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A machine learning approach for country-level deployment of greenhouse gas removal technologies

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ABSTRACT

The suitability of countries to deploy five greenhouse gas removal technologies was investigated using hierarchical clustering machine learning. These technologies include forestation, enhanced weathering, direct air carbon capture and storage, bioenergy with carbon capture and storage and biochar. The use of this unsupervised machine learning model greatly minimises the likelihood of human bias in the assessment of GGR technology deployment potentials and instead takes a more holistic view based on the applied data. The modelling utilised inputs of bio-geophysical and techno-economic factors of 182 countries, with the model outputs highlighting the potential performance of these GGR methods. Countries such as USA, Canada, Brazil, China, Russia, Australia as well as those within the EU and Sub-Saharan Africa were identified as key areas suitable to deploy these GGR technologies. The level of certainty of the obtained deployment suitability categorisation ranged from 65 to 98 %. While the results show the need for regional collaboration between nations, they also highlight the necessity for nations to prioritise and integrate GGR technologies in their revised nationally determined contributions.

1. Introduction

To keep global warming below 1.5 °C by the end of the century, the adoption of greenhouse gas removal (GGR) technologies, sometimes referred to as negative emission technologies (NETs), has been recognised as a crucial and essential strategy (IPCC, 2022). Under this scenario, global net anthropogenic CO_2 emissions is expected to be reduced by about 45 % from 2010 levels by 2030 with net zero achieved by 2050 (IPCC, 2018). Attaining this mitigation target will require substantial efforts ranging from proactive emission reduction solutions to the reactive GGR methods. These GGR technologies include forestation, habitat restoration, enhanced weathering (EW), soil carbon sequestration (SCS), ocean fertilisation, biochar, direct air carbon capture and storage (DACCS), bioenergy with carbon capture and storage (BECCS), and ocean alkalinity, among others. While they are currently at various levels of technological readiness (Haszeldine et al., 2019; The Royal Society, 2018), their performance and future deployment is influenced by techno-economic, bio-geophysical and socio-political variables (Asibor et al., 2021; Fuss et al., 2018; Hepburn et al., 2019; Rueda et al., 2021). While GGR technologies such as forestation, DACCS and BECCS are only focussed on carbon dioxide removal (CDR) which is the dominant greenhouse gas, others such as Biochar have the co-benefit and additional potential to reduce other greenhouse gas emissions especially when applied for soil amendment (Woolf et al., 2010).

With the exception of forestation and some land management measures, the nationally determined contributions (NDCs) that nations have made to the United Nations Framework Convention on Climate Change (UNFCCC) show a low intent to use these GGR technologies (Pozo et al., 2020), thus, making the 1.5 °C objective difficult to achieve (Roe et al., 2019; Rogelj et al., 2016; Schiermeier, 2015). There is therefore a great need for a global country-level assessment of these GGR technologies for potential deployment and inclusion in the respective NDCs of countries. Reports, however, indicate that only a small number of nations have conducted analyses locally to determine the viability of deploying these technologies in their individual regions while considering their bio-geophysical, techno-economic and social resource characteristics (Alcalde et al., 2018; Baik et al., 2018; Donnison et al., 2020; Haszeldine et al., 2019; Jiang et al., 2018; Karlsson et al., 2017; Moreira et al., 2016; Mulligan et al., 2020; Pour et al., 2018; The Royal Society, 2018; Thoni et al., 2020).

On the global country-level front, not much has been reported in the literature with regards to identifying countries suitable for the deployment of these GGR technologies based on their bio-geophysical and techno-economic characteristics. Some major prior efforts have largely

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been focussed on land-based climate mitigation measures. Griscom et al. (2020) investigated the deployment potential of natural climate solutions at the country-level, consisting of a suite of ecosystem management pathways. This study was, however, limited to countries in the tropical region. Priority regions and nations with high GGR deployment potentials have also been identified by Roe et al. (2019) and Roe et al. (2021). While this study was based on a literature assessment of mitigation strategies and modelled pathways, the GGR methods studied were, however, limited to land-based measures including forestry, agriculture, BECCS and land use change. In a different study by Pozo et al. (2020), carbon dioxide removal (CDR) quotas were distributed globally at the country-level based on the equity sharing principles of responsibility (historic emission contribution), capability (financial capacity) and equality (population). While this study was only focussed on reforestation, BECCS and DACCS, country-level investigation of their deployment potential was limited to the European Union.

Machine Learning (ML) which is an application of artificial intelligence (AI) allows systems to learn from their past performance without having to be explicitly programmed (Garbade, 2018; Jordan and Mitchell, 2015). There are three major types of ML: the Supervised ML, the Unsupervised ML and the Reinforcement ML (ExpertAI, 2022). The unsupervised ML, which is the focus of this study, operates by examining patterns in the input data to evaluate the output. Though constrained by elements including ethics, data quality and availability, improper application and interpretability (Stewart, 2019), some advantages of ML include ease of identification of trends and patterns, minimal human intervention (automation), ability to improve continuously as well as high efficiency in the handling of multi-dimensional and multi-variety data.

While ML has found wide application in several fields of human endeavours including finance, retail, security, healthcare among others (Jordan and Mitchell, 2015; Kumar, 2019), its deployment in the area of climate change mitigation *via* GGR technologies has been limited. Some efforts have however been reported in the literature covering areas such as reforestation planning (Ordóñez Galán et al., 2009), selecting site for afforestation deployment based on type of tree species (Chen et al., 2019; Yousefi et al., 2021) as well as biochar yield prediction from the pyrolysis of different materials (Alabdrabalnabi et al., 2022; Li et al., 2022; Zhu et al., 2019). With increased availability of data brought about by the expected development and deployment of GGR technologies in the near future, the prospects for ML application in climate change mitigation are largely promising ranging from smart grids to disaster management (Rolnick et al., 2022) as well as carbon capture, utilisation and storage (Yan et al., 2021).

In this study, the deployment potential of five GGR technologies for 182 countries was assessed using an unsupervised machine learning technique known as hierarchical clustering. The use of this ML technique ensures that the output is based on the applied data while greatly minimising the likelihood of human bias. The five GGR technologies studied are forestation, EW, DACCS, BECCS and biochar. The performance and deployment suitability of GGR technologies is very much dependent on bio-geophysical and techno-economic variables. Hence, this suitability categorisation was done by evaluating the similarity of each country's factors with those required for good performance of the various GGR technologies. To evaluate the uncertainty in the results, a sensitivity analysis was also conducted.

