JUDE ODIANOSEN ASIBOR

COUNTRY-LEVEL ASSESSMENT OF THE DEPLOYMENT POTENTIAL OF GREENHOUSE GAS REMOVAL TECHNOLOGIES

SCHOOL OF WATER, ENERGY AND ENVIRONMENT
PhD in Energy and Sustainability

PhD
Academic Year: 2019 - 2023

Supervisor: Dr Peter T. Clough
Associate Supervisor: Dr. Seyed Ali Nabavi and Prof. Vasilije Manovic
July 2023

CRANFIELD UNIVERSITY

SCHOOL OF WATER, ENERGY AND ENVIRONMENT
PhD in Energy and Sustainability

PhD

Academic Year 2019 - 2023

JUDE ODIANOSEN ASIBOR

COUNTRY-LEVEL ASSESSMENT OF THE DEPLOYMENT POTENTIAL OF GREENHOUSE GAS REMOVAL TECHNOLOGIES

Supervisor: Dr Peter T. Clough
Associate Supervisor: Dr. Seyed Ali Nabavi and Prof. Vasilije Manovic
July 2023

This thesis is submitted in partial fulfilment of the requirements for the degree of PhD

© Cranfield University 2023. All rights reserved. No part of this publication may be reproduced without the written permission of the copyright owner.

Abstract

The deployment of greenhouse gas removal (GGR) technologies has been identified as an indispensable option in meeting the warming target of 1.5 °C by the end of the century. Despite the importance of this pathway, the Nationally Determined Contributions (NDCs) of countries indicates a low intent to deploy these technologies. Among the major factors responsible for this low level of inclusion is the lack of robust country-level bio-geophysical and techno-economic feasibility assessments to ascertain national GGR deployment potential. Herein lies the challenge that this thesis aimed to address.

This study investigated the potential of 182 countries to deploy five of the most promising GGR technologies, including forestation, enhanced weathering, direct air carbon capture and storage, bioenergy with carbon capture and storage, and biochar. A comparative literature-based assessment was carried out to identify and rank the major factors required for optimum performance of these GGR methods. Based on the bio-geophysical and techno-economic characteristics, Machine Learning (ML) was applied to identify the range of GGR technologies that respective countries can suitably and effectively deploy. ML models were also developed for predictive locational resource mapping of these technologies. Furthermore, the extent of carbon dioxide removable by 2100 via these technologies for each country (national potential) was evaluated using a Multi Criteria Decision Analysis approach. An assessment of domestic and regional sufficiency was also carried out to provide an evidence base for international collaboration.

Priority regions for the deployment of these GGR technologies were identified, with Latin America and Sub-Saharan Africa regions found to have surplus potentials, and thus, expected to serve as a major hub to support other regions of the world. While the obtained results indicate the need for regional cooperation among countries, it also provides useful evidence on the need for countries to include and prioritise GGR technologies in their revised NDCs.

Research Sponsor:

Petroleum Technology Development Fund (PTDF), Nigeria. Doctoral study scholarship, award number: PTDF/ED/OSS/PHD/JOA/077/19.

Keywords:

Negative emission technologies; BECCS; climate change mitigation; machine learning; carbon capture and storage; artificial neural network

Acknowledgements

Firstly, I would like to express my sincere gratitude to my supervisors, Dr Peter Clough, Dr. Seyed Ali Nabavi, and Prof. Vasilije Manovic for their understanding, motivation and continuous support of my PhD study. I would like to thank Peter for his immense support and guidance, providing me with multiple opportunities for development during my study. This includes co-supervision of master's students projects, involvement in various industry-based projects, secondment and programmes. I will be always grateful for these opportunities through which I have gained invaluable experience and exposure. I'm immensely grateful to Ali for his valuable research insights and suggestions which will be helpful in my career. Special thanks to Vasilije for the scientific discussions and inspirations during my PhD project. I would also like to express my profound gratitude to my PhD progress reviewer, Prof. Nazmiye Ozkan and the Chair, Prof. Naresh Magan, who provided many useful suggestions and guidance to enhance the research and ensure timely delivery of the PhD.

I would also like to express my thanks to all the amazing past and current members of the Clough Research Group: Dr Yongliang (Harry) Yan, Dr. Fatih Gulec, Dr. Aleks Gonciaruk, Dr. Tosin Adedipe, Paula Nkulikiyinka, Serap Ozmen, Ziqi Shen and Siqi Wang, for their insightful suggestions and assistance throughout my PhD journey. I greatly value our friendship and research collaborations, and I eagerly look forward to seeing it flourish in the coming years. Special thanks to my colleagues at the University of Benin, Nigeria for your immense support.

Furthermore, I would like to express immense appreciation to Prof. Martin Freer, Faye McAnulla, Dr. Kathryn North, Chris Sims and the amazing team at HyDEX and CDICE, for their mentorship and support during the course of my secondment. I have gained significant knowledge and experience which will be immensely beneficial in my journey. Special thanks to my colleagues and staff of the Energy and Sustainability theme, and members of the Nigerian Society in Cranfield, for the community spirit and support throughout the course of my PhD study. I'm immensely grateful.

Finally, I wish to thank my parents, Mr and Mrs C. O. Asibor, my siblings, Faith, Patience, Peter and Paul for their love and support throughout my life's journey. Last, but not least, to my amazing wife, Isowamwen Imarhiagbe, thank you for your love, care, encouragement and support during my PhD study.

Thanks be to God, the Almighty for the gift of life and the success of this journey.

TABLE OF CONTENTS

Abstract i
Acknowledgements iii
Declaration x
List of Figures xi
List of Tables xv
List of Abbreviations xvii
1 Introduction 1
1.1 Background 1
1.2 Project Aims and Objectives 5
1.3 Novelty 6
1.4 Thesis Outline 7
1.5 List of published/submitted work 9
1.6 References 10
2 Assessment of Optimal Conditions for the Performance of Greenhouse Gas Removal Methods 13
Abstract 13
2.1 Introduction 14
2.2 Assessing the GGR technologies 18
2.3 Forestation 19
2.3.1 Land availability 20
2.3.2 Climatic condition 20
2.3.3 Vegetation 22
2.3.4 Other considerations 22
2.4 Enhanced Weathering 24
2.4.1 Climatic condition 25
2.4.2 Geology 25
2.4.3 Energy and Cost 26
2.4.4 Other considerations 27
2.5 Soil carbon sequestration 28
2.5.1 Management Practices 29
2.5.2 Climate 31
2.5.3 Vegetation and Soils 31
2.5.4 Other considerations 32
2.6 Biochar 32
2.6.1 Land availability 33
2.6.2 Biomass Feedstock 34
2.6.3 Soil 35
2.6.4 Other considerations 36
2.7 Direct Air Carbon Capture and Storage (DACCS) 37
2.7.1 Land 40

2.7.2 Water 40
2.7.3 Energy 40
2.7.4 CO_2 Storage 41
2.7.5 Cost 42
2.8 Bioenergy with Carbon Capture and Storage (BECCS) 42
2.8.1 Land and water requirement 43
2.8.2 Biomass 44
2.8.3 Other considerations 44
2.9 Discussion 45
2.10 Recent trends and outlook 50
2.11 Conclusions 52
2.12 References 53
3 Methodology 67
3.1 Introduction 67
3.2 Input Data Characteristics 67
3.3 Data Collection 68
3.3.1 Climatic factor 69
3.3.2 Land availability 69
3.3.3 Water availability (WA) 69
3.3.4 Geological CO_2 storage potential (GSP) 69
3.3.5 Financial capability 70
3.3.6 Low carbon energy availability (LCEA) 70
3.3.7 Biomass availability (BA) 70
3.3.8 Rock availability 71
3.4 Data Pre-processing 71
3.5 Categorisation of GGR Deployment Suitability of Countries Using Hierarchical Clustering ML 73
3.5.1 Machine Learning 73
3.5.2 Hierarchical clustering ML 75
3.5.3 Determination of the optimal number of clusters 77
3.5.4 Clustering and cluster characteristics 79
3.5.5 Cluster sorting into suitability categories 81
3.5.6 Forestation 82
3.5.7 Enhanced weathering 84
3.5.8 DACCS 85
3.5.9 BECCS 86
3.5.10 Biochar 87
3.6 Application of Supervised ML for Resource Mapping of GGR Methods 88
3.6.1 Logistic Regression 90
3.6.2 Decision Tree 91
3.6.3 k-Nearest Neighbour (k-NN) 92
3.6.4 Naïve Bayes 93

3.6.5 Random Forest 94
3.6.6 Gradient Boost 96
3.6.7 Artificial Neural Network (ANN) 97
3.6.8 Model interpretation 100
3.7 Country-level Assessment of the Deployment Potential of GGR Technologies 102
3.7.1 Multi-Criteria Decision Analysis (MCDA) 103
3.7.2 Setting the criteria weighting system 104
3.7.3 Evaluating the maximum cumulative GGR potential 105
3.7.4 Assessing the CDR quotas 106
3.7.5 Sensitivity analysis of weight 107
References 109
4 A Machine Learning Approach for Country-level Deployment of Greenhouse Gas Removal Technologies 115
Abstract 115
4.1 Introduction 116
4.2 Methodology 118
4.2.1 GGR Methods 119
4.2.2 Indicator selection 122
4.2.3 Data collection and pre-processing 125
4.2.4 Hierarchical clustering 126
4.2.5 Determination of the optimal number of clusters 128
4.2.6 Cluster characteristics 129
4.3 Results and Discussions 130
4.4 Assessing Impact of Key Resource Availability on Suitability Categorisation 135
4.5 Limitations and recommendations 139
4.6 Conclusion 140
4.7 References 141
5 A Machine Learning Approach for Resource Mapping Analysis of Greenhouse Gas Removal Technologies 149
Abstract 149
5.1 Introduction 150
5.2 Methods 152
5.2.1 Data collection and pre-processing 153
5.2.2 Hierarchical clustering 156
5.2.3 Supervised ML modelling 157
5.3 Results and discussion 159
5.3.1 Supervised ML modelling 159
5.3.2 Modelling case study – Scotland 160
5.3.3 Model interpretation and limitation 162
5.4 Conclusions 165

5.5 References 166
6 A Country-level Assessment of the Deployment Potential of Greenhouse Gas Removal Technologies 175
Abstract 175
6.1 Introduction 176
6.2 Methods 178
6.2.1 Multi-Criteria Decision Analysis (MCDA) 178
6.2.2 Criteria selection 179
6.2.3 Setting the criteria weighting system 180
6.2.4 Country-level data collection and pre-processing 181
6.2.5 Maximum Cumulative GGR potential 181
6.3 Results and discussion 182
6.3.1 Global GGR potential 182
6.3.2 Assessing the CDR quotas 188
6.3.3 Sensitivity Analysis of weight 191
6.3.4 Limitations and recommendations 193
6.4 Conclusion 194
6.5 References 195
7 General Discussions 201
7.1 Introduction 201
7.2 Forestation 202
7.3 Enhanced Weathering 203
7.4 DACCS 205
7.5 BECCS 207
7.6 Biochar 208
7.7 Recent Trends, Development and Outlook 209
7.7.1 Current status of GGR deployment and the warming target 210
7.7.2 Growth in GGR research 210
7.7.3 Growth in GGR innovation 211
7.7.4 GGR technologies and the society 211
7.8 References 212
8 Conclusions and Recommendations 213
8.1 Conclusions and contributions made 213
8.1.1 Major factors required for optimum performance of GGR methods 213
8.1.2 What GGR technologies can nations suitably deploy? 215
8.1.3 Role for Machine Learning in GGR assessment 216
8.1.4 National Potential and Evidence for International Collaboration 217
8.2 Future works 220
8.2.1 Inclusion of other factors 220
8.2.2 Co-deployment of GGR methods 220
8.2.3 Compatibility with other priorities 221
8.2.4 Assessing other GGR methods 221

8.2.5 Other roles for Machine Learning 221
APPENDICES 223
Appendix A : List of countries 223
Appendix B : A Machine Learning Approach for Country-level Deployment of Greenhouse Gas Removal Technologies 224
Appendix C : Application of Supervised ML for Resource Mapping of GGR Methods 228

Declaration

I declare that this thesis is an original report of my research, which has been written by myself and has not been submitted for any other degree or professional qualification.

It includes two papers published by Elsevier which allows the reuse and reproduction of the entire published material in an unchanged form in the PhD Thesis.

ELSEVIER[1]:

“Theses and dissertations which contain embedded PJAs (Published Journal Articles) as part of the formal submission can be posted publicly by the awarding institution with DOI links back to the formal publications on ScienceDirect”

[1] ELSEVIER https://www.elsevier.com/about/policies/sharing (accessed January 5, 2023).

List of Figures

Figure 1-1 Process of CO_2 removal and storage for each GGR method (The Royal Society, 2018). 3

Figure 1-2 An illustration of the respective technological readiness levels (TRLs) of the various GGR methods (Lomax et al., 2015; The Royal Society, 2018). 4

Figure 1-3 Structure and linkage of each work package in this thesis 8

Figure 2-1 An illustration of a tree showing the carbon cycle for plants (TERC, 2020) 19

Figure 2-2 Climate services in tropical, temperate and boreal forests (reprinted with permission from Bonan (2008), Copyright 2008 Science) 21

Figure 2-3 An illustration of the enhanced weathering process showing how rushed rocks that is dispersed over land captures atmospheric CO_2 24

Figure 2-4 Land management practices for SCS (reprinted with permission from Mulligan et al. (2020), Copyright 2020 World Resources Institute). 29

Figure 2-5 The various forms of biomass feedstocks and their sources (Ladanai and Vinterbäck, 2009) 34

Figure 2-6 Schematic illustration of DACCS (reprinted with permission from Mulligan et al. 2020), Copyright 2020 World Resources Institute). 37

Figure 2-7 Companies active in the field of CO_2 DAC. Abbreviations: moisture swing adsorption, MSA, temperature swing adsorption, TSA (reprinted with permission from Fasihi et al., (2019), Copyright 2019 Elsevier). 39

Figure 2-9 Schematic illustration of BECCS (reprinted with permission from Consoli (2019), Copyright 2019 Global CCS Institute). 43

Figure 3-1 Methodology framework for the suitability categorisation of countries for GGR deployment using hierarchical clustering machine learning 74

Figure 3-2 Plot to determine the optimum number of clusters (*k*) for the forestation dataset using the elbow method 78

Figure 3-3 Python code for determining optimum number of clusters for the forestation dataset. 79

Figure 3-4 Dendrogram for the forestation dataset clustering 80

Figure 3-5 Heatmap showing the forestation cluster characteristics 81

Figure 3-6 (a) Optimum number of clusters (k) determined by the elbow method for EW, (b) EW dendrogram 84

Figure 3-7 Heatmap of EW cluster characteristics 84

Figure 3-8 (a) Optimum number of clusters (k) determined by the elbow method for DACCS, (b) DACCS dendrogram 85

Figure 3-9 Heatmap of DACCS cluster characteristics 86

Figure 3-10 (a) Optimum number of clusters (k) determined by the elbow method for BECCS, (b) BECCS dendrogram 86

Figure 3-11 Heatmap of BECCS cluster characteristics 87

Figure 3-12 (a) Optimum number of clusters (k) determined by the elbow method for Biochar, (b) biochar dendrogram 87

Figure 3-13 Heatmap of Biochar cluster characteristics 88

Figure 3-14 Method framework for the supervised machine learning modelling 89

Figure 3-15 Schematic showing the structure of a Decision Tree (Chauhan, 2022a) 91

Figure 3-16 Diagram showing how a new data point is classified by k-NN (Christopher, 2021) 93

Figure 3-17 An example of a Random Forest comprising of nine decision trees (Yiu, 2019). 95

Figure 3-18 Network diagram of ANN showing the input layer, one hidden layer, output layer as well as weights and biases. 98

Figure 3-19 Python code for evaluating the feature importance score for the forestation dataset. 102

Figure 3-20 Method framework for the MCDA assessment showing the steps applied in obtaining the GGR potential of nations. 103

Figure 3-21 Curves of GGR technologies potential for 2020–2100. a) forestation, b) biochar, c) BECCS, d) DACCS, e) EW (reprinted with permission from Rueda et al. (2021), Copyright 2021 Elsevier). 105

Figure 4-1 Methodology framework for the suitability categorisation of countries for GGR deployment using hierarchical clustering machine learning 119

Figure 4-2 Plots showing (a) Optimum number of clusters (*k*) determined by the elbow method for the forestation dataset, (b) Dendrogram for the forestation dataset. 128

Figure 4-3 Heat map showing the cluster characteristics for forestation 129

Figure 4-4 Global maps showing the suitability of countries to deploy five GGR methods: Forestation (a), Enhanced weathering (b), DACCS (c), BECCS (d) and Biochar (e). 132

Figure 4-5 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. 136

Figure 4-6 Impact of model input variation (pessimistic and optimistic scenarios) on the deployment suitability categorisation of the UK and Nigeria. 138

Figure 5-1 Method framework for the supervised machine learning modelling 153

Figure 5-2 Comparison of ML algorithms performance for the suitability categorisation of 5 GGR methods 159

Figure 5-3 Bar chart showing the suitability of Scotland to deploy five GGR methods..... 161

Figure 5-4 Plots of the feature importance score showing the impact of the ML input variables on the deployment suitability of the GGR methods. A) Forestation, B) DACCS, C) BECCS, D) EW and E) Biochar. 163

Figure 6-1 Method framework for MCDA analysis showing the steps applied in obtaining the GGR potential of nations. 179

Figure 6-2 Curves of GGR technologies potential for 2020–2100. a) forestation, b) biochar, c) BECCS, d) DACCS, e) EW (reprinted with permission from Rueda et al. (2021), Copyright 2021 Elsevier). 182

Figure 6-3 Maximum cumulative carbon dioxide removal (CDR) potential of countries by 2100 from five GGR methods: Forestation (a), Enhanced weathering (b), DACCS (c), BECCS (d) and Biochar (e). 184

Figure 6-4 Comparison of Country-level cumulative CDR quotas (Pozo et al., 2020) and the obtained potential by 2100: a) Asia, b) LAM, c) MNAF, d) OECD, e) REF, f) ECOWAS, and g) ECSA. 189

Figure 6-5 Comparing regional cumulative CDR quotas and potential by 2100. 190

Figure 6-6 Sensitivity analysis of weighting system: Forestation (a), Enhanced weathering (b), DACCS (c), BECCS (d) and Biochar (e). 193

Figure B-1 Impact of land availability on Forestation ……..226

Figure B-2 Impact of GNI on Enhanced Weathering 226

Figure B-3 Impact of LCEA on Enhanced Weathering 226

Figure B-4 Impact of GNI on DACCS 226

Figure B-5 Impact of LCEA on DACCS 227

Figure B-6 Impact of Biomass availability on BECCS 227

Figure B-7 Impact of Biomass availability on Biochar..... 227

Figure C-1 Python code for Logistic Regression. 228
Figure C-2 Python code for Decision Tree 229
Figure C-3 Python code for k-Nearest Neighbour. 229
Figure C-4 Python code for Naïve Bayes. 230
Figure C-5 Python code for Random Forest..... 230
Figure C-6 Python code for Gradient Boost. 231
Figure C-7 Python code for Artificial Neural Network. 231

List of Tables

Table 2-1 Summary of existing review studies/reports on a suite of GGR methods 15

Table 2-2 Summary of the criteria adopted in selecting the GGR methods..... 17

Table 2-3 Comparison of the characteristics and deployment requirements of GGR technologies. 46

Table 2-4 The 0-5 scale ranking of the factors that impact on the performance of GGR technologies 49

Table 3-1 Input variables applied for the assessment of the GGR technologies 68

Table 3-2 Description of input data characteristics and applied pre-processing72

Table 3-3 The bio-geophysical and techno-economic requirements selected for GGR deployment..... 81

Table 3-4 Description of deployment suitability categories..... 82

Table 3-5 Description of Forestation cluster characteristics 83

Table 3-6 Description of EW cluster characteristics 85

Table 3-7 Description of DACCS cluster characteristics 86

Table 3-8 Description of BECCS cluster characteristics..... 87

Table 3-9 Description of Biochar cluster characteristics..... 88

Table 3-10 Applied criteria weights for the MCDA assessment of GGR potential 104

Table 3-11 Forestation criteria weighting scenarios 107

Table 3-12 EW criteria weighting scenarios 108

Table 3-13 DACCS criteria weighting scenarios..... 108

Table 3-14 BECCS criteria weighting scenarios..... 108

Table 3-15 Biochar criteria weighting scenarios..... 108

Table 4-1 Selected bio-geophysical and techno-economic GGR deployment requirements..... 123

