence lead to access to improved sources of drinking water for those communities.

For any further geo-spatial questions, please contact Dr Clara Mundia who led the subnational analysis at clara.mundia@dalberg.com.