2. Methodology

2.1. GGR methods

Fig. 1 presents the methodology framework applied in this study. Five GGR methods were considered in this study based on their CDR potential and technological readiness levels. They are forestation, EW, DACCS, BECCS and biochar. These methods and requirements for their deployment are briefly discussed in the following sections.

2.1.1. Forestation

Forestation is a collective term that includes afforestation and reforestation. With co-benefits ranging from food and fuels production to erosion control among others (Asibor et al., 2021), and with a cost requirement of US$5–50/$tCO_2$ (Fuss et al., 2018), it is generally regarded as one of the cheapest carbon sequestration pathways. Despite the minimal cost impact, it's deployment is however impacted by two major factors (land availability and climate). With the annual land intensity projected to range from 0.03 to 0.16 ha/ tCO_2 over 100 years (Smith et al., 2015), there is need to ensure that the deployment of this technology does not impact on other competing land use. For climatic factors, the tropical region characterised by high average temperature of 25 °C, high precipitation and deciduous broadleaved native mixed

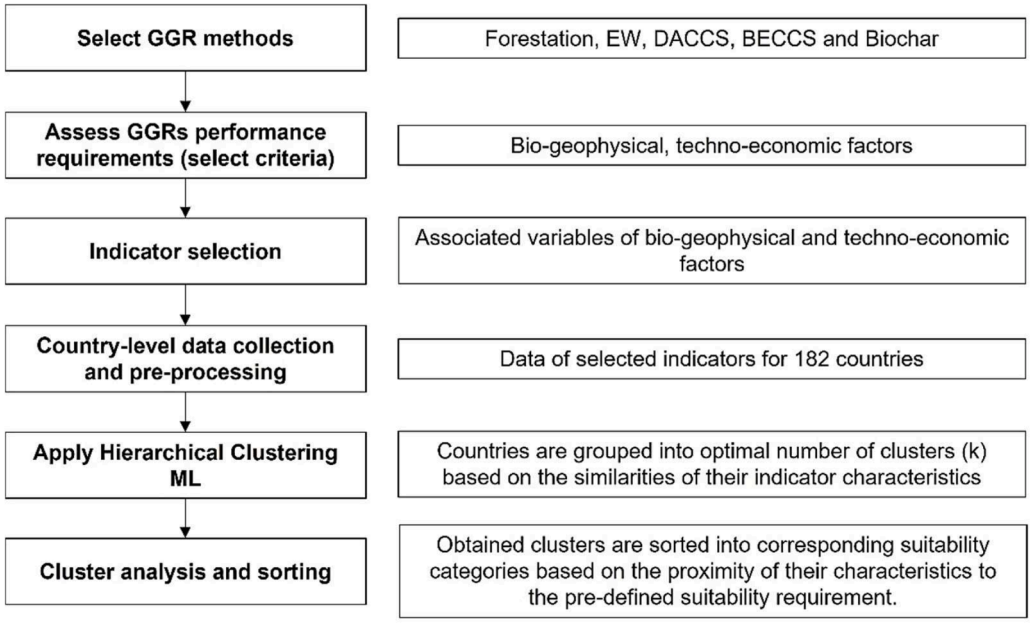


Fig. 1. Methodology framework for the study.

species has been generally identified as the most suitable location for this GGR method (Abbas et al., 2017; Favero et al., 2018; Hartman, 2017; Raihan et al., 2019). With water availability expected to be largely based on precipitation, the need for additional water supply is a minor requirement.

2.1.2. Enhanced weathering (EW)

In EW, rocks containing calcium or magnesium are ground up and the resulting minute grains are dispersed over land or ocean surfaces to serve as storage sites for the CO_2 removed from the atmosphere (Andrews and Taylor, 2019). Co-benefits of this GGR method range from soil productivity improvement to ocean acidity reduction. It is a capital and energy intensive option, characterised by significant energy requirement estimated at a range of 0.81–12.5 GJ/tCO_2 and cost requirement in the range of US$52–480/t$CO_2$ (Renforth, 2012; Strefler et al., 2018). Another major requirement for the deployment of this technology is the availability of basaltic and/or dunite rocks (Schuiling, 2017). Other requirements for the deployment of this technology include availability of agricultural land for application of the crushed rocks (Kantola et al., 2017). Climatic factors are also expected to impact on EW. Warm tropical and humid regions have generally been identified as most suited for this GGR technique (Meysman and Montserrat, 2017).

2.1.3. DACCS

This GGR method involves the removal of atmospheric CO_2 by exposing sorbents with high CO_2 affinity to air (Fasihi et al., 2019). It enjoys advantages of minimal competition for land and nutrients as well as absence of climatic constraints. Given the low concentration of CO_2 in atmospheric air, DACCS requires high energy estimated at 9–12.3 GJ/tCO_2 removed (Fajardy et al., 2019; Smith et al., 2015). It is also characterised by a high-cost requirement ranging from US $600-1000/t$CO_2$ which is projected to decrease to US$100–300/t$CO_2$ by 2050 due to expected advancement in the technology (Fuss et al., 2018; Psarras et al., 2017). Another major requirement for the deployment of this technology is the availability of storage site for the captured CO_2. This includes depleted oil and gas fields, aquifers, *in-situ* mineralisation, structural traps and coal beds. Water requirement is dependent on the DAC technology adopted ranging from 4.7 to 30 m^3/tCO_2 (Viebahn et al., 2019).

2.1.4. BECCS

BECCS which has the co-benefit of generating bioenergy in various forms while removing atmospheric CO_2 at the same time, has been part of many Integrated Assessment Models (IAMs) scenarios (IPCC, 2022). Major requirements for the deployment of this method are availability of CO_2 storage site and biomass. Options for biomass supply include primary sources requiring dedicated plant growth (lignocellulosic and herbaceous bioenergy crops), wastes from industries and urban centres as well as agricultural and forest residues. Land requirement is dependent on the choice of biomass feedstock and typically ranges from 0.01 to 0.5 ha/tCO_2 (Smith et al., 2015; The Royal Society, 2018). Water requirement for this GGR method is high ranging from 60 to 218 m^3/tCO_2. This covers the biomass production and the CCS use with the actual value dependent on the CCS technology adopted. Cost estimates for BECCS is projected to range from US $100 to 200/t$CO_2$ by 2050 with actual cost dependent on choice of biomass source and adopted technology (Fuss et al., 2018).