Table 4-2 Input data variables for the GGR technologies..... 126

Table 4-3 Description of deployment suitability categories..... 127

Table 4-4 Description of Forestation cluster characteristics 130

Table 5-1 Data variables for the GGR methods 154

Table 5-2 Description of deployment suitability categories 157

Table 5-3 Description of the applied supervised ML algorithms (Dey, 2016; Pareek, 2019; Singh et al., 2016) 158

Table 6-1 Selected criteria for the MCDA assessment of GGR potential 180

Table 6-2 Applied weights for the selected criteria for the MCDA assessment of GGR potential 180

Table A-1 List of countries 223

Table B-1 Sensitivity Analysis Results 225

List of Abbreviations

AgLu	Agricultural Land use
AI	Artificial Intelligence
ANN	Artificial Neural Network
BA	Biomass Availability
BECCS	Bioenergy with Carbon Capture and Storage
CCS	Carbon Capture and Storage
CDR	Carbon Dioxide Removal
CO_2	Carbon Dioxide
DACCS	Direct Air Carbon Capture and Storage
ECOWAS	Economic Community of West African States
ECSA	East, Central and Southern Africa
EW	Enhanced Weathering
FLu	Forest Land use
GGR	Greenhouse Gas Removal
GHG	Greenhouse Gas
GNI	Gross National Income Per Capita
GSP	Geological Storage Potential
HS	Highly Suitable
HT DAC	High Temperature Aqueous Solutions Direct Air Capture
IAMs	Integrated Assessment Models
k	Optimum Number of Clusters
k-NN	k-Nearest Neighbour
LAM	Latin America and the Caribbean
LCEA	Low Carbon Energy Availability
LT DAC	Low Temperature Solid Sorbent Direct Air Capture
MCDA	Multi Criteria Decision Analysis
ML	Machine Learning
MNAF	Middle East and North Africa
MRV	Monitoring, Reporting and Verification
MSA	Moisture Swing Adsorption
NCS	Natural Climate Solutions
NDCs	Nationally Determined Contributions

NETs	Negative Emission Technologies
OECD	Organisation of Economic Co-operation and Development
P	Possible
PSA	Pressure Swing Adsorption
QP	Quarterly Mean Precipitation
QT	Quarterly Mean Temperature
REF	Reforming Economies of Central and Eastern Europe and the Former Soviet Union
S	Suitable
SCS	Soil Carbon Sequestration
SOC	Soil Organic Carbon
SSA	Sub-Saharan Africa
TRLs	Technological Readiness Levels
TSA	Temperature Swing Adsorption
U	Unsuitable
UNFCCC	United Nations Framework Convention on Climate Change
WA	Water Availability

1 Introduction

1.1 Background

The Earth is warming, with its surface temperature reported to be increasing by ~0.2 °C per decade (UNFCCC, 2015). Wildfires, droughts, and a rising global mean sea level are just a few of the effects of this climate change that are now felt globally (NOAA, 2022). Nine of the hottest years on record occurred between 2013 and 2021. The year 2021 ranked as the 6th warmest, with average global surface temperature increased by 1.04 ± 0.15 °C compared to that of the pre-industrial period (1880-1900) (NOAA, 2022). This observed increase in the global average surface temperature over the decades is majorly caused by the continuous increase in net anthropogenic greenhouse gas (GHG) emissions. These GHG emissions which is predominantly composed of carbon dioxide (CO_2) from fossil fuel combustion, industrial processes and land use related activities, also includes methane, nitrous oxide and fluorinated gases. The Sixth Assessment Report (AR6) by the Intergovernmental Panel on Climate Change (IPCC) indicates that the global net anthropogenic GHG emissions are increasing, with the 2019 value (59 ± 6.6 $GtCO_2$-eq) about 12% higher than in 2010 and 54% higher than in 1990 (IPCC, 2022). In 2022, the global energy-related CO_2 emissions was reported to reach a record high of over 36.8 Gt, which is a 0.9% increase from the previous year (IEA, 2022). There is therefore a great and urgent need to drastically reverse this increasing trend and thus prevent the ensuing climate breakdown. To this end, the IPCC has set an ambitious target of limiting the average global temperature rise to 1.5 °C by the end of the century (IPCC, 2022, 2018).

Meeting this target will involve a combination of two major approaches. The first involves the deployment of low to zero carbon dioxide emitting technologies/ methods such as fuel switching (biomass, green hydrogen), nuclear energy, renewable energy, as well as carbon capture and storage (CCS). While the second approach involves the removal of greenhouse gases (especially CO_2) currently present in the atmosphere. For this latter approach, a number of greenhouse gas removal (GGR) methods, sometimes referred to as negative

emission technologies (NETs) or carbon dioxide removal (CDR) techniques (McLaren, 2020), have been proposed. It is important to note that the deployment of GGR technologies has been identified as a major requirement in limiting global warming to 1.5 °C by the end of the century (IPCC, 2022, 2018). Under this scenario, between 100 and 1000 gigatonnes of global net anthropogenic CO_2 emissions is expected to be removed from the atmosphere before 2100 (Maher and Symons, 2022). In addition to removing historical emissions, GGR deployment will also serve to reduce the emission impact of hard-to-decarbonise sectors and provide a means for emission offset.

GGR methods typically involves the capture and removal of greenhouse gases (predominantly CO_2) from the atmosphere and their storage for an extended period of time. This process could be nature-based, engineered or a combination of both (hybrid). Storage options range from land-based biomass, oceans, underground geological reservoirs and the built environment (Figure 1-1). For land-based option, the carbon is stored in various forms such as plants, soil organic matter, carbonate materials and biochar. This storage option has the lowest permanence as they are vulnerable to reversals brought about by human actions such as deforestation, agricultural activities and fire, among others. Though oceans provide a promising option and high potential for carbon storage, it is, however, not currently being used owing to the significant uncertainties associated with it. Underground geological reservoirs are the most recommended options for CO_2 storage. This is on account of their permanence reliability and deployment readiness having been used in oil and gas exploration. These sub-surface storage options include depleted oil and gas fields, aquifers, in-situ mineralisation, structural traps and coal beds. The use of trees as building materials also offers storage option for carbon. The longevity of such storage is limited to the lifetime of the wood product or building for which it has been used. Events such as fires, however, renders this option vulnerable to reversals.

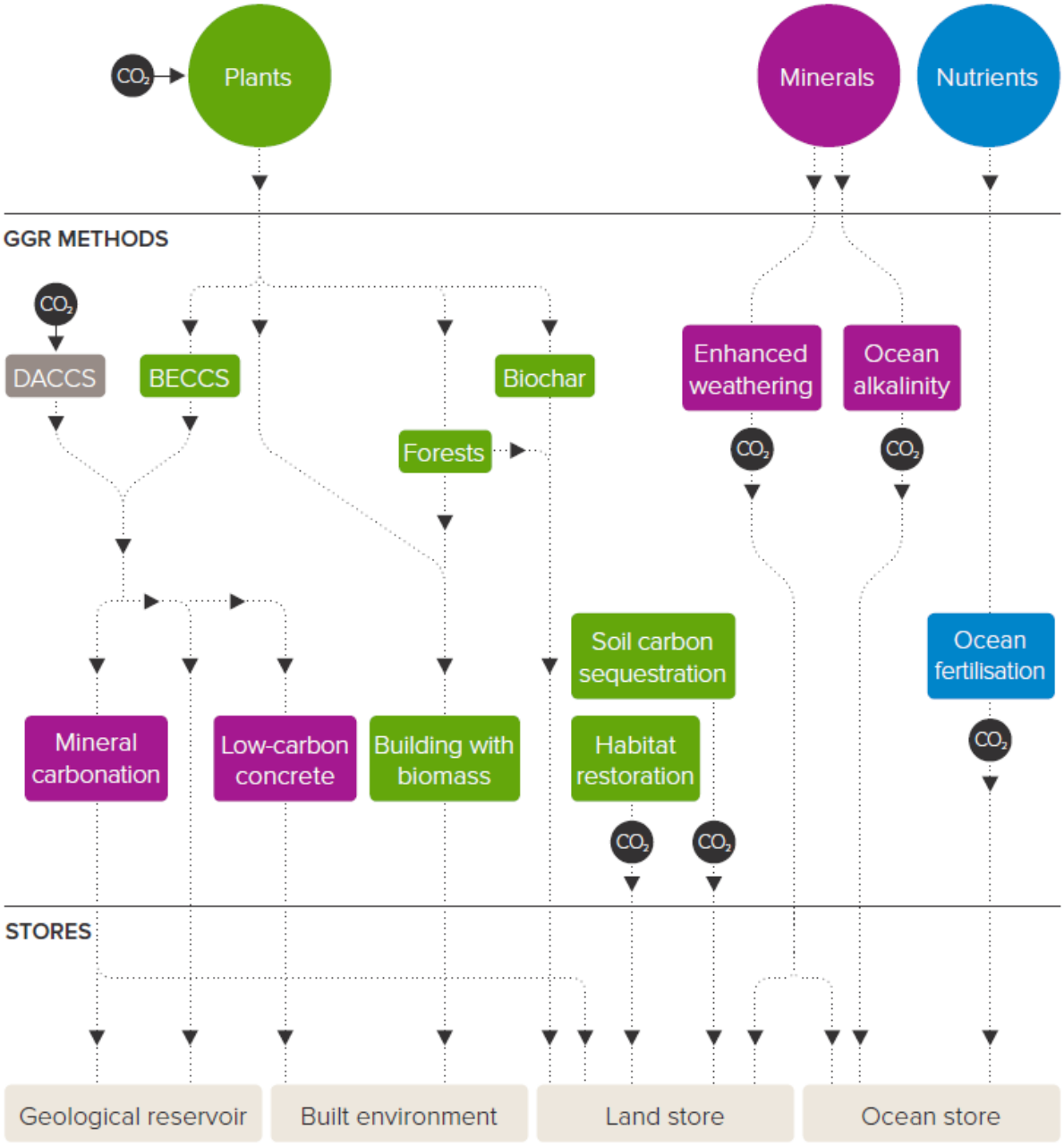


Figure 1-1 Process of CO_2 removal and storage for each GGR method (The Royal Society, 2018).

GGR methods include forestation, enhanced weathering (EW), soil carbon sequestration (SCS), biochar, direct air capture with carbon storage (DACCS), bioenergy with carbon capture and storage (BECCS), ocean fertilisation and habitat restoration, among others. While some of these methods like forestation and SCS have been fully developed and can be conveniently deployed for the

purpose of CO_2 removal, the other technologies are at various levels of technological readiness (TRLs) (Figure 1-2).

Despite the importance of GGR methods deployment in limiting warming to 1.5 °C, the nationally determined contributions (NDCs) submitted to the United Nations Framework Convention on Climate Change (UNFCCC) by countries indicate a low intent to deploy these technologies. Though with the exclusion of forestation measures (Pozo et al., 2020), this low level of inclusion of these technologies thus makes the 1.5 °C target unattainable (Roe et al., 2019; Rogelj et al., 2016; Schiermeier, 2015). Factors responsible for this low level of inclusion include; uncertainty about the technical potential, particularly given that some of the technologies are only at low- to mid TRLs (Figure 1-2), and uncertainty about socio-political factors (Bui and Mac Dowell, 2022; Buylova et al., 2021; Maher and Symons, 2022). Lack of thorough country-level bio-geophysical and techno-economic feasibility analyses to determine national GGR deployment potential is another important contributing factor. It is this latter factor that this study aims to address.

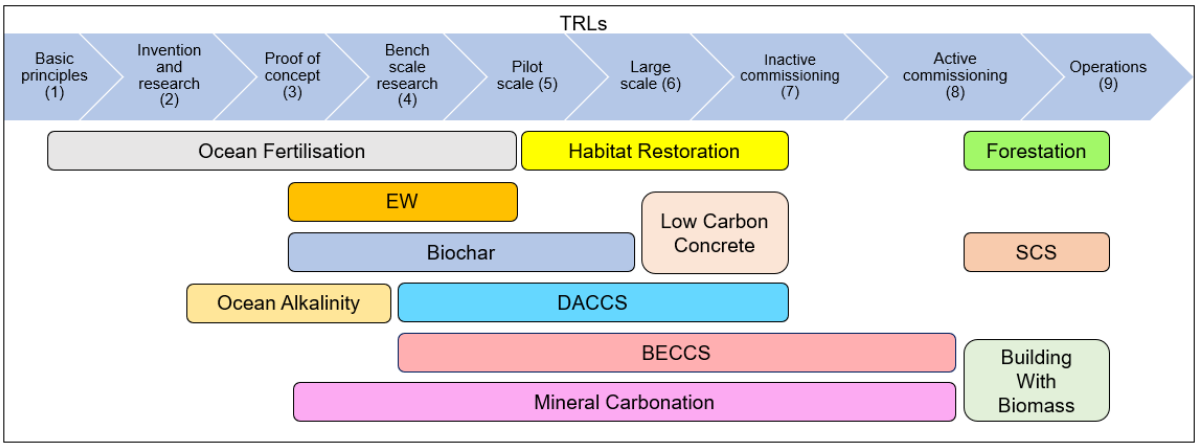


Figure 1-2 An illustration of the respective technological readiness levels (TRLs) of the various GGR methods (Lomax et al., 2015; The Royal Society, 2018).

With the performance of these technologies dependent on the prevailing bio-geophysical and techno-economic factors, this study seeks to assess the GGR deployment potential of 182 nations based on these factors. Bio-geophysical factors refers to a composite of the biological, geological and physical or

ecological characteristics or resources available in an area such as climate, land use, geological storage, vegetation and water. Techno-economic factors on the other hand refers to characteristics that assess the technological performance and economic feasibility of a process, system or value chain. While the former is largely natural, the latter is man-made and includes factors such as cost (capital and operational), gross national income and availability of utilities like low carbon energy. Considering the complexity of interaction of these factors and the need to greatly minimise human bias, Machine Learning (ML) as well as Multi – Criteria Decision Analysis (MCDA) approaches were adopted in the study. Five GGR technologies were considered based on their relatively higher CO_2 removal potential and advanced TRL. They are forestation, enhanced weathering (EW), direct air carbon capture and storage (DACCS), bioenergy with carbon capture and storage (BECCS) and biochar.

This study aims to provide useful insights for countries on the range of GGR methods that can be sustainably and effectively deployed in their territories. It could also provide an evidence-base to drive the need for international collaboration and resource sharing. It includes the development of a novel ML predictive model for national and sub-national GGR deployment assessments. These insights may enhance the decision-making process of concerned stakeholders, drive the development and scale-up of these technologies globally, and thus, promote their inclusion in the revised NDCs of nations.

1.2 Project Aims and Objectives

The aim of this research is to assess the country-level deployment potential of greenhouse gas removal pathways based on their respective bio-geophysical and techno-economic characteristics using ML and a multi-criteria decision analysis (MCDA) approach.

The objectives of this thesis can be articulated as follows:

1. Assess and identify the operational conditions required for optimum performance of GGR methods.
2. Categorise the global deployment suitability of GGR methods at the country-level using hierarchical clustering ML.

3. Apply supervised ML algorithms for resource mapping of GGR methods.
4. Evaluate the cumulative amount of CO_2 removable by 2100 via these GGR methods by each country using a MCDA approach, assessing sufficiency to meet quotas, and identify areas of regional competitive advantages and collaborations.

1.3 Novelty

The novel contributions of the research in this study can be outlined as follows:

- The major factors and conditions for optimum performance of these GGR methods are identified and assessed. Based on the assessment, a quantification of the impact of these operational factors on the performance of these GGR methods on a scale of 0 – 5 (low to high) is developed.
- A novel categorisation of the suitability of 182 countries to deploy five GGR methods (Forestation, EW, DACCS, BECCS and Biochar) was obtained. This was done via a novel application of an unsupervised ML algorithm known as hierarchical clustering. The range of GGR technologies that respective countries can suitably deploy are obtained. Priority regions and countries suitable for the deployment of these technologies are identified.
- For the first time, the applicability of Machine Learning in assessing GGR deployment suitability is comprehensively investigated. Supervised ML models to predict the suitability of a location to deploy five GGR methods based on the bio-geophysical and techno-economic characteristics of the location are developed.
- The projected cumulative amount of carbon dioxide removable by 2100 via five GGR methods (Forestation, EW, DACCS, BECCS and Biochar) is evaluated for each of the182 countries. Regions and countries with surplus deployment potentials are identified and evidence for international collaboration is developed.

1.4 Thesis Outline

The structure of this research and linkages of each part of the project are illustrated in Figure 1-3. The thesis outline is described as follows:

Chapter 1 – This chapter presents the background, aims and objectives of this project, as well as an overview of the thesis and linkages between publications and project outputs.

Chapter 2 – This chapter (published in Journal of Environmental Management, DOI: https://doi.org/10.1016/j.jenvman.2021.113039) addresses objective 1. It presents a review of the five selected GGR methods and soil carbon sequestration (SCS). It identifies and assesses the operational conditions (bio-geophysical and techno-economic factors) required and their impact on the performance of GGR methods. These identified factors formed the input variables for the assessment (objective 2 – 4), while the obtained impact ranking were applied in the MCDA assessment (objective 4).

Chapter 3 – This chapter presents details of the methodology applied in achieving the objectives of this study. It includes details of the data collection and pre-processing; description of the Hierarchical Clustering methodology, including a review on Machine Learning and description of applied codes; description of the Supervised ML methodology, including general description of the ML packages that were used, how they work mathematically, model interpretation and applied codes. It also includes the description of the methodology of the MCDA-based GGR potential evaluation, including description of MCDA, applied CDR quotas and some mathematical equations.

Chapter 4 – This chapter addresses objective 2. It presents the categorisation of 182 countries based on their suitability to deploy the selected GGR methods. This was done using the hierarchical clustering ML approach. It also includes sensitivity analysis to explore the robustness of the obtained categorisation. The output from this work package (suitability category) also served as label for the dataset that was applied in the supervised ML modelling (objective 3).

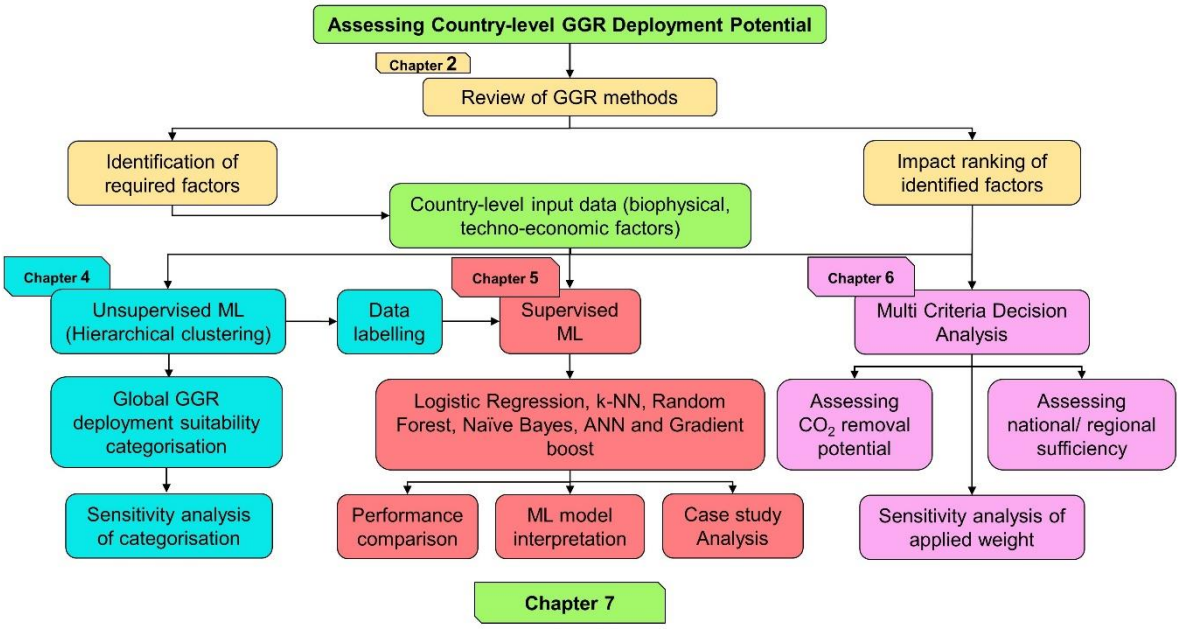


Figure 1-3 Structure and linkage of each work package in this thesis

Chapter 5 – This chapter, published in Energy in Climate Change, (DOI: https://doi.org/10.1016/j.egycc.2023.100112) is linked to objective 3. It explores the applicability of supervised ML algorithms in predicting GGR deployment suitability based on locational characteristics (resource mapping). It includes a case study analysis that was carried out to validate the ML model as well as model interpretation to assess the decision-making logic of the ML model.