2.1.5. Biochar

When organic material is thermally degraded in the absence of oxygen, biochar is produced. Biochar ensures a longer sequestration time of carbon (1000–4000 years) as it is more stable than soil organic matter (Brassard et al., 2016; Lorenz and Lal, 2014). In addition to producing energy from the pyrolysis process, the deployment of biochar also improves soil and can be used to treat wastes (Tisserant and Cherubini, 2019). Major requirement for the deployment of this method includes availability of biomass and agricultural land for biochar application. Other factors that can influence its deployment suitability include climatic condition, soil characteristics and cost. With higher temperature negatively impacting on the residence time, temperate and humid regions have been recommended for deployment of this technique (Brassard et al., 2016; Zimmermann et al., 2012). Depending on the choice of biomass feedstock, the technique used to produce the biochar, and the application strategy chosen, the cost requirement is predicted to range from US$30 to 120/t$CO_2$ (Fuss et al., 2018).

Based on the impact ranking of these discussed factors on the deployment and performance of GGR methods (Asibor et al., 2021; Fajardy et al., 2019), their respective requirements were grouped into major and minor as shown in Table 1. To avoid the error of double counting, it is important to note that the land availability requirement for BECCS and biochar is captured within the biomass availability requirement (primary sourcing). The agricultural land use (AgLu) requirement for biochar is for the spreading of the biochar.

2.2. Indicator selection

The evaluation of the GGR deployment suitability of countries was based on the assessment of the domestic availability of the requirements highlighted in Table 1. To do this, associated indicators for these bio-geophysical and techno-economic requirements were selected. These indicators which formed the input data variables are briefly discussed in the following sections.

2.2.1. Climatic factor

For climate, the quarterly mean temperature (Q1T, Q2T, Q3T, Q4T) and precipitation (Q1P, Q2P, Q3P, Q4P) of the various countries from the World Bank climate knowledge portal was used (World Bank, 2022). This data covered a 30-year period from 1991 to 2020.

2.2.2. Land availability

The share of land use for forest and agriculture was adopted to assess land availability (CIA, 2022). For forestation, a mix of the countries' potential for reforestation on forest land and afforestation on agricultural land was assessed. The combined forest and agricultural land use of each country was thus adopted as the indicator for land availability or forest land use (FLu). To ensure that the development of trees did not have a negative influence on food production, arable land suitable for growing crops was not included in the agricultural land use. For EW and biochar, agricultural land use (AgLu) was adopted to indicate the availability of land for spreading their respective materials.

Table 1
Selected bio-geophysical and techno-economic GGR deployment requirements.

GGR method	Deployment requirement	
	Major	Minor
Forestation	Climatic factor (Tropical region with high ave. temperature and high precipitation), land availability	Water availability (WA)
EW	Rock availability, low carbon energy availability (LCEA), cost consideration (good financial capability)	Climatic factor (Warm tropical and humid regions with ave. temperature of 25 °C and high precipitation), land availability
DACCS	Geological storage potential (GSP), LCEA, good financial capability	WA
BECCS	GSP, Biomass Availability	WA, good financial capability
Biochar	Biomass Availability	Climatic factor (Temperate and humid regions with ave. temperature of 20 °C and moderate precipitation), good financial capability, AgLu

2.2.3. Water availability (WA)

For water availability (WA), the indicator, level of water stress, which is a measure of the freshwater usage compared to the total renewable freshwater resources available was adopted (FAO, 2022). This indicator is suited for water availability as it highlights not just the amount of water available but its level of sufficiency in relation to the demand. This will thus show nations that have excess for GGR deployment and those that are already highly stressed.

2.2.4. Geological CO_2 storage potential (GSP)

Due to its favourable economic aspects, widespread geographical distribution, and environmental issues, underground geological storage has often been suggested as the most practical solution for CO_2 storage (Aminu et al., 2017; Bui et al., 2018). GSP data for the various countries were obtained from the world geological storage suitability map (IEAGHG, 2011), and validated with the sedimentary basins data reported by Kearns et al. (2017).

2.2.5. Financial capability

The impact of cost on deployment suitability was based on the assessment of the financial capability of countries. Richer countries are expected to spearhead the development and implementation of the more expensive GGR options. Gross national income per capita (GNI) was adopted as the indicator to measure financial capability of countries (World Bank, 2021).

2.2.6. Low carbon energy availability (LCEA)

For energy availability, only low carbon energy sources were considered. This is to prevent the use of energy-intensive GGR techniques from increasing CO_2 emissions. These low carbon energy sources included nuclear and renewable sources (hydropower, solar, wind, geothermal, bioenergy, wave, and tidal). The indicator applied was the proportion of each nation's energy that is produced using low carbon energy sources (IEA, 2020; Ritchie et al., 2020). The higher the share, the higher the potential to deploy the energy dependent GGR methods.

2.2.7. Biomass availability (BA)

Given the need to minimise competition with food supply, lignocellulosic feedstocks such as switchgrass, wood, Miscanthus, and agricultural residues have been suggested as viable sources of biomass either through dedicated planting or importation (Smith et al., 2015; The Royal Society, 2018). Country-level biomass potential data, measured in terms of the net primary production (tC/ha/yr) was sourced from the International Renewable Energy Agency (IRENA, 2021). The obtained net primary production, which is a measure of the biomass productivity of the various countries, was multiplied by their respective forest and agricultural (arable) land use to obtain the current biomass potential (tC/yr). Potential biomass from imports and municipal wastes were not considered.

These selected indicators of bio-geophysical and techno-economic variables constitute the primary indicators as they represent the breadth of major available resources necessary for the siting and deployment of these technologies. Other factors, especially those within the highly dynamic socio-political sphere, are considered secondary as their impact only comes into play after the viable range of GGR technologies deployable has been identified, which is where the focus of this manuscript's efforts lie. Thus, these secondary factors are therefore not required in this study which is aimed at exploring and assessing the range of suitable GGR technologies that can be deployed on the basis on bio-geophysical and techno-economic factors. It is important to also add that this approach is apolitical and whilst final investment decisions would no doubt be influenced by the political will of the respective governments; political factors have no influence on the identification of the range of technologies that could be utilised in a particular location to achieve net zero.

2.3. Data collection and pre-processing

Most recent available country-level data for the selected indicators were obtained for 182 countries. Country-level data for rock availability, a key indicator for deployment of EW was unavailable. To account for this, a scenario in which all countries have the needed rock resources was assumed. This assumption is supported by basalt's vast abundance which makes up about 4.56 % of the earth's surface, with considerably greater quantities present below the surface and beneath the oceans (Dessert et al., 2003).