Chapter 6 – This chapter (published in Journal of Environmental Management, DOI: https://doi.org/10.1016/j.jenvman.2022.116211) addresses objective 4. This chapter explores the cumulative amount of CO_2 removable by 2100 via these GGR methods by each country using a MCDA approach. It provides an evidence base to drive the need for regional collaborations and inclusion of GGR technologies in NDCs.

Chapter 7 – This chapter presents a general discussion of the findings of the study. It includes insights on how the study has changed the state of the art, reflecting on the aims and objectives, the key outcomes, the field and how the results might impact the deployment pathways and outlook of these technologies.

Chapter 8 – This chapter explores the implications of these findings, provides a summary of conclusion and recommendations for future research.

1.5 List of published/submitted work

Published papers and the chapters in which they are presented in this thesis are as follows:

1. **Asibor, J. O.**, Clough, P. T., Nabavi, S. A., & Manovic, V. (2021). Assessment of optimal conditions for the performance of greenhouse gas removal methods, *Journal of Environmental Management*, 294, 113039. (**Chapter 2**).
2. **Asibor, J. O.**, Clough, P. T., Nabavi, S. A., & Manovic, V. (2022). A Country-level Assessment of the deployment potential of greenhouse gas removal technologies. *Journal of Environmental Management*, *323*, 116211. (**Chapter 6**).
3. **Asibor, J. O.**, Clough, P. T., Nabavi, S. A., & Manovic, V. (2023). A Machine Learning Approach for Resource Mapping Analysis of Greenhouse Gas Removal Technologies. *Energy and Climate Change, 4,* 100112. (**Chapter 5**).

Submitted manuscripts under review and the chapters in which they are presented in this thesis are as follows:

1. **Asibor, J. O.**, Clough, P. T., Nabavi, S. A., & Manovic, V., A Machine Learning Approach for Country-level Deployment of Greenhouse Gas Removal Technologies. Submitted to the *International Journal of Greenhouse Gas Control*. (**Chapter 4**).

The author has also contributed to other publications not directly related to the subject of the thesis:

1. Yan, Y. H., Borhani, T., Subraveti, G., Pai, N., Prasad, V., Rajendran, A., Nkulikiyinka, P., **Asibor, J. O.**, Zhang, Z., Shao, D., Wang, L., Zhang, W., Yan, Y., Ampomah, W., You, J., Wang, M., Anthony, E. J., Manovic V. and Clough, P. T. (2021). Harnessing the power of machine learning for carbon capture, utilisation, and storage (CCUS)–a state-of-the-art

review. *Energy & Environmental Science*. https://doi.org/10.1039/D1EE02395K

1.6 References

Bui, M., Mac Dowell, N., 2022. Greenhouse Gas Removal Technologies. Royal Society of Chemistry.

Buylova, A., Fridahl, M., Nasiritousi, N., Reischl, G., 2021. Cancel (Out) Emissions? The Envisaged Role of Carbon Dioxide Removal Technologies in Long-Term National Climate Strategies. Front. Clim. 3. https://doi.org/10.3389/fclim.2021.675499

IEA, 2022. CO2 Emissions in 2022, International Energy Agency.

IPCC, 2022. Summary for Policymakers, in: Shukla, P.R., Skea, J., Slade, R., Al Khourdajie, A., van Diemen, R., McCollum, D., Pathak, M., Some, S., Vyas, P., Fradera, R., Belkacemi, M., Hasija, A., Lisboa, G., Luz, S., Malley, J. (Eds.), Climate Change 2022: Mitigation of Climate Change. Cambridge University Press, Cambridge, UK, pp. 1–30.

IPCC, 2018. Global warming of 1.5°C An IPCC Special Report on the impacts of global warming of 1.5°C above pre-industrial levels and related global greenhouse gas emission pathways, in the context of strengthening the global response to the threat of climate change,.

Lomax, G., Lenton, T.M., Adeosun, A., Workman, M., 2015. Investing in negative emissions. Nat. Clim. Chang. 5, 498–500. https://doi.org/10.1038/nclimate2627

Maher, B., Symons, J., 2022. The International Politics of Carbon Dioxide Removal: Pathways to Cooperative Global Governance. Glob. Environ. Polit. 22, 44–68. https://doi.org/10.1162/glep_a_00643

McLaren, D., 2020. Quantifying the potential scale of mitigation deterrence from greenhouse gas removal techniques. Clim. Change 162, 2411–2428. https://doi.org/10.1007/s10584-020-02732-3

NOAA, 2022. Assessing the Global Climate in 2021 [WWW Document]. Natl. Centers Environ. Inf. URL https://www.ncei.noaa.gov/news/global-climate-202112 (accessed 11.19.22).

Pozo, C., Galán-martín, Á., Reiner, D.M., Dowell, N. Mac, Guillén-gosálbez, G., 2020. Equity in allocating carbon dioxide removal quotas. Nat. Clim. Chang. https://doi.org/10.1038/s41558-020-0802-4

Roe, S., Streck, C., Obersteiner, M., Frank, S., Griscom, B., Drouet, L., Fricko, O., Gusti, M., Harris, N., Hasegawa, T., Hausfather, Z., Havlík, P., House, J., Nabuurs, G.J., Popp, A., Sánchez, M.J.S., Sanderman, J., Smith, P.,

Stehfest, E., Lawrence, D., 2019. Contribution of the land sector to a 1.5 °C world. Nat. Clim. Chang. 9, 817–828. https://doi.org/10.1038/s41558-019-0591-9

Rogelj, J., Elzen, M. Den, Höhne, N., Fransen, T., Fekete, H., Winkler, H., Schaeffer, R., Sha, F., 2016. Paris Agreement climate proposals need a boost to keep warming well below 2 ° C. Nature 534. https://doi.org/10.1038/nature18307

Schiermeier, Q., 2015. Combined climate pledges of 146 nations fall short of 2 ° C target. Nature 2–4. https://doi.org/10.1038/nature.2015.18693

The Royal Society, 2018. Greenhouse Gas Removal.

UNFCCC, 2015. Adoption of the Paris Agreement.

2 Assessment of Optimal Conditions for the Performance of Greenhouse Gas Removal Methods

Jude O. Asibor, Peter T. Cough, Seyed Ali Nabavi, Vasilije Manovic

Energy and Sustainability Theme, School of Water, Energy and Environment, Cranfield University, Bedford, Bedfordshire MK43 0AL, UK.

Submitted 30 April 2021; Accepted 6 June 2021

Published in the Journal of Environmental Management 294 (2021) 113039

DOI: https://doi.org/10.1016/j.jenvman.2021.113039

Abstract

In this study, a comparative literature-based assessment of the impact of operational factors such as climatic condition, vegetation type, availability of land, water, energy and biomass, management practices, cost and soil characteristics was carried out on six greenhouse gas removal (GGR) methods. These methods which include forestation, enhanced weathering, soil carbon sequestration, biochar, direct air capture with carbon storage and bioenergy with carbon capture and storage were accessed with the aim of identifying the conditions and requirements necessary for their optimum performance. The extent of influence of these factors on the performance of the various GGR methods was discussed and quantified on a scale of 0-5. The key conditions necessary for optimum performance were identified with forestation, EW, SCS and biochar found to be best deployed within the tropical and temperate climatic zones. The CCS technologies which have been largely projected as major contributors to the attainment of the emission mitigation targets were found to have a larger locational flexibility. However, the need for cost optimal siting of the CCS plant is necessary and dependent on the presence of appropriate storage facilities, preferably geological. The need for global and regional cooperation as well as some current efforts at accelerating the development and deployment of these GGR methods were also highlighted.

Keywords

Forestation; Enhanced weathering; Soil carbon sequestration; Biochar; Carbon capture and storage

2.1 Introduction

In order to mitigate against climate change, limiting the average global temperature rise to under 1.5 °C by the end of the century as stated in the Paris Agreement has been identified as a major need (UNFCCC, 2015). Meeting this target will involve a combination of various pathways which broadly includes a zero CO_2 emission technology deployment approach and an approach of reducing the amount of greenhouse gases (especially CO_2) currently present in the atmosphere (IPCC, 2018; Smith, 2016). For the latter approach, some greenhouse gas removal (GGR) technologies have been proposed. These include forestation, enhanced weathering (EW), soil carbon sequestration (SCS), biochar, direct air capture with carbon storage (DACCS), bioenergy with carbon capture and storage (BECCS), ocean fertilisation and wetland restoration among others. While some of these techniques, such as SCS and forestation, have been fully developed and easily applicable for CO_2 removal, the other technologies are at varying TRLs (Lomax et al., 2015; The Royal Society, 2018).

Several reviews on the state of development of these GGR methods have been reported in the literature. These studies which cover diverse areas provide salient information that is necessary for the development of these technologies to levels of safe and efficient deployment. A summary of these review studies and reports on multiple GGR methods published over the past decade are presented in Table 2-1.

Though the various reviews covering suites of GGR methods do address different focus areas as seen in Table 2-1, they however do generally agree that no single GGR method will be sufficient in meeting the climate warming target alone. There is therefore a need for a combination of various technologies which will also reduce risks of poor performance that could be associated with adopting a single method (McLaren, 2020). Though no particular combination of methods has been

explicitly adopted globally on account of the uncertainties associated with large-scale deployment (Thoni et al., 2020) and variations in prevailing regional bio-geophysical, techno-economic and socio-political factors, Integrated Assessment Models (IAMs) scenarios however consider BECCS and forestation as major applicable options in meeting the mitigation target (IPCC, 2018).

Table 2-1 Summary of existing review studies/reports on a suite of GGR methods

Reference	Study area of focus
McLaren (2011)	Technical assessment of NETs and their implications for climate policy.
McGlashan et al. (2012)	Techno-economic assessment of NETs.
Smith et al. (2015)	Assessed the potential biophysical and economic limits to be associated with the large-scale deployment of NETs.
Minx et al. (2018)	Assessed the role of NETs in mitigation scenarios, ethical implications and deployment challenges.
Fuss et al. (2018)	Reviewed and assessed the costs, potentials and side-effects of seven selected GGR technologies.
Nemet et al. (2018)	Reviewed the innovations and scaling challenges to be addressed to ensure effective NETs deployment.
The Royal Society (2018)	Provided a robust report on the range of globally available GGR methods with special focus on their effective deployment potential in the UK.
Haszeldine et al. (2018)	Assessed the progress journey of NETs within the framework of their readiness for deployment and contribution in meeting the emission mitigation target.
Hepburn et al. (2019)	Reviewed ten CO_2 utilisation and removal pathways with focus on their techno-economic prospects.
Roe et al. (2019)	A combined review of modelled pathways and literature on mitigation strategies aimed at assessing the contribution of the land-based GGRs to attaining the mitigation target.
Smith et al. (2019)	Assessed the opportunities and risks of land management based GGR options based on their impacts on ecosystem services and United Nations Sustainable Development Goals (SDGs)

Hilaire et al. (2019)	Reviewed NETs systematically while providing adequate linkage between the literature findings and the 1.5 °C/ 2 °C scenario evidence data.
Gough & Mander (2019)	Assessed the contribution of social science in enhancing the large-scale implementation of CCS and BECCS technologies.
Pires (2019)	Assessed recent works on NETs with the focus on project findings and probable challenges.
Goglio et al. (2020)	Reviewed the challenges and advances associated with life cycle analysis of GGR technologies.
Waller et al. (2020)	Reviewed the political and social dimensions of large scale GGR with focus on BECCS and forestation.

As summarised in Table 2-1, several existing literature reviews have been reported covering broad focus areas ranging from techno-economic to scaling and deployment issues as well as socio-political aspects. While reviews covering realistic deployment perspectives in regards to the extent of carbon removal and cost (Fuss et al., 2018) as well as biophysical limits (Smith et al., 2015) have been reported, a review to identify conditions for optimum performance of these GGR methods as well as perspectives on quantification of the impact of operational factors on the performance of these GGR methods are lacking.

With the performance of these GGR methods dependent on prevailing bio-geophysical, techno-economic and socio-political factors, there is a need to assess the conditions that will ensure optimum performance of the various GGR methods regarding locational characteristics. This knowledge is very important for the rapid scale up deployment of these technologies as it will assist in providing a pool of information that will aid policy makers and stakeholders at various levels in making decisions. Thus far, no review has been carried out in this regard, hence the need for this work.

The study involved a literature-based assessment of the impact of operational factors such as climatic condition, vegetation type, availability of land, water, energy and biomass, cost and soil characteristics on six GGR methods, namely: forestation, EW, SCS, biochar, DACCS and BECCS. The assessment was carried out with a view to identify conditions for optimum performance. The choice of this six GGR method was made based on their carbon removal potential,

technological readiness level (shown in Figure 1-2), CO_2 storage permanence, availability of information in the literature and public acceptance, especially considering their existing applications in agriculture and enhanced oil recovery. Table 2-2 presents a summary of the GGR selection criteria and the overall output (selected GGRs). The various GGR technologies were ranked based on the five selection criteria, using a traffic-light colour code system. For each criterion, green indicates high ranking, yellow indicates medium, while red indicates low.

Table 2-2 Summary of the criteria adopted in selecting the GGR methods

GGR Method	**Selection criteria**					**Overall output**
	Annual Potential ($GtCO_2$) [a, b]	**TRL** [b, c, d]	**CO_2 storage permanence** [a, b, d]	**Public acceptance** [b, d]	**Literature information availability**	
Forestation	0.5 – 3.6	8 - 9				
SCS	1 - 5	8 - 9				
EW	2 - 4	3 - 5				
DACCS	0.5 - 5	4 - 7				
BECCS	0.5 - 5	4 - 8				
Biochar	0.5 - 2	3 - 6				
Ocean fertilisation	1 - 3	1 - 5				
Ocean alkalinity	40	2 - 4				
Habitat restoration	0.2	5 - 7				
Mineral carbonation	-	3 - 8				
Building with biomass	0.5 - 1	8 - 9				
Low carbon concrete	>0.1	6 - 7				

[a] Fuss et al. (2018), [b] The Royal Society (2018), [c] Lomax et al. (2015), [d] Bui and Mac Dowell, (2022).

The paper is divided into three main sections. The first section covers the review of the major operational factors on the various GGR methods under consideration. In the second section, a comparison and assessment of the levels of impact of the various factors on the respective GGR methods will be carried out with a final section that briefly covers current trends and future outlook on GGR methods development.

2.2 Assessing the GGR technologies

Based on the current scale of deployment, TRL and mode of storage employed, GGR or CDR methods can be broadly classified into two groups: Conventional CDR on land and Novel CDR (Smith et al., 2023). The former refers to fully established methods (TRL 8-9) which are currently being deployed at scale, with the captured carbon stored in land or product. They include forestation, soil carbon sequestration practices as well as habitat restoration. Novel CDR, on the other hand refers to methods yet to be deployed at full scale (TRLs less than 8-9), with storage options ranging from geological sites, oceans or products such as biomass. They include DACCS, BECCS, EW, biochar, ocean alkalinity among others.

In this section, the applicable operational factors required for optimum performance of the six selected GGR methods were assessed from published works obtained from available academic literature. This section consists of six sub-sections dedicated to the respective GGR methods under consideration. Each assessment is preceded by a concise introduction covering the operational principle, co-benefits, advantages and disadvantages of the respective GGR method and concludes with a summary table highlighting the identified conditions and requirements for optimum performance.

2.3 Forestation

The growth and development of plants is dependent on the process of photosynthesis which is characterised by CO_2 absorption from the environment as shown in Figure 2-1. As a means of exploiting this natural means of CO_2 removal, the planting of trees which is collectively referred to as forestation has been identified as one of the GGR techniques (The Royal Society, 2018). This can be done by planting trees on lands not previously forested (afforestation) or on previously forested lands that have been harvested (reforestation) as well as the restocking of recently depleted land (restoration) with an emphasis on restoring ecological processes (Anderson et al., 2011). The estimated potential for GGR from forestation has been reported to vary from 3 to 12 $GtCO_2$ pa by 2100 with variations dependent on factors such as land availability, location, forest type and management as well as economic and biophysical constraints (The Royal Society, 2018).

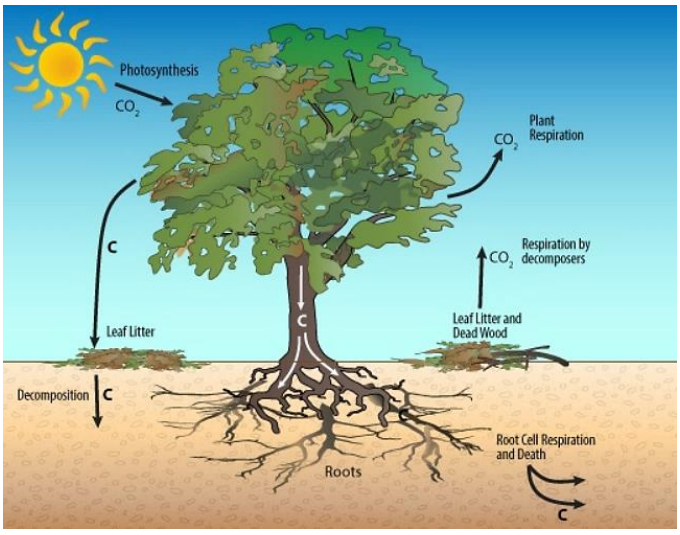


Figure 2-1 An illustration of a tree showing the carbon cycle for plants (TERC, 2020)

Aside carbon sequestration, co-benefits of this technique have been identified to include production of food, fuels and fibre, regulation of water services and air quality (Bonan, 2008), habitat for biodiversity (Ellison et al., 2017), erosion control, small floods mitigation, job creation as well as recreation (Smith et al., 2019). Alternatively, risks and negative consequences such as natural

disturbances, fire, climate variability (e.g. drought), enhancement of GHG fluxes from soils, permafrost thawing, deforestation, land use changes as well as albedo change especially in northern latitudes have also been identified (Doelman et al., 2019). The aspect of reversibility due to climate changes and/or direct human actions (Canadell and Raupach, 2008) as well as reduction in effectiveness of forestation with time on account of growth rate and land constraints have also been raised (Nunes et al., 2020). Smith (2016) even reports that forestation, potentially, may not be available after 2050 or less effective if implemented too soon.

In order to optimally apply this GGR technology, it is necessary to assess the major factors that affect its implementation with a view to identifying the optimum conditions for performance.

2.3.1 Land availability

The availability of land has been identified as a major constraint to the effective implementation of this GGR method on account of its competing use in agricultural, social and economic applications (Kreidenweis et al., 2016). Smith et al. (2015) reported a global land requirement of 320 to 970 Mha (about 2.3 – 6.5% of the global land mass) in order to attain the expected GGR potential by 2100 with a land intensity of forestation estimated at around 0.03 – 0.16 ha/tCO_2 pa. In order to maximise this scarce resource for GGR while ensuring that other land uses do not suffer, various forest management techniques and practices such as thinning optimisation, improved rotation as well as agroforestry among others have been prescribed. Abbas et al. (2017) identified agroforestry as a favourable management practice that ensures a good combination of environmental sustainability and agro-based activities.

2.3.2 Climatic condition

It is generally reported that carbon sequestration rate declines as latitude increases (Hartman, 2017; Mykleby et al., 2017). Tropical forests have been reported to have the highest aboveground carbon density and carbon sequestration potential compared to the subtropical, temperate and boreal forests

and are thus best suited for GGR by forestation (Bala, 2014; Goodman and Herold, 2015). This is due to factors such as higher productivity, increased evapotranspiration and increased surface reflectivity (albedo) effects which results in net cooling in the tropical forests (Fuss et al., 2018). Aside from local cooling, The Royal Society, (2018) also reports other favourable effects such as air and water filtering as well as rainfall recycling.

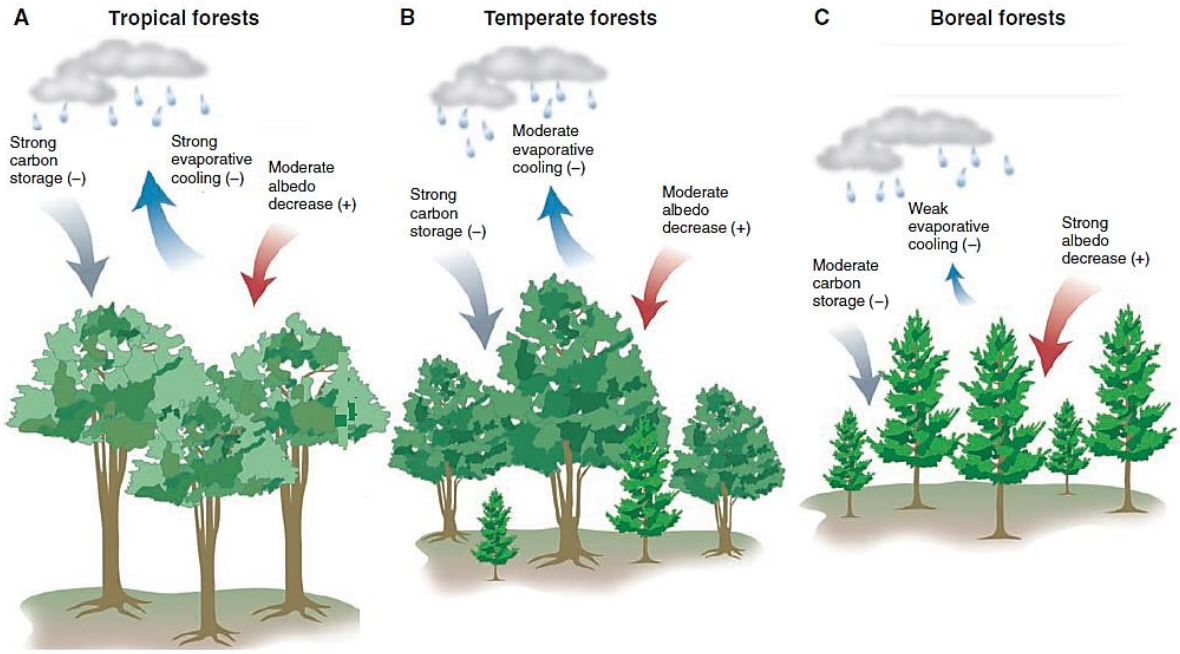


Figure 2-2 Climate services in tropical, temperate and boreal forests (reprinted with permission from Bonan (2008), Copyright 2008 Science)

Tropical forests are typically characterised by high tree growth rate and carbon sequestration rate of about 1 to 3.4 tC/ha pa (or 3.7 – 12.5 tCO_2/ha pa) (Abbas et al., 2017) capturing about 2.2–2.7 GtC pa (or 8.1 – 9.9 tCO_2 pa) (Goodman and Herold, 2015) which is up to three times that of boreal forests per unit of land (Arora and Montenegro, 2011). The effects of afforestation in the various climatic regions with variations in details (shown in Figure 2-2) was summarised as follows: cooling in the tropics, negligible or variable effects in temperate regions, and warming in higher latitudes. This warming effect is generally attributed to the reduction in albedo (heat-absorbing forest), changes in land cover as well as rate and magnitude of evapotranspiration (Favero et al., 2018; Kreidenweis et al., 2016).

2.3.3 Vegetation

While Hartman (2017) reported varying results for the impact of coniferous and deciduous forest species on carbon sequestration potential, Naudts et al., (2016) reported how an increase in afforestation in Europe (for over two and half centuries) did not result in net CO_2 removal from the atmosphere on account of reversibility effects (release of carbon stored in the biomass, litter, dead wood, and soil carbon pools) and change in vegetation type (from the deciduous broadleaf species to evergreen coniferous species (27% increase)). This change in species, which was commercially motivated, led to a reduction in evapotranspiration, thus decreasing atmospheric emissivity due to changes in albedo and canopy structure leading to warming (0.08 °C increase) rather than mitigating it. They therefore recommended deciduous species for GGR via forestation. Similar recommendation was made by Bonan (2008) and Anderson et al. (2011) who reported that deciduous species generally had a higher albedo and higher evapotranspiration in comparison to evergreen coniferous species.

In regards to choice of species and distribution, there is general agreement on the need to use diverse species of native origin (Mader, 2019; Matthies and Valsta, 2016). Hall et al. (2012) and Locatelli et al. (2015) explained that the use of native species in afforestation was considered superior in comparison to plantations for habitat quality and species diversity. They listed benefits to include reduced susceptibility to local conditions, greater variety of subsistence products and services, enhanced local management and acceptability. Hartman (2017) also identified reduction in catastrophic losses due to insect outbreak, disease, and fungal infection. Alvarez et al. (2016) reported a higher carbon sequestration potential for forest comprising of mixed wood species in comparison to monocultures. Similar result was reported by Hartman (2017), for both native and non-native mixed species plantations.

2.3.4 Other considerations

GGR using forestation is characterised by relatively very low if not negligible energy requirement thus making it applicable in areas of poor energy availability. In regard to water requirement, the proper siting of forest in high rainfall regions

ensures that this requirement is typically low and mostly insignificant as irrigation is often not required.

In regards to forest management practices, Naudts et al. (2016) reported that not all forest management practices contributed to climate change mitigation. Practices such as application of fertiliser can sometimes lead to emission increase depending on fertiliser type, application rate and soil characteristics (Snyder et al., 2009). For soil characteristics, Bouwman et al. (2002) on analysis of over 900 NOx emission measurements reported increased nitrous oxide (N_2O) emission to be favoured by fine soil texture, restricted drainage and neutral to acidic soil conditions with that of nitric oxide (NO) emissions enhanced by well-drained, coarse textured neutral soils. Monoculture planting has also been reported to increase runoff and reduce evapotranspiration (Anderson et al., 2011). As a means of managing competing land uses and conserving existing biomes, agroforestry (planting trees within agricultural environments) (Abbas et al., 2017; Ellison et al., 2017) and reforestation (Bond et al., 2019) have been recommended.

In regards to cost, Raihan et al. (2019) identified afforestation to be the most low-cost carbon sequestration option in comparison to other forestry options such as reforestation and forest management. While Fuss et al. (2018) reported the global afforestation cost per tCO_2 to range from US$2-150/$tCO_2$, Raihan et al. (2019) reported that a consideration of other management options will give a larger marginal cost per tCO_2 captured ranging from US$0-433/$tCO_2$ in 2011 prices (US$0-497.75 in 2020 prices). At the regional level, they reported that the cost of afforestation to be highest in Europe ranging from US$158-185/$tCO_2$ (US$180-210/$tCO_2$ in 2020 prices) and lowest in tropical regions ranging from US$0-7/$tCO_2$ (US$0-8.08/$tCO_2$ in 2020 prices). This was corroborated by Fuss et al. (2018) who opined that the global cost of afforestation could be reduced to a range of US$5-50/$tCO_2$ if afforestation were to be constrained for deployment in 500 Mha of tropical lands. This regional cost discrepancy is due to factors such as higher tropical tree growth rate and carbon sequestration rate, labour availability, labour cost as well as land opportunity cost.

2.4 Enhanced Weathering

Enhanced weathering involves the artificial stimulation (acceleration) of the natural weathering process thus transforming it from geological to a humanly relevant time scale (Andrews & Taylor, 2019; Hartmann et al., 2013).

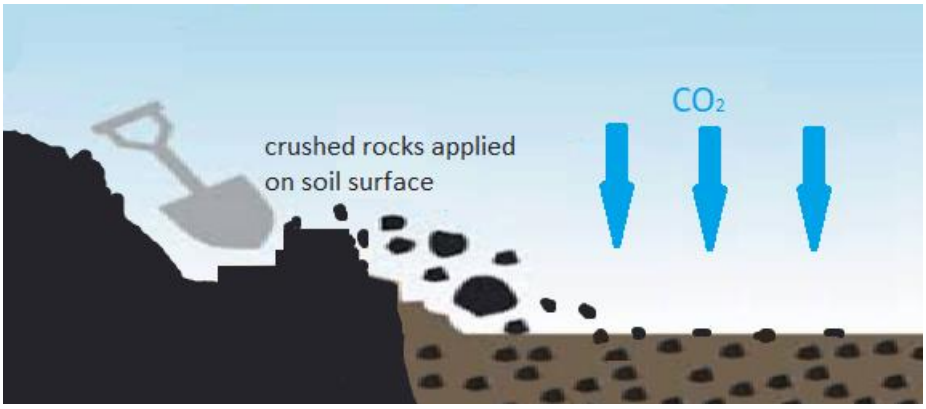


Figure 2-3 An illustration of the enhanced weathering process showing how rushed rocks that is dispersed over land captures atmospheric CO_2

As shown in Figure 2-3, it involves the grinding of selected rocks usually of calcium or magnesium content and spreading the resulting small grain sized rock over land (top-soils) or ocean surfaces which serve as storage sites for the CO_2 removed from the atmosphere. The grinding is aimed at increasing the reactive surface area and thus enhancing the mineral dissolution and CO_2 removal either as dissolved inorganic carbon and/or as carbonate minerals (Bach et al., 2019). Aside natural rocks, Fuss et al. (2018) identified other applicable materials to include mine waste, concrete or alkaline waste. Global removal potential by this GGR method assuming application in 900 Mha (two-thirds of croplands) is estimated to be between 0.5 and 2.0 $GtCO_2$ pa by 2050 (Beerling et al., 2020).

Some of the advantages of this GGR method include little or no additional land requirement as it can be co-deployed with the feedstocks for BECCS and biochars as well as no carbon capture and storage requirement. Aside carbon sequestration, a number of potential co-benefits include; soil productivity improvement, reduced N_2O loss through pH buffering, ocean acidity reduction, reduced usage of fertilisers as well as reduced cultural eutrophication (De Oliveira Garcia et al., 2020; Strefler et al., 2018). Alternatively, the mining process could

lead to challenges in health (e.g. respiratory issues), ecological and environmental negative impacts (Edwards et al., 2017) as well as ethical considerations (Lawford-Smith and Currie, 2017).

With temperature, pH, biological vectors (worms, fungi) and moisture generally identified as the major factors regulating the rate of natural weathering (Oelkers et al., 2018), it is necessary to assess these and other factors that affect enhanced (artificial) weathering process with a view to determining the optimum conditions for performance and application of this GGR method.

2.4.1 Climatic condition

Considering the factors of water availability (for the chemical weathering reaction) throughout the year as well as elevated temperature to enhance a faster weathering process, warm tropical climates as well as humid regions have been generally reported to be most suitable for the application of this GGR method (Bach et al., 2019; Meysman and Montserrat, 2017). Strefler et al. (2018) while recommending average ambient temperature requirement of 25 °C also identified best suited locations capable of realizing 75% of the global potential to include India, Brazil, South-East Asia and China. Water requirement is typically low estimated at 1.5 m^3/tCO_2 (Smith et al., 2015) and it is expected to be based on precipitation.

2.4.2 Geology

The two major rocks with a GGR potential of 4 $GtCO_2$ pa recommended for the application of this method are basalt and dunite rock (Köhler et al., 2010; Schuiling, 2017). The dunite rock is an ultramafic, low silica rock consisting of forsteritic olivine. Though it would ordinarily be considered as best suited on account of its high weathering efficiency, its usage is however hindered by the presence of harmful trace elements (specifically Ni and Cr), which can potentially be released into the environment during dissolution (Amann et al., 2020; Strefler et al., 2018). Basalt (a mafic rock with olivine) on the other hand, though characterised by a lower weathering efficiency (higher grinding cost) is the most recommended option. This is as a result of its advantages and co-benefits such

as widespread abundance accounting for about 6.8M km^2 of the Earth's surface (about 4.56% of the world's land mass), and significantly more beneath the surface and under the oceans (Dessert et al., 2003). It is also characterised by fewer trace elements as well as the presence of nutrients such as phosphorus, magnesium, and calcium, whose application are highly beneficial to croplands (Strefler et al., 2018).

In regards to the most suitable soil for spreading of the weathered rocks, deeply weathered acidic tropical soils have been generally recommended (De Oliveira Garcia et al., 2020; Taylor et al., 2016). This is on account of the soil alkalinity-increasing effect of the added rock powder.

2.4.3 Energy and Cost

GGR by enhanced weathering is characterised by significant energy requirement estimated between 0.81 – 12.5 GJ/tCO_2 pa (0.05 – 8.38$GJ_{electricity}$/tCO_2 and 0.76 – 4.12$GJ_{primary}$/tCO_2) covering the areas of rock extraction (mining and crushing), grinding and transportation which account for 77–94% of the energy requirements collectively (Renforth, 2012). In addition to this high energy requirement, additional CO_2 emissions released during the mineral processing are expected to reduce gains made by enhanced weathering by an estimated 5–30% of potential C sequestered (Kantola et al., 2017). Strefler et al. (2018) reported a target grain size-dependent electricity demand for grinding with a best estimate ranging from 0.07 GJ/t rock for 50 µm to 3 GJ/t rock for 2 µm. This shows that the smaller the target grain size, the higher the overall energy demand.

Closely associated with the energy requirement of this GGR method is the significant cost covering the already identified process areas as well as the distribution on croplands. Fuss et al. (2018) estimated the annual cost requirement for a potential of 2 – 4 $GtCO_2$ from 2050 to be in a range of US$50–200/$tCO_2$. This estimate did not include biological storage in plants brought about by soil fertilisation effect of the applied weathered rock. They also explained that the cost was very much dependent on the chosen technology for rock processing and transport adopted as well as the rock source. The impact of rock source on the cost was reported by Strefler et al. (2018) with costs of carbon removal for

dunite around US$60 per tCO_2 and that of basalt about US$200 per tCO_2. This result was corroborated by Renforth (2012) who assessed the impact of the rock source on the operational costs. He reported operational cost of US$24–123/$tCO_2$ for ultramafic rocks (dunite) and US$70–578/tCO2 for mafic rocks (basalt). The relative cheapness of dunite over basalt as shown in these assessments lies in the high weathering efficiency characteristics of dunite which ensures a lesser grinding energy requirement. Despite this seemingly advantage, basalt still remains the most suitable option on account of its previously discussed advantages and co-benefits.

Overall, Renforth (2012) estimates the cost of enhanced weathering to be in the range of US$52-480/$tCO_2$, dominated by mineral processing and transport. While this significant energy and associated cost requirement could hinder the application of this GGR method in developing areas of the world (characterised by insufficient energy despite having an abundance of the suitable rocks and required climatic conditions), Fuss et al. (2018) offers hope by insisting that the energy requirement would decrease significantly in the future on account of expected transition to renewable energies and technological advancement.

2.4.4 Other considerations

The need for dedicated land requirement is very minimal with land intensity value reported to be less than 0.003 ha/tCO_2 (Smith et al., 2015). This is because aside the mining site and space for processing, the distribution of the milled rocks can be co-deployed on land serving other functions like forests, feedstocks for BECCS and biochars. Agricultural and arable lands have been recommended as most viable options for application of the weathered rocks on account of the logistics cost associated with distribution of the weathered rocks and biological impact (plant roots, organic acids) in increasing weathering rates (Amann et al., 2020; Andrews and Taylor, 2019). Kantola et al. (2017) however called for caution on the choice of farm management practice adopted as carbon losses from agricultural soils could occur due to soil disturbance, crop harvest and microbial activity. To minimise respiratory issues, Strefler et al. (2018) recommends the

use of slurry in the application of fine particles as a means of minimising the risk of dust and respiratory hazards.

2.5 Soil carbon sequestration

Soil carbon sequestration (SCS) is a GGR method that involves deliberate change in land management practices with the aim of increasing the soil organic carbon (SOC) content, thus removing CO_2 from the atmosphere (Lal, 2013). Stockmann et al. (2013) however added that not all increases in SOC were a true net transfer of carbon from the atmosphere to land as some are just a movement of SOC from one location to another, and have no influence either positive or negative, on climate change. Hence the land management practice should be deliberately applied for the GGR purpose relating to either crop, soil nutrient, vegetation, animal or fire. Common forms of SOC include surface plant residue, buried plant residue, particulate organic matter, humus, resistant organic carbon (biochar).

The global annual potential of SCS stands between 1.1 and 11.4 $GtCO_2$ as reported by The Royal Society (2018). The advantages of this GGR method includes low impact on land, water use, albedo, energy requirement and cost (aside the usual cost incurred by farm practices). Co-benefits include improvement in soil health, plant growth and production, thus enhancing food security, increasing biodiversity as well as environmental protection (Abdullahi et al., 2018). Alternatively, SCS is limited by issues of reversibility, feasibility and cost of measuring, monitoring, verification and sink saturation. Smith (2016) reported a saturation time of 20 years and Goh (2004) gave a range of 15-50 years (longer in colder regions). The rate of SCS decreases with time with its efficacy reported to be greatest in the short to medium term (Lassaletta and Aguilera, 2015). Sykes et al. (2019) also identified issues of environmental heterogeneity and differences in agricultural practices as challenges to the practical implementation of SCS.

SCS depends on a variety of factors such as existing SOC, soil type, climate and management practices coupled with social and economic conditions in place such as labour cost and food production needs (Kumar, 2017). The impacts of these factors are assessed in the following sections with a view to identifying the conditions for optimal performance.

2.5.1 Management Practices

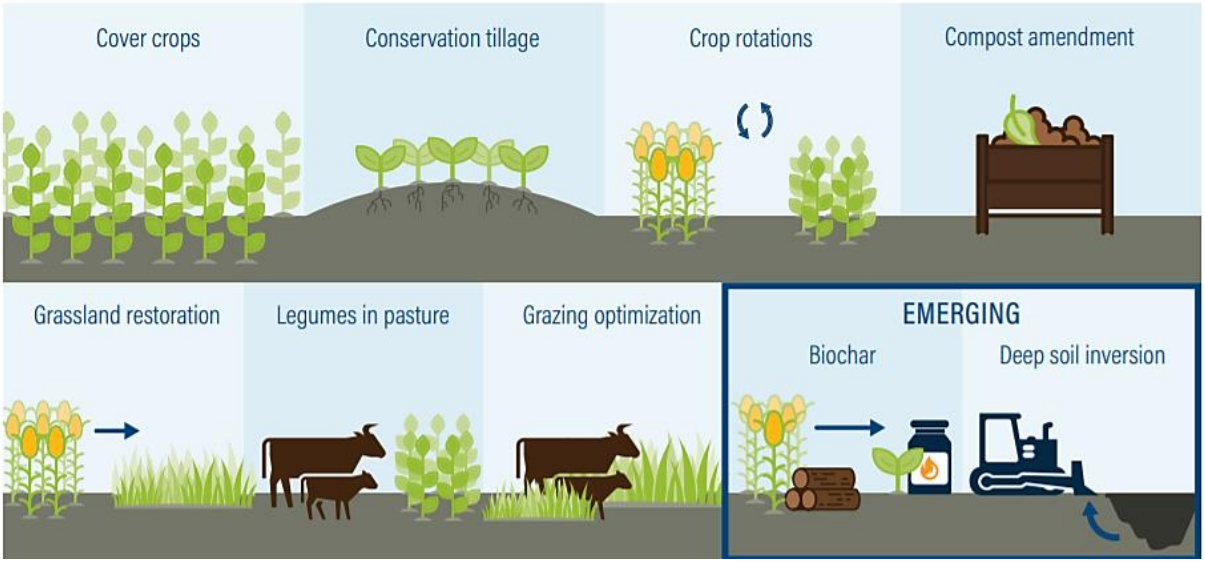


Figure 2-4 Land management practices for SCS (reprinted with permission from Mulligan et al. (2020), Copyright 2020 World Resources Institute).

Sykes et al. (2019) identified the broad classes of management practices to include: soil structure (prevent or control soil erosion, optimise fire frequency and timing, practise reduced or zero tillage), grazing land (optimise stocking density, renovate unimproved pasture), improved rotation (extend perennial phase of crop rotations, implement cover cropping), inorganic resource (optimise soil synthetic nutrient input, practise mineral carbonation of soil, manage soil pH), organic resource (optimise use of organic amendments, retain crop residues, apply biochar), soil water (optimise irrigation (Olsson et al., 2014)) and agroforestry systems implementation (Magnússon et al., 2016). Some of these practices are presented in Figure 2-4.