Through numerical encoding of string-type data and analytical determination of incomplete data, the obtained raw data was pre-processed into a form that could be used in the ML modelling. (details in Supplementary information section). Eq. (1) was used to normalise the dataset between 0 and 1. This was done to eliminate any potential bias brought on by differences in the range of values among the variables and also to situate the respective national data in a comparative global context. Table 2 presents the applied input data variable for assessment of each GGR method based on the selected indicators.

$$x_{ij}^{norm} = \frac{x_{ij} - x_{min}}{x_{max} - x_{min}} \tag{1}$$

where, x_{ij}^{norm} is the normalised data, x_{ij} is the actual data, x_{min} is the minimum data and x_{max} is the maximum data.

2.4. Hierarchical clustering

The hierarchical clustering technique is a stepwise unsupervised ML method that clusters datasets into a specified number of groups (clusters) based on the similarity of the variables of each data (Murtagh and Contreras, 2012; Usama et al., 2019). In this case, for each GGR method, the 182 countries considered were clustered into the optimal number of clusters (k) for the particular dataset based on the similarity of their bio-geophysical and technoeconomic characteristics. The optimal number of clusters (k) for a particular dataset is the number of clusters that ensures that members of the same cluster are similar to one another and uniquely different from members of other clusters.

The code was written in Python using the *Agglomerative Clustering* library imported from the sklearn.cluster module. The Euclidean distance method, which measures the straight-line distance between two points in a Euclidean space, was adopted (Christopher, 2021), while the linkage was set to 'ward' (Hu et al., 2018). The characteristics of the obtained clusters were analysed based on their similarity to the characteristics required for deployment and good performance of the respective GGR method. Based on the level of similarity between the obtained cluster characteristics and those identified in Table 1, the clusters were then sorted into their corresponding level of deployment suitability. The sorting was done based on a consideration of the impact/importance of the various deployment requirements as presented in Table 1. Availability of major requirements were thus

Table 2
Input data variables for the GGR technologies.

GGR technologies	Applied input data variables
Forestation	Average quarterly temperature and precipitation [a], Forestation land use (FLu) and Water availability (WA)
EW	Average quarterly temperature and precipitation [a], GNI, LCEA and AgLu.
DACCS	GNI, GSP, WA and LCEA
BECCS	GNI, GSP, WA and BA
Biochar	Average quarterly temperature and precipitation [a], AgLu, GNI and BA

[a] This consists of a total of 8 variables which comprise data for each quarter in a year for temperature (Q1T, Q2T, Q3T, Q4T) and precipitation (Q1P, Q2P, Q3P, Q4P).

prioritised in the sorting process over the minor requirements for the respective GGR methods.

Four levels of deployment suitability were considered in this assessment: *highly suitable* (HS), *suitable* (S), *possible* (P) and *unsuitable* (U). With reference to the grouping of requirements in Table 1, a description of these suitability categories is presented in Table 3.

A breakdown of the hierarchical clustering methodology is presented in the following sections for the forestation case. The same method was applied for the other GGR technologies under consideration (EW, DACCS, BECCS and Biochar), details of which are provided in the Supplementary Information.

2.4.1. Determination of the optimal number of clusters

For the forestation deployment suitability analysis, ten input data variables, as shown in Table 2, were obtained for the 182 countries. The variables are the mean quarterly temperature (Q1T, Q2T, Q3T, Q4T), the mean quarterly precipitation (Q1P, Q2P, Q3P, Q4P), water availability (WA) as well as forestation land use (FLu). Since the hierarchical model requires the user to specify the number of required clusters, the optimal number of clusters (k) was obtained using the elbow method (Fig. 2(a)) and indicated on the dendrogram shown in Fig. 2(b). The elbow method attempts to find a balance between accuracy of the model and computation/time expense of the calculation, with the crux of the elbow curve indicating an approximate location of this balance point (Saji, 2023). Obtaining the optimal number of clusters using the elbow method can sometimes be subjective, especially when there is no clear turning point (elbow) on the graph. To minimise this and ensure certainty of the obtained optimal number of clusters, multiple iterations of the method was done using different range of clusters. As shown in Fig. 2 (a), the optimum number of clusters (k) for the forestation dataset is approximately 4. This value is indicated on the dendrogram in Fig. 2(b) as the point at which four vertical lines are cut by the red dashed horizontal line.

2.4.2. Cluster characteristics

After running the hierarchical clustering algorithm, the 182 countries were grouped optimally into the 4 clusters labelled 0–3. The characteristics of these obtained clusters were assessed to evaluate the category of deployment suitability they represent for the particular GGR method under consideration (forestation). The characteristics of a cluster is essentially the mean characteristics of its members. This is indicated by the normalised mean value of each input variable for each cluster as presented in the heatmap shown in Fig. 3. The darker the shade, the larger the mean value of the particular variable. For example, the first quarter temperature (Q1T) of member countries in *cluster 0* (0.93) is higher than those of *cluster 3* (0.43). Also, members of *cluster 1* have a higher water availability (WA – 0.91) in comparison to those of *cluster 2* (0.05).

Based on the similarity of the provided cluster characteristics in Fig. 3 with those required for deployment of forestation, as presented in Table 1, these obtained clusters were then sorted into their corresponding categories of deployment suitability (HS, S, P and U). The description of the respective cluster characteristics (Fig. 3) and their corresponding categories are presented in Table 4.

Table 3
Description of deployment suitability categories.

Suitability category	Description
Highly suitable	Satisfies major and minor requirements for deployment
Suitable	Satisfies some major and minor requirements for deployment
Possible	Satisfies core geo-locational requirement which are not likely to change in a long time (climatic factors and GSP), but currently lacks the highly dynamic requirements such as GNI, LCEA, BA. Given the presence of required geo-locational indicators, the suitability status of nations in this category are expected to improve with improvement in their dynamic indicators. This improvement could be because of factors ranging from economic development to international collaborations.
Unsuitable	Satisfies neither major and nor minor requirements for deployment

3. Results and discussions

Using hierarchical clustering machine learning model, 182 countries were categorised into four levels of deployment suitability for five GGR methods based on their bio-geophysical and techno-economic characteristics. These methods include forestation, EW, DACCS, BECCS and biochar. Fig. 4 presents the obtained global maps showing the suitability categorisation of countries to deploy these GGR methods.

According to Fig. 4(a), countries within the tropical regions were found to be most *suitable* for the deployment of forestation. This is majorly on account of their favourable climatic and vegetation characteristics. These nations, which include those of South America, Sub-Saharan Africa as well as Australia concur with the priority zones highlighted by Roe et al. (2019). North African as well as Middle Eastern nations, on the other hand, were typically *unsuitable* for forestation deployment because of their arid climatic conditions. Most of the EU countries were found to be in the *possible* category. This is largely because of their limited land availability and unfavourable climatic conditions (temperate and boreal forests) which leads to warming effect on account of reduction in albedo with increase in latitude (Favero et al., 2018; Fuss et al., 2018).

From Fig. 4(b), the countries with highest potential for enhanced weathering deployment include Canada, EU countries, New Zealand, Chile, Japan and Argentina. This is because of their high financial capability, availability of low carbon energy (LCE) and agricultural land for dispersal of the weathered rocks. Other rich nations such as USA, Russia, China were identified in the *suitable* category on account of their low share of LCE. Other *suitable* countries for EW deployment largely on account of their favourable climatic condition which is required to assist in the weathering process (Andrews and Taylor, 2019; Meysman and Montserrat, 2017) and land availability though with relatively lower financial capability include Brazil, Colombia, Singapore, Panama, Malaysia, the Caribbeans and Thailand among others. Countries in Central and Southern African as well as Southeast Asia and Australia were found to be in the *possible* category as they lacked one or both dynamic requirements (GNI and LCEA) though they met required climatic conditions. Parts of the West Africa, India, Iran, Pakistan and North Africa among others were identified in the *unsuitable* category.

Given the biophysical independence of DACCS deployment, with the major factor being the availability of appropriate geological storage sites, this technology was found to be possible for deployment in most countries, as shown in Fig. 4(c). The level of suitability however depends on their respective financial capability indicated by their respective GNI per capita and availability of LCE. The USA, Canada, Russia, EU, Kazakhstan, Australia, Argentina and Norway among others ranked highest in suitability for deployment. Among a handful of countries found *unsuitable* for the deployment of this GGR method largely due to the absence of appropriate storage sites include Burkina Faso, Djibouti, Mauritius, Estonia, Finland, Sweden, The Bahamas, Haiti, and Moldova. While this assessment was based on a consideration of the availability of in-country geological storage sites, it is important to add that some of these nations identified in the *unsuitable* category could still deploy this technology with the possibility of transporting the captured CO_2 *via* ships or pipelines to other nations that have adequate storage sites (IEA, 2022). For the CCS-based technologies (BECCS and DACCS), while countries with unproven geological storage potential (Burundi, Cameroon, North Korea, Laos, Lesotho and Zimbabwe) owing to availability of data, were assumed to have a low GSP in this study, it is advised that their categorisation results be revised when new estimates become available.

The availability of biomass and suitable geological storage locations

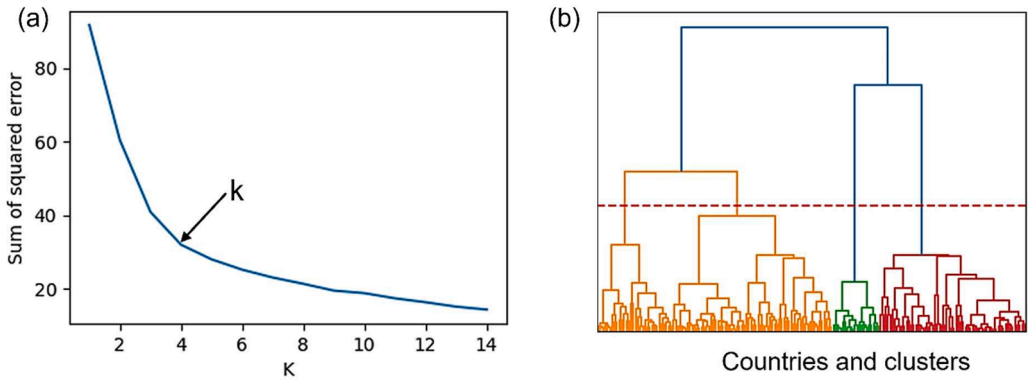


Fig. 2. (a) Optimum number of clusters (*k*) determined by the elbow method, (b) Forestation dendrogram.

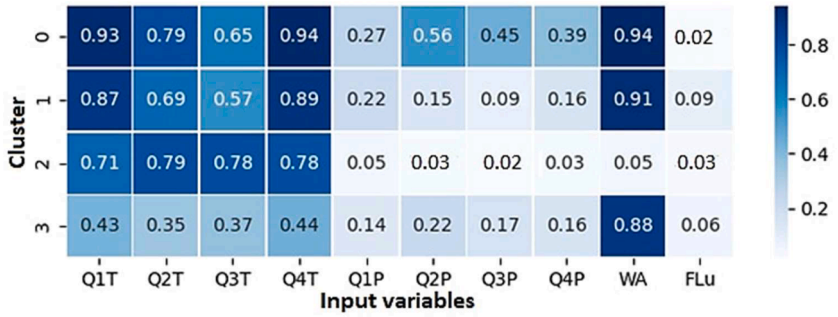


Fig. 3. Heat map showing the cluster characteristics for forestation.

Table 4
Forestation cluster characterisation.

Suitability category	Characteristics	Cluster label
Highly suitable	Typical tropical climate of high temperature and medium precipitation coupled with high water availability and high land availability.	1
Suitable	Overall high annual temperature and precipitation and water availability, though with relatively low land availability.	0
Possible	Prevailing climatic conditions (low temperature and medium precipitation) are not ideally suited for tropical type forest that have been recommended. It's however characterised by high water and land availability for forest use.	3
Unsuitable	Typical desert climate characteristics of high annual temperature, very low precipitation, water and land availability for forest use.	2

are key determinants of how well BECCS can be deployed. Due to storage availability, same nations that were *unsuitable* to deploy DACCS were also found to be *unsuitable* for BECCS. However, with some of these nations having readily available biomass, they might still play a significant part in the deployment of this GGR method. They could become biomass supply hubs for other nations, and they could also deploy the technology while sharing storage sites with neighbours. As shown in the BECCS suitability map (Fig. 4(d)), major countries with *high suitability* include the USA, Canada, EU, China, Russia, Australia as well as the tropical countries in South America. Similar regions were also identified by Roe et al. (2019). India, Kazakhstan, South-East Asia and Sub-Saharan Africa were found to be *suitable* also. Most of North Africa and the Middle East were identified to be in the *possible* category on account of limited biomass availability. However, their relatively high financial capacity, especially in the Middle East could significantly increase their deployment suitability as biomass could be sourced *via* importation.

For biochar, most nations of the world were found to be suitable for deployment as shown in Fig. 4(e) with the most suitable including China, USA, Canada, EU and Russia, among others. While these findings agree with the identified priority zones of Roe et al. (2019), it is significant to highlight that because of the intricacy of its interrelated elements (Lorenz and Lal, 2014; Nair et al., 2017) and lack of data at the country-level, the impact of soil characteristics was not taken into consideration in this study. Based on the widely acknowledged fact that biochar effects on soil are biochar-, soil-, and plant-specific (Li et al., 2018), all countries were thus assumed to have the necessary soil properties. Some countries were however found to be *unsuitable* for the deployment of this GGR on account of other influencing factors such as BA, climate and financial capacity (relatively low GNI per capita). These countries include those of the Middle East, Libya and Mongolia, Kyrgyzstan, Mexico, Kosovo and Moldova, among others.