Considering the large number of management practices in existence, the specific choice applicable to a particular land area is dependent on factors such as region

(climate and vegetation), use, maturity and resource availability. Aside these factors, it is recommended that the ease of deployment of the chosen management practice by farmers and land managers should also be considered. For GGR application, it is recommended that chosen practice should be able to sequester carbon for a long time and improve soil characteristics. Conservation agriculture (including no-till agriculture, cover cropping, and crop rotation) have been reported to perform fairly well in this regard as it ensures that the soil structure is not disturbed while carrying out agricultural activities (Hunt et al., 2020; Kumar, 2017). Powlson et al. (2014) and Powlson et al. (2016) however added that its implementation was limited by factors such as land area constraint, availability of suitable machinery as well as likelihood of rapid decomposition at elevated temperatures. They therefore recommended other practices related to water and nutrient management (manure) as well as through improved feeding practices and management of ruminant livestock. The use (planting) of perennial grass on account of its deep root system that assists in sequestering carbon has also been recommended (Franzluebbers, 2012; Whitmore et al., 2015).

In regards to land use change, Stockmann et al. (2013) reported based on reviewed literature that land use change from cropland to pasture or cropland to permanent forest resulted in the greatest gains of SOC. De Stefano & Jacobson (2017) in a meta analytic study went further to report changes in SOC on account of land use change with increase for cropland-agroforestry (26-34%), pasture-agroforestry (9-10%), uncultivated land to agroforestry (25%) and decrease in the case of forest-agroforestry (26-24%) in top soil layer. These changes were mainly due to minimised carbon losses brought about by tillage and other soil structure distorting activities.

Lal (2008) outlined best management practices for temperate and tropic climatic regions on the basis of potential rates of carbon sequestration. Conservation tillage and soil restoration in humid conditions had highest sequestration for temperate climatic biomes (0.5 – 1.0 tC/ha pa or 1.8 – 3.7 tCO_2/ha pa). For tropical climatic biomes under humid condition, soil restoration (0.8 – 1.2 tC/ha pa or 2.9 – 4.4 tCO_2/ha pa), improved grazing (0.4 – 0.8 tC/ha pa or 1.5 – 2.9

tCO_2/ha pa) and agroforestry (0.4 – 0.8 tC/ha pa or 1.5 – 2.9 tCO_2/ha pa) had highest sequestration potentials.

2.5.2 Climate

The impact of temperature and precipitation on the sequestered carbon has also been assessed. While Sykes et al. (2019) reported that the high susceptibility of SOC to erosion in areas with high amount of rainfall could impede SCS performance, Stockmann et al. (2013) explained that there was room for further investigation on erosion impact as eroded SOC were likely to be reburied in a different location via terrestrial sedimentation. Godde et al. (2016) reported that SOC sequestration decreased with increase in both temperature and rainfall on account of increased soil water content and high soil temperature that enhanced SOC decomposition. There is a general agreement in the literature on the enhancing effect of high temperature on the SOC decomposition with Stockmann et al. (2013) making a case for cool/cold, humid climate regions as viable options for this GGR method. This was corroborated by Anderson et al. (2011) and Lal et al. (2015) who reported that the rate of SOC sequestration was higher in soils of cool and humid than warm and dry climates. Godde et al. (2016) however, reported that high temperature and rainfall could also increase SOC sequestration under certain conditions by enhancing plant growth and subsequent biomass return to the soil. They concluded that the influence of climate on SOC was dependent on other variables such as soil characteristics and adopted farming practices.

2.5.3 Vegetation and Soils

In regards to SOC sink capacity, boreal or snow forest (Taiga), tropical forest as well as temperate grassland/ savannah were reported to have the highest storage capacity (471 GtC, 316 GtC and 295 GtC respectively) in comparison to other biomes regardless of the soil depth considered (Stockmann et al., 2013). This is equivalent to 1728 $GtCO_2$, 1160 $GtCO_2$ and 1083 $GtCO_2$ respectively. They also reported a fairly large SOC storage capacity for tropical grassland/shrubland as well as wetlands and added that increased plant diversity could increase SOC.

For soil type, Laganière et al. (2010) reported that clay-rich soils (>33%) had a greater SCS capacity than soils with lower clay content on account of its fine particles which assist in the stabilisation of organo-mineral complexes. This was corroborated by Lal et al. (2015) who reported that the rate of SOC sequestration was higher in soils of heavy or clayey than light or sandy texture and added that soils of agroecosystems (such as croplands, grazing lands, drastically disturbed and degraded lands) were also favourable or SCS on account of their large carbon sink capacity (high potential for SOC).

2.5.4 Other considerations

Additional land requirement is almost negligible on account of no land use associated competition in the deployment of this GGR method. Smith (2016) however puts the average land requirement at 0.27 – 8.99 ha/tCO_2 (which could be cropland, grassland and/or degraded land restoration). Cost is typically low and dependent on adopted management practice with Fuss et al. (2018) reporting an estimate of US$0–100/t$CO_2$. Lal et al. (2015) reported the effect of governance policy in regard to land right and supporting policy as a major factor that could contribute to soil degradation especially in the developing countries of the world.

2.6 Biochar

Biochar is obtained from the thermal degradation of organic material in the absence of oxygen (pyrolysis) (Shackley et al., 2013). Other thermochemical processes for producing biochar include gasification, hydro thermal carbonization (HTC) and torrefaction (Qambrani et al., 2017). Considered to be more stable than soil organic matter, biochar ensures long time sequestration of carbon on the soil in which it is applied with mean residence time estimated between 1000 – 4000 years (Brassard et al., 2016; Lorenz and Lal, 2014). Though this method has an estimated global GGR potential in the range of 1.8 to 4.8 GtCO_2 pa, its application has been partly limited by cost factors as well as limited availability of pyrolysis facilities and biomass (The Royal Society, 2018). Considering these

limitations, Fuss et al. (2018) estimated a lower potential range of 0.3 – 2 $GtCO_2$ pa by 2050.

The advantages of GGR using biochar have been reported to include lower impact on land, water use, nutrients, albedo, energy requirement and cost (Blanco-Canqui, 2017). In addition to soil carbon sequestration, other co-benefits of biochar application include energy production from the pyrolysis process (syngas), soil improvement, waste treatment and as fuel (bio-oil) (Tisserant and Cherubini, 2019). Negative aspects of biochar application covering contamination (heavy metals, polycyclic aromatic hydrocarbons (PAHs)), alteration to soil properties, alterations to soil biota, probable wind and water (erosion) effects, soil darkening leading to increase soil temperature, as well as increase in GHG emissions in some cases brought about by factors such as abiotic release of inorganic carbon, the decomposition of labile components of biochars, and the decomposition of organic matters or humus by biochar have been reported in the literature (V. D. Nair et al., 2017; Tisserant & Cherubini, 2019).

This GGR method is dependent on factors such as biomass availability and source, land use, climatic condition, soil characteristics as well as socio-economic factors (Bajamundi et al., 2019; Zimmerman et al., 2011). An assessment of the impact of these factors is carried out in the succeeding sections with a view to identifying the optimal conditions suitable in applying this GGR method.

2.6.1 Land availability

GGR by biochar application has a very low land requirement estimated to be less than 0.3 ha/tCO_2 (Smith, 2016). For the annual GGR potential of 1.8 to 4.8 $GtCO_2$, The Royal Society (2018) estimated the land requirement for biochar spreading to range from 14 and 26 Mha (less than 0.18% of global land area) at an application rate of 50 t biochar per ha. Both studies agreed on the need for additional land to cultivate dedicated biomass feedstock, with the latter reporting a value of over 50 Mha to account for over 50% of the total required biomass.

2.6.2 Biomass Feedstock

Several sustainable sources of biomass feedstock for biochar production have been identified in the literature to include biodegradable materials such as forestry slash, dead biomass, crop residues, and urban yard wastes from carpentry, municipal areas, mills, and factories as shown in Figure 2-5.

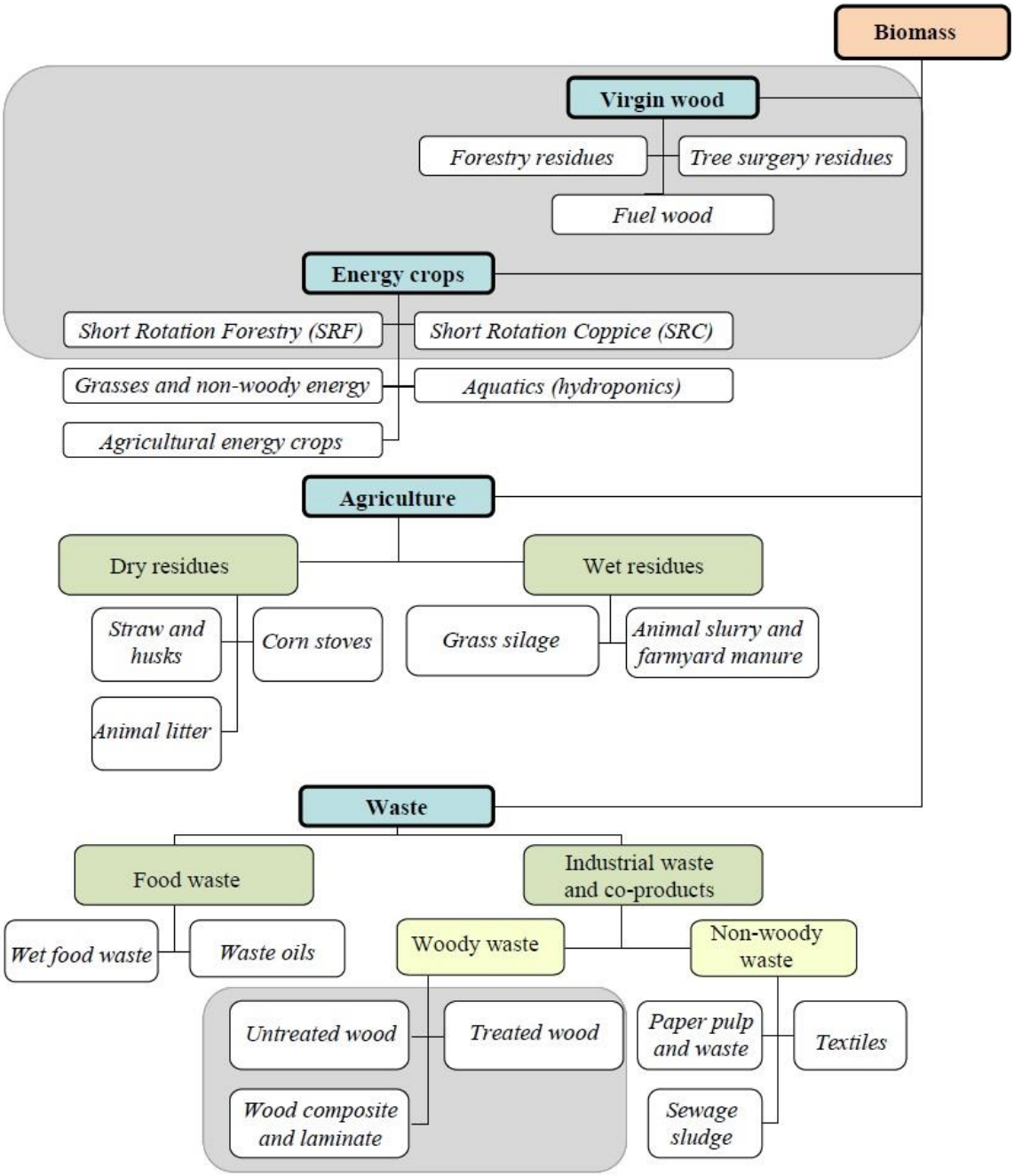


Figure 2-5 The various forms of biomass feedstocks and their sources (Ladanai and Vinterbäck, 2009)

Brassard et al. (2016) and Tisserant & Cherubini (2019) recommended lignocellulose and woody biomass as a viable option for biochar production on account of their carbon richness and enhanced stability in soils. the former however cautioned on the need to ensure that biomass cultivation did not compete with food production. Blanco-Canqui (2017) however argued that biochar from herbaceous feedstocks enhanced soil physical properties better than woody biomass with Liu et al. (2019) suggesting the use of feedstock from crop residue as best option for biochar production on the basis of overall cost reduction. Though the literature mostly recommends plant-based biomass for biochar production, there is need to also incorporate available animal biomass or manure, as biochar from this source has been reported to have higher pH than those pyrolyzed from plants (Li et al., 2018; Zhang et al., 2019).

2.6.3 Soil

The potential of biochar as a GGR method when applied to soils is very much determined by the complex interaction of various factors such as the soil type, soil moisture content, initial soil pH, biochar type, biochar application rate as well as soil organic carbon (SOC) effect (Nair et al., 2017). It is also important to note that in most reported studies, the extent of performance of GGR by biochar varied for the different greenhouse gases (Li et al., 2018; Wang et al., 2020).

In regards to the impact of soil pH and texture, conflicting results do abound in the literature. Tisserant & Cherubini (2019) and Zhang et al. (2019) reported that the greatest positive influence of biochar occurred in acidic and neutral soils. This was attributed to the liming effect of biochar which generally has a high pH with Brassard et al. (2016) reporting an average value of 8.6. Senbayram et al. (2019) on the other hand, reported an increase in greenhouse gas (GHG) emissions (CO_2 and N_2O) in acidic sandy soils on addition of the biochar which they linked to stimulated microbial activity and positive priming driven by biochars liming. A 12% reduction in CO_2 emissions with no significant effect on N_2O emissions was however reported for alkaline clay soil.

For soil texture impact, Zhang et al. (2019) reported that sandy and paddy soils (wet/flooded arable soil for planting crops like rice) had significant GHG

reductions. Tisserant & Cherubini (2019) however favoured soils of high clay content on account of their decomposition reducing property. The results of these studies were further compounded by that of Liu et al. (2019) who reported that soil pH and texture generally had little impact on the response of GHG intensity to biochar application. A general explanation for these discrepancies of observations which is largely reported in most literature lies in the fact that biochar effects on soil are biochar-, soil-, and plant-specific.

More often than not, the biochar sequesters carbon in the soil alongside existing SOC. While Zhang et al. (2019) explained that such interactions could accelerate SOC loss, thus reducing biochar carbon sequestration potential, Brassard et al. (2016) and Majumder et al. (2019) reported that such interactions could enhance biochar stability in high clay content soils as well as well-drained sandy soils with lower SOC and lower total nitrogen contents. Qambrani et al. (2017) made a case for soil moisture content impact noting that higher contents of greater than 70% moisture promoted the anaerobic conditions that enhanced denitrification, thus mitigating N_2O production.

In order to ensure that the co-benefits of soil improvement and increased yield are optimised, it has been largely suggested that biochar be applied on soils with naturally low fertility (Lorenz and Lal, 2014; Woolf et al., 2010; Yadav et al., 2017). Brassard et al. (2016) recommended agricultural soils for biochar application with Li et al. (2018) making a case for forest soils. Overall, the extent of impact of GGR using biochar is specific to the particular soil characteristics, the biochar as well as the management factors.

2.6.4 Other considerations

Biochar is typically one of the products of an energy generation process. According to Sykes et al. (2019), except in cases involving wet feedstock, the energy required for biochar production can be recovered from the gases produced in pyrolysis. Smith (2016) estimated an energy generation potential of 20 – 50 GJ/tC of biochar (or 5.45 – 13.62 GJ/tCO_2), out of which 10% and 20% are process energy cost and energy loss in pyrolysis plants, respectively.

A key characteristic of biochar that distinguishes it from SOC is its stability in the soil over a very long period of time. This high residence time can be lowered under higher temperature typical in tropical and sub-tropical regions coupled with acidic soils (Zimmermann et al., 2012). Brassard et al. (2016) recommended areas with mean annual temperature of 20 °C to ensure stability over a few centuries.

For cost, Fuss et al. (2018) on assessment of the various literature-based cost estimates, reported between US$30 – 120/t$CO_2$ with actual cost expected to be dependent on factors such as feedstock availability, applied biochar production technology and application (spreading) strategy adopted.

2.7 Direct Air Carbon Capture and Storage (DACCS)

This GGR technology involves the exposure of sorbents with high CO_2 affinity to the atmosphere with the aim of removing the atmospheric CO_2 through the formation of chemical bonds with these materials. These sorbents are then recovered by a regeneration process for re-use with the captured CO_2 separated and either utilised or stored as presented in Figure 2-6.

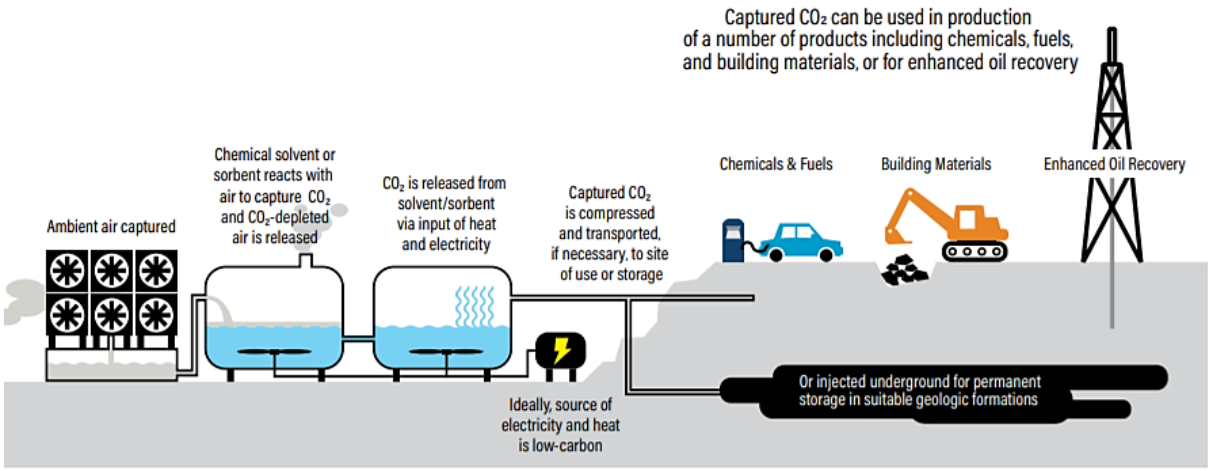


Figure 2-6 Schematic illustration of DACCS (reprinted with permission from Mulligan et al. 2020), Copyright 2020 World Resources Institute).

It is important to note that this technology is not fully developed with a number of demonstration and pilot scale efforts reported in the literature (Fasihi et al., 2019; Viebahn et al., 2019) and large-scale commercial application predicted to be available from 2030 (Bui et al., 2018). With a global GGR potential estimate of between 0.5-5 $GtCO_2$ annually in 2050 and around 40 $GtCO_2$ by 2100 (Fuss et al., 2018), this technology is expected to play a major role in attaining the goals of the Paris Agreement on climate change contributing about 15-20% of global CO_2 emissions reduction by 2050 (Haszeldine et al., 2018).

Some advantages of this technology, though with uncertainties as reported by Gambhir & Tavoni (2019) includes its minimal overall land use, water removal and ecosystem health impact in comparison to other GGR technologies. Though it can be applied at any location worldwide thus making capture possible in regions without concentrated CO_2 sources, herein also lies some of its major challenges of decreased system efficiency brought about by the large flows of air required for a relatively small amount of CO_2 captured with Bui et al. (2018) reporting about 80,000 m^3/s of air required to capture 1 $MtCO_2$ pa. While this will increase the overall capture cost, other constraints and concerns have also been identified to include storage, monitoring and leakage considerations, energy and material intensiveness as well as probable environmental impact (Fasihi et al., 2019; Sanz-Pérez et al., 2016).

Though the captured CO_2 could be utilised as feedstock for power, transport and industrial applications with its attendant benefits of value addition and probable offset of capture cost (Anwar et al., 2020), this however poses a risk to the carbon mitigation effort with large scale deployment (enhanced oil recovery (EOR)-CCS industry) reported to account for about 4-8% of the mitigation challenge (Mac Dowell et al., 2017). Other concerns associated with the utilisation option include its low incentive offering for investment since CO_2 supply vastly exceed demand (Boot-Handford et al., 2014), efficiency of the conversion process as well as the high likelihood of reversibility (Hepburn et al., 2019), thus making it a distraction and a not-so-good idea if emissions targets are to be met.

Various types of DACCS technologies exist mainly dependent on the type of sorbent used which could be in aqueous solution form with common examples being potassium hydroxide (KOH) and sodium hydroxide (NaOH), or in the solid state like the amine-based sorbents (Boot-Handford et al., 2014). On the basis of sorbent type and regeneration mechanism, Fasihi et al. (2019) reviewed and categorised the major DACCS technologies into high temperature aqueous solutions (HT DAC) and low temperature solid sorbent (LT DAC) systems. Examples of these technologies (which are best identified by the name of their respective developing companies) are shown in Figure 2-7.