While the effort of every country is needed in order to meet the emission mitigation target, a comparison of the obtained suitability maps with the Capability maps of Pozo et al. (2020) indicates an agreement on identified priority regions. These countries which were allocated larger CO_2 removal shares on account of their respective financial capability in that study, were also found to have *high suitability* levels of deployment of the cost intensive GGR methods considered in this study. These countries which include the US, Australia, Russia, China, Canada and the EU can potentially lead the global community in meeting the emission mitigation target.

3.1. Assessing impact of key resource availability on suitability categorisation

Having obtained the suitability of countries to deploy the five GGR methods, an assessment of the impact of changes in key dynamic input variables on the obtained categorisation was carried out. This sensitivity analysis was done to ascertain the level of uncertainty in the obtained

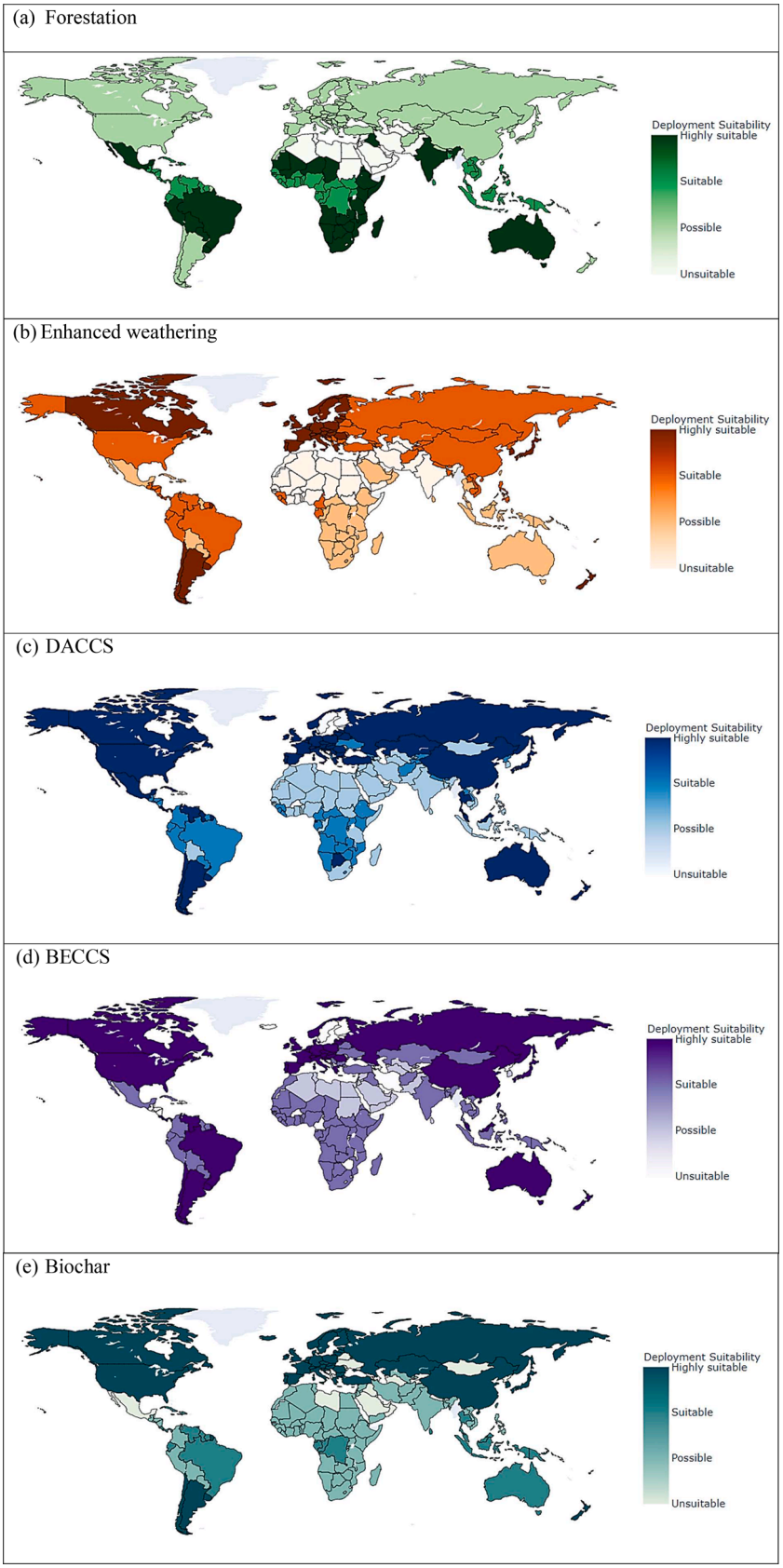


Fig. 4. Global maps showing the suitability of countries to deploy five GGR methods: Forestation (a), Enhanced weathering (b), DACCS (c), BECCS (d) and Biochar (e).

suitability categories which are brought about by probable uncertainties in some of the input variables as well as a consideration of the TRLs of some of the GGR methods. The impact of major input variables such as climatic factor and GSP were not assessed as they are less dynamic with data values not expected to change drastically. The assessment was thus focused on the more dynamic variables (GNI, LCEA, FLu and BA), whose availability can easily be influenced by human factors such as prevailing policies and economic development. These resources were assessed under optimistic (50 % resource increase) and pessimistic (50 % resource decrease) scenarios of availability (Pozo et al., 2020). In carrying out the sensitivity analysis for each of the selected variables, all other conditions and variables applied in the original analysis, including the number of clusters were kept same. Fig. 5 presents the changes in the obtained membership of categories under optimistic and pessimistic scenarios of resource availability for the dynamic input variables. The corresponding optimistic and pessimistic global country-level maps and assessment data table are presented in the Supplementary Information.

Fig. 5(a) presents the impact of land availability (FLu) on forestation deployment. In the optimistic scenario, we considered forestation deployment on all available forest lands (for reforestation) and agricultural lands (for afforestation, agroforestry). While this scenario could have negative impact on food production and is thus not feasible, it is important to note that this added land consideration did not improve the deployment suitability of countries in the *possible* (P)/*unsuitable* (U) categories. This is because of the major role played by climatic factors in the deployment of this GGR method. There were however changes in membership among suitability sub-categories (*highly suitable* (HS) *and suitable* (S)) on account of changes in land availability, with 37 countries (or 20 % of the total number of countries assessed) moving from S to the HS category under optimistic scenario and 31 countries (or 17 % of the total number of countries assessed) moving from HS to S category under the pessimistic scenario.

The impact of availability of low carbon energy (LCEA) on the obtained suitability category of countries was assessed for the two major energy intensive GGR options (EW and DACCS). Under the optimistic scenario of countries increasing the share of their respective current LCE by 50 %, a total of 16 countries moved to higher suitability categories (9 %) for EW (Fig. 5(c)); while a 14 % change (25 countries) was observed for DACCS (Fig. 5(d)). In the pessimistic scenario assessment, 35 countries (19 %) moved to lower suitability categories for EW. Thus, showing the importance of this requirement in EW deployment. In the case of DACCS, pessimistic scenario availability of LCE resulted in a 5 % change in categories (10 countries moved to lower suitability categories). While LCEA is no doubt a key requirement for the deployment of DACCS, its relatively low impact in comparison to EW (under pessimistic scenario) is because of the bigger role played by geological storage consideration (GSP) in the deployment of DACCS.

The impact of cost considerations indicated by GNI was also assessed for the cost intensive options (EW and DACCS). While this assessed the impact of changes in countries' financial capability, it also assesses the impact of the uncertainties associated with expected cost requirements of these technologies given that they are not yet fully matured. Optimistic scenario thus indicates increased GNI or cheaper cost requirement, while pessimistic scenario indicates decreased GNI or higher cost

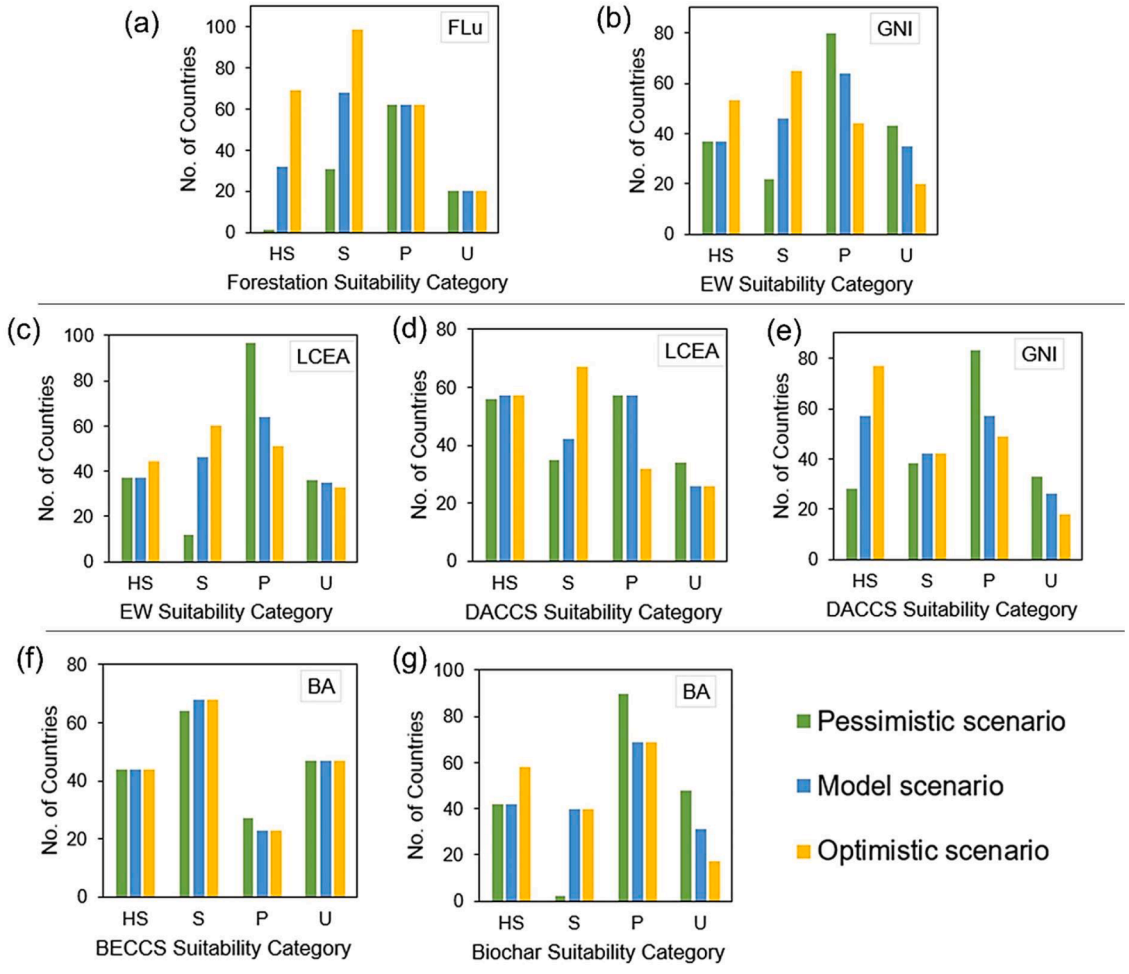


Fig. 5. Impact of resource availability on obtained suitability categorisation (a) FLu on Forestation, (b) GNI on EW, (c) LCEA on EW, (d) LCEA on DACCS, (e) GNI on DACCS, (f) BA on BECCS and (g) BA on biochar.

requirement for deployment. For EW (Fig. 5(b)), optimistic GNI assessment brought about a 34 % change in category membership (63 countries moving to higher suitability categories). A 17 % change (30 countries) was observed in the pessimistic scenario. For DACCS (Fig. 5 (e)), a 16 % change in category membership was observed in the optimistic scenario. The pessimistic scenario brought about 20 % change in category membership (36 countries moving to lower suitability categories).

The impact of biomass availability (BA) on the deployment suitability of countries to deploy BECCS and biochar was also assessed. For BECCS (Fig. 5(f)), there was no change in the deployment suitability category of countries under optimistic BA. While BA remains a key factor in BECCS deployment, this result indicates the significant role of factors such as GSP in determining the deployment suitability of countries. It also indicates that a consideration of other biomass sources such as municipal waste and importation which were not included in this study will not greatly impact on the obtained BECCS suitability categorisation. A 2 % change was however observed in the pessimistic scenario. For biochar (Fig. 5(g)), optimistic BA assessment resulted in 9 % change in category membership. This implies that a consideration of biomass from other sources such as municipal waste impacted the suitability category of countries to deploy biochar. A 20 % change in membership was observed in the pessimistic BA scenario.