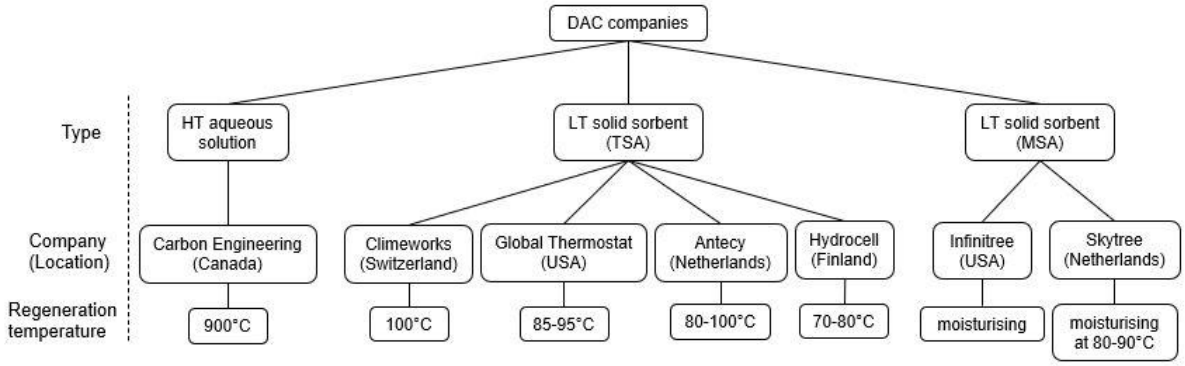


Figure 2-7 Companies active in the field of CO_2 DAC. Abbreviations: moisture swing adsorption, MSA, temperature swing adsorption, TSA (reprinted with permission from Fasihi et al., (2019), Copyright 2019 Elsevier).

Aside these major adsorption based technologies (TSA and MSA), other approaches such as electrochemical systems, ion-exchange resin systems, nanofactory based filters, photocatalytic approach, membranes technology and crystallisation-based systems have also been proposed and reviewed (Fasihi et al., 2019; Sanz-Pérez et al., 2016). It is important to note that pressure swing adsorption (PSA) technology which is highly effective in point source capture from flue gases has been generally reported as a non-viable option for direct air capture on account of the energy-intensive compression requirement of the feed air (Elfving et al., 2017; Stuckert and Yang, 2011; Wurzbacher et al., 2011). A faradaic electro-swing reactive adsorption system has also been proposed with high CO_2 capture effectiveness reported to be limited to flue gases and confined ambient environments (0.6-0.8% CO_2 concentration) (Voskian and Hatton, 2019).

To ensure economic viability, it is recommended that DACCS plants be sited anywhere that assures the availability of low-carbon energy inputs, appropriate CO_2 Storage and/or transport facilities to appropriate storage sites (Bui et al., 2018). It is therefore necessary to assess the impact of these and other factors on DACCS performance with a view to identifying the optimum conditions.

2.7.1 Land

The annual estimated specific land use of the various types of DAC processes has been reported to be less than 0.001ha/tCO_2 (Smith et al., 2015; Viebahn et al., 2019). Though these values did not include the area set aside for energy generation and other auxiliary facilities. A positive aspect of DACCS land use is that lands existing between the units can be co-applied for other purposes like agriculture.

2.7.2 Water

The water requirement for this GGR technology is dependent on the sorbent and regeneration process adopted, with the HT aqueous solution DAC systems reported to require varying values ranging from 4.7 – 30 m^3/tCO_2 (Viebahn et al., 2019). While this could serve as a constraint to the locational flexibility of this technology especially in dry and remote desert regions, Fasihi et al. (2019) however reported that this constraint can be avoided by the application of the LT DAC systems which have no demand for external water. Quite to the contrary, the LT DAC produces water as a by-product which can be utilised for other industrial applications. They reported the amount of water produced to be about 0.9 – 2.3 m^3/tCO_2 captured, depending on the moisture content of the ambient air.

2.7.3 Energy

While passive DACCS processes, like artificial trees require significant land areas and have very low power requirement as they depend on natural circulation of air through the capturing agent, energy (whether electrical or thermal) plays a major role in the operation of most DACCS technologies. This includes the energy for releasing CO_2 from the sorbent, regenerating the sorbent, for fans and pumping,

as well as for pressurizing the CO_2 for transportation (Fuss et al., 2018). On account of the CO_2 concentration in the atmosphere, Viebahn et al. (2019) reported that DACCS would require two to four times as much energy as the capture of exhaust gases from a power plant (point source capture) with (Smith et al., 2015) placing the annual energy requirement value at 9 – 12.3 GJ/tCO_2 removed.

In regards to consumption rate, while The Royal Society (2018) reported a theoretical minimum thermal energy requirement estimate of 0.68 GJ/tCO_2, Fajardy et al. (2019) reported a much larger estimate of about 9-10 GJ/tCO_2 and recommended the need for low carbon energy sources to ensure economic viability and sustainability of the system. Gambhir & Tavoni (2019) suggested probable low carbon sources applicable to include renewable energy sources as well as natural gas combined with capture of the CO_2 released by the gas' combustion.

Fasihi et al. (2019) however recommended the use of the LT DAC systems characterised by lower energy requirement (200-300 kWh_{el}/tCO_2, 1500-2000 kWh_{th}/tCO_2) and costs on account of the possibility of using cheaper low-grade waste heat from other systems (such as electrolysers, industrial plants, or synthesizing plants).

2.7.4 CO_2 Storage

The global total storage potential is reported to range from 200 – 50,000 GtCO_2, with the actual effective potential estimated at 13,500 GtCO_2 (Dooley, 2013; Fuss et al., 2018). This covers storage options such as aquifers, depleted oil and gas fields, coal beds as well as structural traps. Underground geological storage option has been generally recommended as the most viable choice on account of favourable economic factors, wide geographical distribution and environmental concerns (Aminu et al., 2017; Bui et al., 2018). The Royal Society (2018) reported an estimated global capacity of 900 GtCO_2 if only currently existing depleted oil and gas field are to be used. It is also important to note that geographical storage poses some risks such as leakage, unfavourable seismic events and water contamination, hence the need for adequate monitoring.

2.7.5 Cost

DACCS cost requirement is quite high consisting of capital investment, energy costs of capture and operation, energy costs of regeneration, sorbent loss and maintenance as well as post capture costs covering CO_2 compression, transportation and storage. Current studies estimate the cost to range from US$600-1,000/t$CO_2$ with general expectation of decrease to US$100-300/t$CO_2$ by 2050 on account of expected technological advancement with time (Fuss et al., 2018; Psarras et al., 2017). The overall cost can however be minimised by locating DAC systems in cost optimal sites considering factors such as proximity to storage facilities, renewable energy applicability as well as co-locating with waste heat emitting industries, minimal transport and grid cost. Choice of sorbent is also an important factor to consider with Azarabadi & Lackner (2019) stating that a sorbent is expected to survive between tens to hundreds of thousands of loading and unloading cycles to be considered economically viable. Fuss et al. (2018) while making a case for the probable use of wastewater treatment as a means to capture ambient CO_2 also recommended solid sorbent systems (LT DAC) as a cheaper option in comparison to the aqueous solution type as it required less heat for regeneration. This was also corroborated by Fasihi et al. (2019) who referred to it as the more favourable option for today and the future.

2.8 Bioenergy with Carbon Capture and Storage (BECCS)

It involves a combination of biomass combustion in various applications (through power generation, biofuels production, hydrogen plants, bio-synthetic natural gas, heating, and industrial processes) and carbon capture and storage (CCS) (Bhave et al., 2017; Fajardy et al., 2019a). This combination achieves GGR by taking atmospheric CO_2 temporarily locked in plants and storing it permanently in geological formations, while using the biomass to generate energy in various form as shown in Figure 2-8. With an annual bioenergy potential of over 100 EJ (Smith, 2016) and global GGR potential ranging from 1.3 – 10 $GtCO_2$ pa, BECCS implementation offers a great option for the achievement of the less than 2 °C warming target by the end of the century.

Despite its seemingly high prospects coupled with low vulnerability to reversal, it is however characterised by uncertainties and limitations such as availability of land and sustainable biomass (Al-Qayim et al., 2015), the availability of suitable and secure CO_2 sequestration sites globally, environmental and ecological impacts, technical considerations, costs, financing, legal liabilities (Bhave et al., 2017) and public acceptance (Gough and Mander, 2019). Other concerns include impact on food security and prices, biodiversity, water and nutrients.

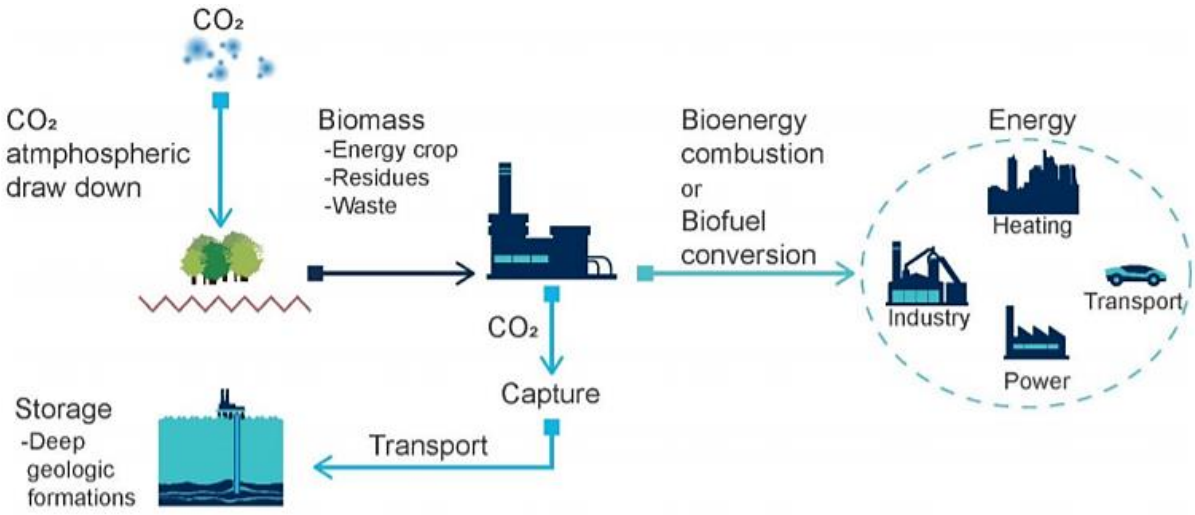


Figure 2-8 Schematic illustration of BECCS (reprinted with permission from Consoli (2019), Copyright 2019 Global CCS Institute).

Unlike DACCS which has a very high flexibility in choice of location, the siting of BECCS plant is very much dependent on a consideration of factors such as proximity to biomass source, carbon storage site as well as transport cost (either in moving the biomass or the captured carbon). These and other factors are assessed briefly as presented in various literature in the following sections with a view to identifying applicable options that will ensure optimal performance of the BECCS system.

2.8.1 Land and water requirement

With these requirements dependent on the choice of biomass feedstock, The Royal Society (2018) reported annual land requirement to range from 0.03 to 0.06 ha/tCO_2 removed and water requirement of about 60 m^3/tCO_2 (not including the CCS use). Higher range of 0.01 – 0.5 ha/tCO_2 was reported by Smith et al. (2015)

with forest residue feedstock accounting for the highest land requirement. They also reported a very large water requirement of about 218 m^3/tCO_2 pa which was obtained by adding bio-energy water use to CCS water use. Aside the probable need for water in the biomass production, water is also needed in the capture process with the amount required dependent on the cooling technology adopted.

2.8.2 Biomass

There exists a relatively wide range of applicable sustainable biomass. These include lignocellulosic and herbaceous bioenergy crops (primary sources requiring dedicated plant growth), urban and industrial wastes, agricultural and forest residues (secondary sources), as well as algae (see section 2.4.2). Lignocellulosic feedstocks like wood, Miscanthus, switchgrass and agricultural residues have been generally recommended in the literature either for dedicated planting or importation as they are less likely to compete with food supply (Smith et al., 2015; The Royal Society, 2018). This biomass can be used as single fuel source for power generation (dedicated use) or in combination with other conventional fossil fuels, such as coal and gas (co-fired generation) especially considering its higher moisture content and a lower heating value in comparison to conventional fossil fuels (Pires, 2019).

2.8.3 Other considerations

Same storage concerns as discussed under DACCS (section 2.5.4) also apply for BECCS coupled with the added aspect of likely carbon emissions from the soil brought about by land-use practices that might be associated with the biomass management.

In regards to energy generation, Smith et al. (2015) reported the net generating capacity of BECCS to range from 0.82 – 10.89 GJ/tCO_2 pa with actual value dependent on the biomass source ranging from forest biomass to crop residues respectively. In regard to cost of deployment, Fuss et al. (2018) reported literature estimates to range from US\$15-400/tCO_2 with actual cost highly sensitive to factors such as biomass cost, electricity sales price, transport and logistics, technology adopted, plant lifetime and efficiency. They however projected a

range of US$100-200/tCO2 by 2050 hinged on the management intensity that will be required to ensure sustainable deployment and land use.

2.9 Discussion

The review of the major operational factors required for the optimum performance of the various GGR methods under consideration has been carried out with a summary of identified factors presented in Table 2-3. This is important for providing a guide (point of reference) to policy makers at various levels as well as investors on the type of GGR technology that can be deployed in a particular area based on the locational characteristics and available resources. In this section, a comparison and assessment of the extent of influence of the various factors on the respective GGR methods is presented. It is concluded with the assessed levels of impact being quantified using a weighting scale of 0 – 5 (where zero (0) represents no impact and five (5) represents maximum impact) based on the authors' perspective as presented in Table 2-4.

In regard to land availability, and considering the competing uses of this resource, conclusions in Fajardy et al. (2019a) suggest that there is need for a conservative approach in the deployment of the various GGR technologies. While Afforestation typically has the highest requirement, EW and DACCS have the least, thus making them viable options for most areas as they can be co-applied alongside other activities. Land requirement for SCS is mostly dependent on the management practice adopted which could be very low if applied alongside forestation and high for no-tillage practice. Land requirement for BECCS and biochar are largely dependent on the choice of biomass feedstock.

Table 2-3 Comparison of the characteristics and deployment requirements of GGR technologies.

	Forestation	**EW**	**SCS**	**Biochar**	**DACCS**	**BECCS**
TRL	8-9	3-5	8-9	3-6	4-7	4-8
Climatic condition	Tropical region (high rainfall and temperature)	Warm tropical and humid regions (Ave. temperature of 25 °C and high rainfall)	Temperate and humid tropical regions.	Temperate and humid regions (Ave. temperature of 20°C)	Very much applicable in any climatic area though cost optimal sites are highly recommended.	
Annual land requirement (ha/tCO_2)	0.03 – 0.16	<0.003	Dependent on adopted practice.	<0.3	< 0.0003	0.01-0.5
Annual energy requirement (GJ/tCO_2)	Negligible	0.81 – 12.5 (electricity: 0.05 – 8.38, primary: 0.76 – 4.12)	Negligible	-5.45 to -13.62	9 – 12.3 (electricity: 0.72-2.3, thermal: 9-10)	-0.82 to -10.89
Levelised cost of CO_2 removed ($US\$/tCO_2$)	0 – 8.08 (for afforestation in tropical regions)	52 – 480	0–100 (depending on adopted practice)	30-120	600-1000 (expected decrease to 100-300 by 2050)	100-200
Annual water requirement (m^3/tCO_2)	No additional water required	1.5	-	-	4.7 - 30	60 – 218

	in high rainfall regions.					
Vegetation	Deciduous broadleaved native mixed species	-	Boreal forest (Taiga), tropical forest and grassland/ savannah	preferably crop residue and herbaceous feedstock	-	-
Geological storage	-	-	-	-	Applicable	Applicable
Other requirements/ recommendations	Management practice: Afforestation with agroforestry practice to maximise land use.	Rock type: Basaltic and or dunite rocks. Proximity of mining site to particle application site Low carbon energy for rock processing.	Management practice: Conservation tillage (temperate region) and improved grazing (tropical region)	Arable (agricultural) land for application	Preferable technology: Low Temperature (LT) DAC Plants. Low carbon energy sources are also recommended.	-

Climate is a major factor in the performance of forestation, EW, SCS, and biochar though with varying levels of impact as shown in Table 2-4, thus limiting their global deployment to areas of favourable climate features. The performance of BECCS and DACCS are largely independent of climatic factors and thus applicable in most locations. Despite the seemingly locational flexibility of these latter GGR technologies, the need for selection of cost-optimal sites is important, with factors such as proximity to geological storage and biomass availability (in the case of BECCS) playing an indispensable role in their operation and performance.

With vegetation closely linked with climate, biomass availability for BECCS and biochar could be impacted by climatic factors especially in cases where the feedstock is sourced from dedicated local seasonal crops. This is however minimal on account of the diverse options of feedstock sources ranging from domestic to industrial waste as well as importation from other locations that can be adopted. Extreme temperature however does affect biochar mean residence time (Fuss et al., 2018).

In the deployment of GGR technologies, energy requirement and cost are closely related with DACCS and EW ranking highest. While this could serve as a hindrance to the deployment of these GGR technologies especially in areas still grappling with sufficient energy and/or using fossil fuel-based power systems which could reduce the emission removal gains, the need to adopt low carbon emission energy sources in the operation of these technologies have been generally advanced, coupled with optimistic projections of DAC cost reduction on account of technological improvement. BECCS and biochar are less expensive than DACCS and EW with the co-benefit of being a source of energy, thus making them viable options for areas with insufficient energy (Fajardy and Mac Dowell, 2018). It is, however, important to add that this cost advantage of BECCS and biochar is dependent on locational factors especially the availability of biomass. Energy and cost requirement for forestation and SCS are typically low but could increase depending on the management system adopted which are subject to the prevailing ecological factors of the particular area.

Using the comparative analysis in Table 2-3 and discussions in the preceding paragraphs, a quantification of the importance of these factors on the performance of the six GGR methods is presented in Table 2-4. This quantification which is based on the authors' perspective was carried out by ranking each factor on a scale of 0 – 5. While a weight of zero (0) indicates that a factor has no impact and not required for the deployment of a GGR method, a weighting of five (5) indicates that a factor is highly important and indispensable in the deployment of a GGR method. For instance, while geological storage has been ranked a weight of 5 for DACCS and BECCS on account of its importance in the deployment of these two technologies; it was ranked 0 for the other four methods as they do not require geological storage. The other intermediate scores indicate varying levels of importance of these factors and the extent of dependence of the GGR methods on them as discussed in the preceding paragraphs.

Table 2-4 The 0-5 scale ranking of the factors that impact on the performance of GGR technologies

		Forestation	EW	SCS	Biochar	DACCS	BECCS
Climatic condition		5	4	4	3	1	2
Soil	Type	3	2	4	3	0	2
	pH	1	3	3	4	0	1
*Land	Availability	4	2	2	2	1	2
	Quality	3	0	1	1	0	2
	Accessibility	1	3	3	3	1	2
Vegetation		4	0	3	2	0	3
*Water requirement		3	0	2	0	1	2
Energy requirement		1	4	1	2	3	2
Geography		2	4	2	2	1	1
Geological Storage		0	0	0	0	5	5
Cost		1	4	1	2	4	3

*Data for the GGR technologies, except SCS, is adapted from Fajardy, Patrizio, et al. (2019).

Though the impact ranking of factors adopts a subjective approach, the following steps were, however, taken to minimize bias in the outcome. Firstly, rigorous care was taken to ensure the ranking was wholly based on a comparative assessment of information available in the literature. Secondly, the obtained ranking was then independently reviewed by five experts in the GGR research area. Finally, a sensitivity analysis was conducted to assess the impact of variations in the ranking on the performance of the GGR methods (see Section 6.6.3). For each GGR method, four ranking scenarios were considered: The equal ranking scenario in which same score were assigned to all the variables. Then three dominant variables scenarios in which the ranking was biased towards major factors (land availability, cost, energy availability, geological storage potential and biomass availability) by 50%, 60% and 70%. Based on this sensitivity analysis, the uncertainty in the impact ranking system for forestation, EW, DACCS and BECCS is set to 5%, while that of biochar is set to 20%.

With CCS-based technologies expected to play a major role in attaining the mitigation target on account of their versatility and potential and bearing in mind that no single GGR technology can individually shoulder the emission mitigation burden, an understanding of how these factors impact on the performance of the various GGR is key in making the appropriate choice of combination of the various technologies for particular areas.