Based on the maximum changes that occurred in the category membership under the optimistic and pessimistic scenarios, the uncertainty associated with each of the categorisation results (maps) presented in Fig. 4 is set as follows: Forestation: 20 %, DACCS: 20 %, Biochar: 20 %, EW: 35 % and BECCS: 2 %.

Fig. 6 presents two case studies (the UK and Nigeria) to illustrate the discussed sensitivity analysis. For the UK (Fig. 6(a)), variation in the model input variables under pessimistic and optimistic scenarios did not change their obtained GGR deployment suitability categories for all scenarios. In the case of Nigeria (Fig. 6(b)), changes in category membership were observed for the EW and DACCS optimistic modelling scenarios. For EW, the suitability category changed from *unsuitable* (U) to *possible* (P) while in the case of DACCS, the deployment suitability category of Nigeria changed from *possible* (P) to *suitable* (S). Both changes were on account of increase in GNI and LCEA. Overall, for both countries, the sensitivity analysis thus indicates the robustness of their respectively obtained categorisation.

3.2. Limitations and recommendations

The suitability category of 182 countries to deploy five GGR technologies has been obtained. To help with and assure the greatest use of the results, this section outlines limitations and suggestions. With this study based on the Hierarchical clustering ML model, it consequently inherits the advantages and disadvantages of this algorithm (Madhulatha, 2012; Sultana, 2020). Hierarchical clustering is one of the most commonly used unsupervised machine learning algorithms. Although it has been applied in many research areas, its use in GGR deployment categorisation is novel. While the method has worked well in providing a data-based objective categorisation, key limitations include its black-box nature which is associated with ML and its dependence on the available dataset. Since this study is mostly based on currently available data, it is advised that the categorisation results be revised when new estimates become available.

The use of average national data to represent the characteristics of countries is another aspect that is directly related to the limitation of data availability. Although this approach is appropriate for assessments at the country level, it is unable to account for the sub-national variations that exist, particularly in large countries. It is thus recommended that multiple data points at regional or local levels be explored when globally available. It is, however, important to add that this factor has no bearing on the correctness of the categorisation. This is because the idea of suitability in this study does not imply that every region of a country, regardless of size, is suitable or unsuitable. Instead, it indicates the relative potential of countries to deploy the GGR technologies based on their characteristics, in comparison to other countries within a global context.

Another limitation which is commonly associated with categorisation-based study is the lack of consideration for individual variations, scale, grey areas and uniqueness. That nations are in the same suitability category does not necessarily indicate similar potential to deploy a technology. It also ignores probable existence of outliers as they could be erroneously categorised. While this study has explored and presented the range of suitable GGR technologies that can be sustainably and efficiently deployed in 182 countries of the world based on the country's bio-geophysical and techno-economic characteristics, there will be need for further assessment to evaluate the individual potential of nations.

It is also important to note that the role of government and the prevailing social systems of the various countries will impact on the extent and selection of GGR technologies that will ultimately be implemented from these results. Government has a major role to play in creating policies that would support investments to aid the development of these technologies if the 1.5 °C target is to be met. There is also a need for regional and/or bilateral cooperation among countries especially in regard to exploiting comparative advantage of one another's resources *via* trading and agreements. This could take the form of richer countries investing in the deployment of the more expensive GGR options in low-income nations that have the required bio-geophysical resources. It could also involve supply of low carbon energy and biomass as well as sharing of CO_2 storage sites with neighbouring nations, among others.

4. Conclusion

The suitability of countries to deploy five GGR technologies (forestation, enhanced weathering, DACCS, BECCS and biochar) has been carried out using a machine learning (ML) hierarchical clustering

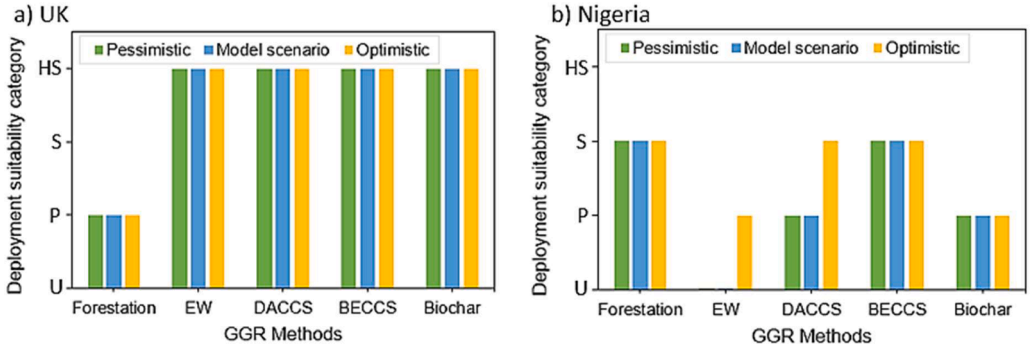


Fig. 6. Impact of model input variation (pessimistic and optimistic scenarios) on the deployment suitability categorisation of the UK and Nigeria.

approach. This assessment which was based on the bio-geophysical and techno-economic variables influencing the performance of these technologies indicate that many countries are well suited to deploy them. Countries such as the US, Canada, Brazil, China, Russia, Australia, the EU and Sub-Saharan Africa have been identified as key areas suitable to deploy these technologies. While the results show the need for regional collaboration between nations, they also highlight the necessity for nations to prioritise and integrate GGR technologies in their revised NDCs. Moreover, government policies will be key in driving the development and implementation of these methods. While the applied ML methodology has greatly minimized human bias in the categorisation, the outcome is however limited by its dependence on the available dataset with the certainty of the obtained deployment suitability categorisation ranging from 65 to 98 %. It is advised, thus, to update the categorization results whenever fresh estimates become available.

Supplementary information

This section includes information on the data pre-processing and hierarchical clustering procedure for the other four GGR methods - enhanced weathering (EW), DACCS, BECCS and biochar. It also presents the corresponding optimistic and pessimistic global country-level maps and assessment data table.

CRediT authorship contribution statement

Jude O. Asibor: Conceptualization, Methodology, Software, Formal analysis, Investigation, Writing – original draft. **Peter T. Clough:** Conceptualization, Writing – review & editing, Supervision, Project administration. **Seyed Ali Nabavi:** Conceptualization, Writing – review & editing, Supervision. **Vasilije Manovic:** Conceptualization, Writing – review & editing, Supervision.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data underlying this study can be accessed through the Cranfield University repository (CORD) at: https://doi.org/10.17862/cranfield.rd.21187129. Data are available under the terms of the [Creative Commons Attribution 4.0 International (CC BY 4.0)].

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.ijggc.2023.103995.

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