2.10 Recent trends and outlook

It is agreed that the deployment of GGR methods is an indispensable option in meeting the 1.5 °C warming target with forestation and BECCS featuring prominently in most IAMs scenarios (IPCC, 2018). While nature-based solutions such as forestation and SCS, though having a lower carbon storage permanence, are matured and already being deployed at various scales. Other GGR methods with emphasis on the CCS-based methods are still at relatively lower TRLs as captured in Figure 1-2. These engineered solutions ensure high storage permanence thus require more attention and funding both from government and corporate bodies to deliver their prompt deployment.

On the commercialisation front, there has been an increased interest in investment in GGR methods in recent times. In January 2020, Microsoft announced a US$1billion climate innovation fund aimed at achieving a carbon negative goal by 2030. This commitment which is exclusively focused on projects that remove carbon from the atmosphere is currently funding projects from 15 organisations representing a combined removal potential of more than 1.3 $MtCO_2$ pa (Chay et al., 2021; Microsoft, 2021). Stripe, a global financial service company has also made its negative emission commitment with a pledge to invest a minimum of US$1 million per year in projects involving direct removal of carbon dioxide from the atmosphere (Cullenward et al., 2020; Orbuch, 2020). Other organisations providing major investments, incentives and collaborations for the development of GGR methods include Shopify, Audi, ExxonMobil as well as Elon Musk and the Musk Foundation who are currently funding a US$100 million XPRIZE carbon removal competition. These and other efforts if continued, would ensure an acceleration in the development and deployment of these GGR methods, providing continued governmental commitments to net zero and decarbonisation targets.

On account of the economic downturn and overall drop in energy demand brought about by the global coronavirus pandemic, the International Energy Agency estimated an 8% (about 2.8 Gt) drop in global CO_2 emissions in 2020 (IEA, 2020). This drop which had no detectable impact on atmospheric CO_2 or climate change is expected to be temporary as they do not actually reflect structural changes in economic, transport or energy systems (Le Quéré et al., 2020). The post-COVID era however offers governments of the global community a great opportunity to put in place structural adjustments that will maintain and even enhance this emission drop in the coming years. This can be achieved through the adoption of economic stimuli programmes centred around low carbon emission pathways (Le Quéré et al., 2020), increased investment as well as favourable policy incentives and legislations that will enhance technological development and social awareness regarding the scaling and deployment of GGR methods. With GGR methods expected to feature more prominently in the next round of submissions of countries' nationally determined contributions (NDCs), the need for sustainable

global and regional co-operation will be key in the development and deployment of these GGR methods.

2.11 Conclusions

In this study, an assessment of the impact of operational factors on six GGR technologies (forestation, EW, SCS, biochar, DACCS and BECCS) has been carried out from the literature with a view to identifying the conditions and requirements necessary for optimum performance of these technologies. The factors considered include climatic condition, management practices, availability of land, water, energy and biomass, cost and soil characteristics. From the assessment, the extent of influence of these factors on the various GGR technologies have been discussed and highlighted on a 0 – 5 scale with the major findings as follows.

- For forestation, the tropical climatic region has been identified for deployment with afforestation and/or reforestation with agroforestry practice recommended to maximise land use and minimise cost while using deciduous broadleaved native mixed species.
- In the case of EW, warm tropical and humid regions have been identified for optimum deployment using the more common basaltic rocks on preferably arable land with acidic soil. Low carbon renewable energy sources have also been prescribed as means of reducing the high energy and cost requirement.
- For SCS, the boreal or snow forest has been identified for deployment with adopted management practices generally dependent on particular regions: conservation tillage (temperate region) and improved grazing (tropical region). Soils of heavy and clayey texture and agroecosystems lands have also been recommended for SCS deployment.
- For biochar, temperate and humid regions have been highlighted for optimum deployment in arable land characterised by well drained sandy soil with low SOC and naturally low fertility with pH preferably acidic and

neutral. Plant-based biomass (preferably crop residue and herbaceous feedstock) have also been recommended as feedstock.

- Lastly, the CCS technologies (BECCS and DACCS) which have been largely projected as major contributors to the attainment of the emission mitigation target have been found to have a larger locational flexibility. However, the need for cost optimal siting of the CCS plant is very much necessary and dependent on the presence of appropriate geological storage facility.

Though specific regions have been identified for optimum performance of these GGR methods on account of favourable resource availability, the need for international co-operation and collaboration cannot be over-emphasised if the mitigation target is to be met. Socio-political factors are expected to also play a major role, with nature-based solutions like forestation and SCS expected to be highly favoured in this regard ahead of the engineered solutions (CCS). While these nature-based solutions are already being deployed owing to their low cost, technological maturity and social acceptance, their reliability and sustainability in the long run is however limited by factors such as permanence of storage, competing land use and lower removal potential. Hence, there is need for accelerated social sensitization and technological development of the CCS based methods which offer a higher removal potential and more reliable permanence of storage of the captured carbon.

2.12 References

Abbas, F., Hammad, H.M., Fahad, S., Cerdà, A., Rizwan, M., Farhad, W., Ehsan, S., Bakhat, H.F., 2017. Agroforestry: a sustainable environmental practice for carbon sequestration under the climate change scenarios—a review. Environ. Sci. Pollut. Res. 24, 11177–11191. https://doi.org/10.1007/s11356-017-8687-0

Abdullahi, A.C., Siwar, C., Shaharudin, M.I.I., Anizan, I., 2018. Carbon Sequestration in Soils: The Opportunities and Challenges. IntechOpen 13. https://doi.org/http://dx.doi.org/10.5772/intechopen.79347

Al-Qayim, K., Nimmo, W., Pourkashanian, M., 2015. Comparative techno-economic assessment of biomass and coal with CCS technologies in a

pulverized combustion power plant in the United Kingdom. Int. J. Greenh. Gas Control 43, 82–92. https://doi.org/10.1016/j.ijggc.2015.10.013

Alvarez, S., Ortiz, C., Díaz-Pinés, E., Rubio, A., 2016. Influence of tree species composition, thinning intensity and climate change on carbon sequestration in Mediterranean mountain forests: a case study using the CO2Fix model. Mitig. Adapt. Strateg. Glob. Chang. 21, 1045–1058. https://doi.org/10.1007/s11027-014-9565-4

Amann, T., Hartmann, J., Struyf, E., De Oliveira Garcia, W., Fischer, E.K., Janssens, I., Meire, P., Schoelynck, J., 2020. Enhanced Weathering and related element fluxes - A cropland mesocosm approach. Biogeosciences 17, 103–119. https://doi.org/10.5194/bg-17-103-2020

Aminu, M.D., Nabavi, S.A., Rochelle, C.A., Manovic, V., 2017. A review of developments in carbon dioxide storage. Appl. Energy 208, 1389–1419. https://doi.org/10.1016/j.apenergy.2017.09.015

Anderson, R.G., Canadell, J.G., Randerson, J.T., Jackson, R.B., Hungate, B.A., Baldocchi, D.D., Ban-Weiss, G.A., Bonan, G.B., Caldeira, K., Cao, L., Diffenbaugh, N.S., Gurney, K.R., Kueppers, L.M., Law, B.E., Luyssaert, S., O'Halloran, T.L., 2011. Biophysical considerations in forestry for climate protection. Front. Ecol. Environ. 9, 174–182. https://doi.org/10.1890/090179

Andrews, M., Taylor, L., 2019. Combating Climate Change Through Enhanced Weathering of Agricultural Soils. Elements 15, 325–330. https://doi.org/10.2138/gselements.15.4.253

Anwar, M.N., Fayyaz, A., Sohail, N.F., Khokhar, M.F., Baqar, M., Yasar, A., Rasool, K., Nazir, A., Raja, M.U.F., Rehan, M., Aghbashlo, M., Tabatabaei, M., Nizami, A.S., 2020. CO2 utilization: Turning greenhouse gas into fuels and valuable products. J. Environ. Manage. 260. https://doi.org/10.1016/j.jenvman.2019.110059

Arora, V.K., Montenegro, A., 2011. Small temperature benefits provided by realistic afforestation efforts. Nat. Geosci. 4, 514–518. https://doi.org/10.1038/ngeo1182

Azarabadi, H., Lackner, K.S., 2019. A sorbent-focused techno-economic analysis of direct air capture. Appl. Energy 250, 959–975. https://doi.org/10.1016/j.apenergy.2019.04.012

Bach, L.T., Gill, S.J., Rickaby, R.E.M., Gore, S., Renforth, P., 2019. CO2 Removal With Enhanced Weathering and Ocean Alkalinity Enhancement: Potential Risks and Co-benefits for Marine Pelagic Ecosystems. Front. Clim. 1. https://doi.org/10.3389/fclim.2019.00007

Bajamundi, C.J.E., Koponen, J., Ruuskanen, V., Elfving, J., Kosonen, A., Kauppinen, J., Ahola, J., 2019. Capturing CO2 from air: Technical performance and process control improvement. J. CO2 Util. 30, 232–239. https://doi.org/10.1016/j.jcou.2019.02.002

Bala, G., 2014. Can planting trees help to reduce global warming? Curr. Sci. 106, 1551–1552. https://doi.org/10.1111/ner.12135

Beerling, D.J., Kantzas, E.P., Lomas, M.R., Wade, P., Eufrasio, R.M., Renforth, P., Sarkar, B., Andrews, M.G., James, R.H., Pearce, C.R., Mercure, J.F., Pollitt, H., Holden, P.B., Edwards, N.R., Khanna, M., Koh, L., Quegan, S., Pidgeon, N.F., Janssens, I.A., Hansen, J., Banwart, S.A., 2020. Potential for large-scale CO2 removal via enhanced rock weathering with croplands. Nature 583, 242–248. https://doi.org/10.1038/s41586-020-2448-9

Bhave, A., Taylor, R.H.S., Fennell, P., Livingston, W.R., Shah, N., Dowell, N. Mac, Dennis, J., Kraft, M., Pourkashanian, M., Insa, M., Jones, J., Burdett, N., Bauen, A., Beal, C., Smallbone, A., Akroyd, J., 2017. Screening and techno-economic assessment of biomass-based power generation with CCS technologies to meet 2050 CO2 targets. Appl. Energy 190, 481–489. https://doi.org/10.1016/j.apenergy.2016.12.120

Blanco-Canqui, H., 2017. Biochar and Soil Physical Properties. Soil Sci. Soc. Am. J. 81, 687–711. https://doi.org/10.2136/sssaj2017.01.0017

Bonan, G.B., 2008. Forests and climate change: Forcings, feedbacks, and the climate benefits of forests. Science (80-.). 320, 1444–1449. https://doi.org/10.1126/science.1155121

Bond, W.J., Stevens, N., Midgley, G.F., Lehmann, C.E.R., 2019. The Trouble with Trees: Afforestation Plans for Africa. Trends Ecol. Evol. 34, 963–965. https://doi.org/10.1016/j.tree.2019.08.003

Boot-Handford, M.E., Abanades, J.C., Anthony, E.J., Blunt, M.J., Brandani, S., Mac Dowell, N., Fernández, J.R., Ferrari, M.C., Gross, R., Hallett, J.P., Haszeldine, R.S., Heptonstall, P., Lyngfelt, A., Makuch, Z., Mangano, E., Porter, R.T.J., Pourkashanian, M., Rochelle, G.T., Shah, N., Yao, J.G., Fennell, P.S., 2014. Carbon capture and storage update. Energy Environ. Sci. 7, 130–189. https://doi.org/10.1039/c3ee42350f

Bouwman, A.F., Boumans, L.J.M., Batjes, N.H., 2002. Emissions of N 2 O and NO from fertilized fields: Summary of available measurement data . Global Biogeochem. Cycles 16, 6-1-6–13. https://doi.org/10.1029/2001gb001811

Brassard, P., Godbout, S., Raghavan, V., 2016. Soil biochar amendment as a climate change mitigation tool: Key parameters and mechanisms involved. J. Environ. Manage. 181, 484–497. https://doi.org/10.1016/j.jenvman.2016.06.063

Bui, M., Adjiman, C.S., Bardow, A., Anthony, E.J., Boston, A., Brown, S., Fennell, P.S., Fuss, S., Galindo, A., Hackett, L.A., Hallett, J.P., Herzog, H.J., Jackson, G., Kemper, J., Krevor, S., Maitland, G.C., Matuszewski, M., Metcalfe, I.S., Petit, C., Puxty, G., Reimer, J., Reiner, D.M., Rubin, E.S., Scott, S.A., Shah, N., Smit, B., Trusler, J.P.M., Webley, P., Wilcox, J., Mac Dowell, N., 2018. Carbon capture and storage (CCS): The way forward. Energy Environ. Sci. 11, 1062–1176. https://doi.org/10.1039/c7ee02342a

Bui, M., Mac Dowell, N., 2022. Greenhouse Gas Removal Technologies. Royal Society of Chemistry.

Canadell, J.G., Raupach, M.R., 2008. Managing forests for climate change mitigation. Science (80-.). 320, 1456–1457. https://doi.org/10.1126/science.1155458

Chay, F., Cullenward, D., Hamman, J., Freeman, J., 2021. insights from analyzing a new round of carbon removal projects / research / carbonplan [WWW Document]. CarbonPlan. URL https://carbonplan.org/research/microsoft-2021-insights (accessed 3.21.21).

Consoli, C., 2019. Bioenergy and Carbon Capture and Storage, Global CCS Institute.

Cullenward, D., Hamman, J., Freeman, J., 2020. insights from our first project reports / research / carbonplan [WWW Document]. CarbonPlan. URL https://carbonplan.org/research/stripe-2020-insights (accessed 3.21.21).

De Oliveira Garcia, W., Amann, T., Hartmann, J., Karstens, K., Popp, A., Boysen, L.R., Smith, P., Goll, D., 2020. Impacts of enhanced weathering on biomass production for negative emission technologies and soil hydrology. Biogeosciences 17, 2107–2133. https://doi.org/10.5194/bg-17-2107-2020

De Stefano, A., Jacobson, M.G., 2017. Soil carbon sequestration in agroforestry systems: a meta-analysis. Agrofor. Syst. 92, 285–299. https://doi.org/10.1007/s10457-017-0147-9

Dessert, C., Dupré, B., Gaillardet, J., François, L.M., Allègre, C.J., 2003. Basalt weathering laws and the impact of basalt weathering on the global carbon cycle. Chem. Geol. 202, 257–273. https://doi.org/10.1016/j.chemgeo.2002.10.001

Doelman, J.C., Stehfest, E., van Vuuren, D.P., Tabeau, A., Hof, A.F., Braakhekke, M.C., Gernaat, D.E.H.J., van den Berg, M., van Zeist, W.J., Daioglou, V., van Meijl, H., Lucas, P.L., 2019. Afforestation for climate change mitigation: Potentials, risks and trade-offs. Glob. Chang. Biol. 26, 1576–1591. https://doi.org/10.1111/gcb.14887

Dooley, J.J., 2013. Estimating the supply and demand for deep geologic CO2 storage capacity over the course of the 21st century: A meta-analysis of the literature. Energy Procedia 37, 5141–5150. https://doi.org/10.1016/j.egypro.2013.06.429

Dou, X., Zhou, W., Zhang, Q., Cheng, X., 2016. Greenhouse gas (CO2, CH4, N2O) emissions from soils following afforestation in central China. Atmos. Environ. 126, 98–106. https://doi.org/10.1016/j.atmosenv.2015.11.054

Edwards, D.P., Lim, F., James, R.H., Pearce, C.R., Scholes, J., Freckleton, R.P., Beerling, D.J., 2017. Climate change mitigation: Potential benefits and pitfalls of enhanced rock weathering in tropical agriculture. Biol. Lett. 13. https://doi.org/10.1098/rsbl.2016.0715

Elfving, J., Bajamundi, C., Kauppinen, J., 2017. Characterization and Performance of Direct Air Capture Sorbent. Energy Procedia 114, 6087–6101. https://doi.org/10.1016/j.egypro.2017.03.1746

Ellison, D., Morris, C.E., Locatelli, B., Sheil, D., Cohen, J., Murdiyarso, D., Gutierrez, V., Noordwijk, M. van, Creed, I.F., Pokorny, J., Gaveau, D., Spracklen, D. V., Tobella, A.B., Ilstedt, U., Teuling, A.J., Gebrehiwot, S.G., Sands, D.C., Muys, B., Verbist, B., Springgay, E., Sugandi, Y., Sullivan, C.A., 2017. Trees, forests and water: Cool insights for a hot world. Glob. Environ. Chang. 43, 51–61. https://doi.org/10.1016/j.gloenvcha.2017.01.002

Fajardy, M., Köberle, A., Dowell, N.M.A.C., Fantuzzi, A., 2019a. BECCS deployment: A reality check, Grantham Institute Briefing paper No 28.

Fajardy, M., Mac Dowell, N., 2018. The energy return on investment of BECCS: Is BECCS a threat to energy security? Energy Environ. Sci. 11, 1581–1594. https://doi.org/10.1039/c7ee03610h

Fajardy, M., Patrizio, P., Daggash, H.A., Mac Dowell, N., 2019b. Negative Emissions: Priorities for Research and Policy Design. Front. Clim. 1, 1–7. https://doi.org/10.3389/fclim.2019.00006

Fasihi, M., Efimova, O., Breyer, C., 2019. Techno-economic assessment of CO 2 direct air capture plants. J. Clean. Prod. 224, 957–980. https://doi.org/10.1016/j.jclepro.2019.03.086

Favero, A., Sohngen, B., Huang, Y., Jin, Y., 2018. Global cost estimates of forest climate mitigation with albedo: A new integrative policy approach. Environ. Res. Lett. 13. https://doi.org/10.1088/1748-9326/aaeaa2

Franzluebbers, A.J., 2012. Grass roots of soil carbon sequestration. Carbon Manag. 3, 9–11. https://doi.org/10.4155/cmt.11.73

Freibauer, A., Rounsevell, M.D.A., Smith, P., Verhagen, J., 2004. Carbon sequestration in the agricultural soils of Europe. Geoderma 122, 1–23. https://doi.org/10.1016/j.geoderma.2004.01.021

Fuss, S., Lamb, W.F., Callaghan, M.W., Hilaire, J., Creutzig, F., Amann, T., Beringer, T., De Oliveira Garcia, W., Hartmann, J., Khanna, T., Luderer, G., Nemet, G.F., Rogelj, J., Smith, P., Vicente, J.V., Wilcox, J., Del Mar Zamora Dominguez, M., Minx, J.C., 2018. Negative emissions - Part 2: Costs, potentials and side effects. Environ. Res. Lett. 13. https://doi.org/10.1088/1748-9326/aabf9f

Gambhir, A., Tavoni, M., 2019. Direct Air Carbon Capture and Sequestration: How It Works and How It Could Contribute to Climate-Change Mitigation. One Earth 1, 405–409. https://doi.org/10.1016/j.oneear.2019.11.006

Godde, C.M., Thorburn, P.J., Biggs, J.S., Meier, E.A., 2016. Understanding the impacts of soil, climate, and farming practices on soil organic carbon sequestration: A simulation study in Australia. Front. Plant Sci. 7, 1–15. https://doi.org/10.3389/fpls.2016.00661

Goglio, P., Williams, A.G., Balta-Ozkan, N., Harris, N.R.P., Williamson, P., Huisingh, D., Zhang, Z., Tavoni, M., 2020. Advances and challenges of life cycle assessment (LCA) of greenhouse gas removal technologies to fight climate changes. J. Clean. Prod. 244, 118896. https://doi.org/10.1016/j.jclepro.2019.118896

Goh, K.M., 2004. Carbon sequestration and stabilization in soils: Implications for soil productivity and climate change. Soil Sci. Plant Nutr. 50, 467–476. https://doi.org/10.1080/00380768.2004.10408502

Goodman, R., Herold, M., 2015. Why Maintaining Tropical Forests is Essential and Urgent for a Stable Climate. SSRN Electron. J. https://doi.org/10.2139/ssrn.2622758

Gough, C., Mander, S., 2019. Beyond Social Acceptability: Applying Lessons from CCS Social Science to Support Deployment of BECCS. Curr. Sustain. Energy Reports 6, 116–123. https://doi.org/10.1007/s40518-019-00137-0

Hall, J.M., van Holt, T., Daniels, A.E., Balthazar, V., Lambin, E.F., 2012. Trade-offs between tree cover, carbon storage and floristic biodiversity in reforesting landscapes. Landsc. Ecol. 27, 1135–1147. https://doi.org/10.1007/s10980-012-9755-y

Hartman, P.J., 2017. Reviews of Science for Science Librarians: Forestry as a Climate Change Mitigation Tool. Sci. Technol. Libr. 36, 219–234. https://doi.org/10.1080/0194262X.2017.1337541

Hartmann, J., Kempe, S., 2008. What is the maximum potential for CO2 sequestration by “stimulated” weathering on the global scale? Naturwissenschaften 95, 1159–1164. https://doi.org/10.1007/s00114-008-0434-4

Hartmann, J., West, A.J., Renforth, P., Köhler, P., De La Rocha, C.L., Wolf-Gladrow, D.A., Dürr, H.H., Scheffran, J., 2013. Enhanced chemical weathering as a geoengineering strategy to reduce atmospheric carbon dioxide, supply nutrients, and mitigate ocean acidification. Rev. Geophys. 51, 113–149. https://doi.org/10.1002/rog.20004

Haszeldine, R.S., Flude, S., Johnson, G., Scott, V., 2018. Negative emissions technologies and carbon capture and storage to achieve the Paris Agreement commitments. Philos. Trans. R. Soc. A Math. Phys. Eng. Sci. 376. https://doi.org/10.1098/rsta.2016.0447

Hepburn, C., Adlen, E., Beddington, J., Carter, E.A., Fuss, S., Mac Dowell, N., Minx, J.C., Smith, P., Williams, C.K., 2019. The technological and economic prospects for CO2 utilization and removal. Nature 575, 87–97. https://doi.org/10.1038/s41586-019-1681-6

Hilaire, J., Minx, J.C., Callaghan, M.W., Edmonds, J., Luderer, G., Nemet, G.F., Rogelj, J., del Mar Zamora, M., 2019. Negative emissions and international climate goals—learning from and about mitigation scenarios. Clim. Change 157, 189–219. https://doi.org/10.1007/s10584-019-02516-4

Hunt, J.R., Celestina, C., Kirkegaard, J.A., 2020. The realities of climate change, conservation agriculture and soil carbon sequestration. Glob. Chang. Biol. 0–3. https://doi.org/10.1111/gcb.15082

IEA, 2020. Global energy and CO2 emissions in 2020 [WWW Document]. Glob. Energy Rev. 2020 . URL https://www.iea.org/reports/global-energy-review-2020/global-energy-and-co2-emissions-in-2020 (accessed 3.21.21).

IPCC, 2018. Global warming of 1.5°C An IPCC Special Report on the impacts of global warming of 1.5°C above pre-industrial levels and related global greenhouse gas emission pathways, in the context of strengthening the global response to the threat of climate change,.

Ishimoto, Y., Sugiyama, M., Kato, E., Moriyama, R., Tsuzuki, K., Kurosawa, A., 2017. Putting Costs of Direct Air Capture in Context. SSRN Electron. J. https://doi.org/10.2139/ssrn.2982422

Kantola, I.B., Masters, M.D., Beerling, D.J., Long, S.P., DeLucia, E.H., 2017. Potential of global croplands and bioenergy crops for climate change mitigation through deployment for enhanced weathering. Biol. Lett. 13. https://doi.org/10.1098/rsbl.2016.0714

Kirschbaum, M.U.F., Whitehead, D., Dean, S.M., Beets, P.N., Shepherd, J.D., Ausseil, A.G.E., 2011. Implications of albedo changes following afforestation on the benefits of forests as carbon sinks. Biogeosciences 8, 3687–3696. https://doi.org/10.5194/bg-8-3687-2011

Köhler, P., Hartmann, J., Wolf-Gladrow, D.A., 2010. Geoengineering potential of artificially enhanced silicate weathering of olivine. Proc. Natl. Acad. Sci. U. S. A. 107, 20228–20233. https://doi.org/10.1073/pnas.1000545107

Kreidenweis, U., Humpenöder, F., Stevanović, M., Bodirsky, B.L., Kriegler, E., Lotze-Campen, H., Popp, A., 2016. Afforestation to mitigate climate change: Impacts on food prices under consideration of albedo effects. Environ. Res. Lett. 11. https://doi.org/10.1088/1748-9326/11/8/085001

Kumar, S.K., 2017. Sustainable Management of Soil for Carbon Sequestration. Sci. Technol. J. 5, 132–140. https://doi.org/10.22232/stj.2017.05.02.10

Ladanai, S., Vinterbäck, J., 2009. Global Potential of Sustainable Biomass for Energy, Swedish University of Agricultural Sciences , Department of Energy and Technology.

Laganière, J., Angers, D.A., Paré, D., 2010. Carbon accumulation in agricultural soils after afforestation: A meta-analysis. Glob. Chang. Biol. 16, 439–453. https://doi.org/10.1111/j.1365-2486.2009.01930.x

Lal, R., 2013. Soil carbon management and climate change. Carbon Manag. 4, 439–462. https://doi.org/10.4155/cmt.13.31

Lal, R., 2008. Soil carbon stocks under present and future climate with specific reference to European ecoregions. Nutr. Cycl. Agroecosystems 81, 113–

127. https://doi.org/10.1007/s10705-007-9147-x

Lal, R., Negassa, W., Lorenz, K., 2015. Carbon sequestration in soil. Curr. Opin. Environ. Sustain. 15, 79–86. https://doi.org/10.1016/j.cosust.2015.09.002

Lassaletta, L., Aguilera, E., 2015. Soil carbon sequestration is a climate stabilization wedge: Comments on Sommer and Bossio (2014). J. Environ. Manage. 153, 48–49. https://doi.org/10.1016/j.jenvman.2015.01.038

Lawford-Smith, H., Currie, A., 2017. Accelerating the carbon cycle: The ethics of enhanced weathering. Biol. Lett. 13. https://doi.org/10.1098/rsbl.2016.0859

Le Quéré, C., Jackson, R.B., Jones, M.W., Smith, A.J.P., Abernethy, S., Andrew, R.M., De-Gol, A.J., Willis, D.R., Shan, Y., Canadell, J.G., Friedlingstein, P., Creutzig, F., Peters, G.P., 2020. Temporary reduction in daily global CO2 emissions during the COVID-19 forced confinement. Nat. Clim. Chang. 10, 647–653. https://doi.org/10.1038/s41558-020-0797-x

Li, Yongfu, Hu, S., Chen, J., Müller, K., Li, Yongchun, Fu, W., Lin, Z., Wang, H., 2018. Effects of biochar application in forest ecosystems on soil properties and greenhouse gas emissions: a review. J. Soils Sediments 18, 546–563. https://doi.org/10.1007/s11368-017-1906-y

Liu, X., Mao, P., Li, L., Ma, J., 2019. Impact of biochar application on yield-scaled greenhouse gas intensity: A meta-analysis. Sci. Total Environ. 656, 969–976. https://doi.org/10.1016/j.scitotenv.2018.11.396

Locatelli, B., Catterall, C.P., Imbach, P., Kumar, C., Lasco, R., Marín-Spiotta, E., Mercer, B., Powers, J.S., Schwartz, N., Uriarte, M., 2015. Tropical reforestation and climate change: Beyond carbon. Restor. Ecol. 23, 337–343. https://doi.org/10.1111/rec.12209

Lomax, G., Lenton, T.M., Adeosun, A., Workman, M., 2015. Investing in negative emissions. Nat. Clim. Chang. 5, 498–500. https://doi.org/10.1038/nclimate2627

Lorenz, K., Lal, R., 2014. Biochar application to soil for climate change mitigation by soil organic carbon sequestration. J. Plant Nutr. Soil Sci. 177, 651–670. https://doi.org/10.1002/jpln.201400058

Mac Dowell, N., Fennell, P.S., Shah, N., Maitland, G.C., 2017. The role of CO2 capture and utilization in mitigating climate change. Nat. Clim. Chang. 7, 243–249. https://doi.org/10.1038/nclimate3231

Mader, S., 2019. Plant trees for the planet: the potential of forests for climate change mitigation and the major drivers of national forest area. Mitig. Adapt. Strateg. Glob. Chang. https://doi.org/10.1007/s11027-019-09875-4

Magnússon, R., Tietema, A., Cornelissen, J.H.C., Hefting, M.M., Kalbitz, K., 2016. Tamm Review: Sequestration of carbon from coarse woody debris in forest soils. For. Ecol. Manage. 377, 1–15. https://doi.org/10.1016/j.foreco.2016.06.033

Majumder, S., Neogi, S., Dutta, T., Powel, M.A., Banik, P., 2019. The impact of biochar on soil carbon sequestration: Meta-analytical approach to evaluating environmental and economic advantages. J. Environ. Manage. 250, 109466. https://doi.org/10.1016/j.jenvman.2019.109466

Matthies, B.D., Valsta, L.T., 2016. Optimal forest species mixture with carbon storage and albedo effect for climate change mitigation. Ecol. Econ. 123, 95–105. https://doi.org/10.1016/j.ecolecon.2016.01.004

McGlashan, N., Shah, N., Caldecott, B., Workman, M., 2012. High-level techno-economic assessment of negative emissions technologies. Process Saf. Environ. Prot. 90, 501–510. https://doi.org/10.1016/j.psep.2012.10.004

McLaren, D., 2020. Quantifying the potential scale of mitigation deterrence from greenhouse gas removal techniques. Clim. Change 162, 2411–2428. https://doi.org/10.1007/s10584-020-02732-3

McLaren, D., 2012. A comparative global assessment of potential negative emissions technologies. Process Saf. Environ. Prot. 90, 489–500. https://doi.org/10.1016/j.psep.2012.10.005

McLaren, D., 2011. Negatonnes - An Initial Assessment of The Potential for Negative Emission Techniques to Contributr Safely and Fairly to Meeting Carbon Budgets in the 21st Century., Friends of the Earth.

Meysman, F.J.R., Montserrat, F., 2017. Negative CO2 emissions via enhanced silicate weathering in coastal environments. Biol. Lett. 13. https://doi.org/10.1098/rsbl.2016.0905

Microsoft, 2021. Microsoft carbon removal - Lessons from an early.

Minx, J.C., Lamb, W.F., Callaghan, M.W., Fuss, S., Hilaire, J., Creutzig, F., Amann, T., Beringer, T., De Oliveira Garcia, W., Hartmann, J., Khanna, T., Lenzi, D., Luderer, G., Nemet, G.F., Rogelj, J., Smith, P., Vicente Vicente, J.L., Wilcox, J., Del Mar Zamora Dominguez, M., 2018. Negative emissions - Part 1: Research landscape and synthesis. Environ. Res. Lett. 13. https://doi.org/10.1088/1748-9326/aabf9b

Mulligan, J., Rudee, A., Lebling, K., Levin, K., Anderson, J., Christensen, B., 2020. CarbonShot: Federal Policy Options for Carbon Removal in the United States, World Resources Institute.

Mykleby, P.M., Snyder, P.K., Twine, T.E., 2017. Quantifying the trade-off between carbon sequestration and albedo in midlatitude and high-latitude North American forests. Geophys. Res. Lett. 44, 2493–2501. https://doi.org/10.1002/2016GL071459

Nair, V.D., Nair, P.K.R., Dari, B., Freitas, A.M., Chatterjee, N., Pinheiro, F.M., 2017. Biochar in the agroecosystem-climate-change-sustainability Nexus. Front. Plant Sci. 8. https://doi.org/10.3389/fpls.2017.02051

Naudts, K., Chen, Y., McGrath, M.J., Ryder, J., Valade, A., Otto, J., Luyssaert,

S., 2016. Mitigate Climate Warming. Science (80-.). 351, 597–601. https://doi.org/10.1126/science.aac9976

Nemet, G.F., Callaghan, M.W., Creutzig, F., Fuss, S., Hartmann, J., Hilaire, J., Lamb, W.F., Minx, J.C., Rogers, S., Smith, P., 2018. Negative emissions - Part 3: Innovation and upscaling. Environ. Res. Lett. 13. https://doi.org/10.1088/1748-9326/aabff4

Nunes, L.J.R., Meireles, C.I.R., Gomes, C.J.P., Ribeiro, N.M.C.A., 2020. Forest contribution to climate change mitigation: Management oriented to carbon capture and storage. Climate 8. https://doi.org/10.3390/cli8020021

Oelkers, E.H., Declercq, J., Saldi, G.D., Gislason, S.R., Schott, J., 2018. Olivine dissolution rates: A critical review. Chem. Geol. 500, 1–19. https://doi.org/10.1016/j.chemgeo.2018.10.008

Olsson, A., Campana, P.E., Lind, M., Yan, J., 2014. Potential for carbon sequestration and mitigation of climate change by irrigation of grasslands. Appl. Energy 136, 1145–1154. https://doi.org/10.1016/j.apenergy.2014.08.025

Orbuch, R., 2020. Stripe's first carbon removal purchases [WWW Document]. Stripe. URL https://stripe.com/blog/first-negative-emissions-purchases (accessed 3.21.21).

Pires, J.C.M., 2019. Negative emissions technologies: A complementary solution for climate change mitigation. Sci. Total Environ. 672, 502–514. https://doi.org/10.1016/j.scitotenv.2019.04.004

Powlson, D.S., Stirling, C.M., Jat, M.L., Gerard, B.G., Palm, C.A., Sanchez, P.A., Cassman, K.G., 2014. Limited potential of no-till agriculture for climate change mitigation. Nat. Clim. Chang. 4, 678–683. https://doi.org/10.1038/nclimate2292

Powlson, D.S., Stirling, C.M., Thierfelder, C., White, R.P., Jat, M.L., 2016. Does conservation agriculture deliver climate change mitigation through soil carbon sequestration in tropical agro-ecosystems? Agric. Ecosyst. Environ. 220, 164–174. https://doi.org/10.1016/j.agee.2016.01.005

Psarras, P., Krutka, H., Fajardy, M., Zhang, Z., Liguori, S., Dowell, N. Mac, Wilcox, J., 2017. Slicing the pie: how big could carbon dioxide removal be? Wiley Interdiscip. Rev. Energy Environ. 6, 1–21. https://doi.org/10.1002/wene.253

Qambrani, N.A., Rahman, M.M., Won, S., Shim, S., Ra, C., 2017. Biochar properties and eco-friendly applications for climate change mitigation, waste management, and wastewater treatment: A review. Renew. Sustain. Energy Rev. 79, 255–273. https://doi.org/10.1016/j.rser.2017.05.057

Raihan, A., Begum, R.A., Mohd Said, M.N., Abdullah, S.M.S., 2019. A Review of Emission Reduction Potential and Cost Savings through Forest Carbon Sequestration. Asian J. Water, Environ. Pollut. 16, 1–7.

https://doi.org/10.3233/AJW190027

Renforth, P., 2012. The potential of enhanced weathering in the UK. Int. J. Greenh. Gas Control 10, 229–243. https://doi.org/10.1016/j.ijggc.2012.06.011

Roe, S., Streck, C., Obersteiner, M., Frank, S., Griscom, B., Drouet, L., Fricko, O., Gusti, M., Harris, N., Hasegawa, T., Hausfather, Z., Havlík, P., House, J., Nabuurs, G.J., Popp, A., Sánchez, M.J.S., Sanderman, J., Smith, P., Stehfest, E., Lawrence, D., 2019. Contribution of the land sector to a 1.5 °C world. Nat. Clim. Chang. 9, 817–828. https://doi.org/10.1038/s41558-019-0591-9

Sanz-Pérez, E.S., Murdock, C.R., Didas, S.A., Jones, C.W., 2016. Direct Capture of CO2 from Ambient Air. Chem. Rev. 116, 11840–11876. https://doi.org/10.1021/acs.chemrev.6b00173

Schuiling, R.D., 2017. Olivine Weathering against Climate Change. Nat. Sci. 09, 21–26. https://doi.org/10.4236/ns.2017.91002

Sedjo, R., Sohngen, B., 2012. Carbon Sequestration in Forests and Soils. Annu. Rev. Resour. Econ. 4, 127–144. https://doi.org/10.1146/annurev-resource-083110-115941

Senbayram, M., Saygan, E.P., Chen, R., Aydemir, S., Kaya, C., Wu, D., Bladogatskaya, E., 2019. Effect of biochar origin and soil type on the greenhouse gas emission and the bacterial community structure in N fertilised acidic sandy and alkaline clay soil. Sci. Total Environ. 660, 69–79. https://doi.org/10.1016/j.scitotenv.2018.12.300

Shackley, S., Sohi, S., Ibarrola, R., Hammond, J., Masek, O., 2013. Biochar, tool for climate change mitigation and soil management, in: Geoengineering Responses to Climate Change. Springer, New York, pp. 73–140. https://doi.org/10.1007/978-1-4614-5770-1_6

Smith, P., 2016. Soil carbon sequestration and biochar as negative emission technologies. Glob. Chang. Biol. 22, 1315–1324. https://doi.org/10.1111/gcb.13178

Smith, P., Adams, J., Beerling, D.J., Beringer, T., Calvin, K. V., Fuss, S., Griscom, B., Hagemann, N., Kammann, C., Kraxner, F., Minx, J.C., Popp, A., Renforth, P., Vicente Vicente, J.L., Keesstra, S., 2019. Land-Management Options for Greenhouse Gas Removal and Their Impacts on Ecosystem Services and the Sustainable Development Goals. Annu. Rev. Environ. Resour. 44, 255–286. https://doi.org/10.1146/annurev-environ-101718-033129

Smith, P., Davis, S.J., Creutzig, F., Fuss, S., Minx, J., Gabrielle, B., Kato, E., Jackson, R.B., Cowie, A., Kriegler, E., Van Vuuren, D.P., Rogelj, J., Ciais, P., Milne, J., Canadell, J.G., McCollum, D., Peters, G., Andrew, R., Krey, V., Shrestha, G., Friedlingstein, P., Gasser, T., Grübler, A., Heidug, W.K., Jonas, M., Jones, C.D., Kraxner, F., Littleton, E., Lowe, J., Moreira, J.R., Nakicenovic, N., Obersteiner, M., Patwardhan, A., Rogner, M., Rubin, E.,

Sharifi, A., Torvanger, A., Yamagata, Y., Edmonds, J., Yongsung, C., 2015. Biophysical and economic limits to negative CO2 emissions. Nat. Clim. Chang. 6, 42–50. https://doi.org/10.1038/nclimate2870

Smith, S.M., Geden, O., Nemet, G., Gidden, M., Lamb, W.F., Powis, C., Bellamy, R., Callaghan, M., Cowie, A., Cox, E., Fuss, S., Gasser, T., Grassi, G., Greene, J., Lück, S., A., M., Müller-Hansen, F., Peters, G., Pratama, Y., Repke, T., Riahi, K., Schenuit, F., Steinhauser, J., Strefler, J., Valenzuela, J.M., Minx, J.C., 2023. The State of Carbon Dioxide Removal, 1st ed. https://doi.org/10.17605/OSF.IO/W3B4Z

Snyder, C.S., Bruulsema, T.W., Jensen, T.L., Fixen, P.E., 2009. Review of greenhouse gas emissions from crop production systems and fertilizer management effects. Agric. Ecosyst. Environ. 133, 247–266. https://doi.org/10.1016/j.agee.2009.04.021

Sommer, R., Bossio, D., 2015. Response to the discussion letter of Lassaletta and Aguilera “soil carbon sequestration is a climate stabilization wedge: Comments on Sommer and Bossio (2014).” J. Environ. Manage. 153, 132–133. https://doi.org/10.1016/j.jenvman.2015.01.033

Sommer, R., Bossio, D., 2014. Dynamics and climate change mitigation potential of soil organic carbon sequestration. J. Environ. Manage. 144, 83–87. https://doi.org/10.1016/j.jenvman.2014.05.017

Stockmann, U., Adams, M.A., Crawford, J.W., Field, D.J., Henakaarchchi, N., Jenkins, M., Minasny, B., McBratney, A.B., Courcelles, V. de R. de, Singh, K., Wheeler, I., Abbott, L., Angers, D.A., Baldock, J., Bird, M., Brookes, P.C., Chenu, C., Jastrow, J.D., Lal, R., Lehmann, J., O’Donnell, A.G., Parton, W.J., Whitehead, D., Zimmermann, M., 2013. The knowns, known unknowns and unknowns of sequestration of soil organic carbon. Agric. Ecosyst. Environ. 164, 80–99. https://doi.org/10.1016/j.agee.2012.10.001

Strefler, J., Amann, T., Bauer, N., Kriegler, E., Hartmann, J., 2018. Potential and costs of carbon dioxide removal by enhanced weathering of rocks. Environ. Res. Lett. 13. https://doi.org/10.1088/1748-9326/aaa9c4

Stuckert, N.R., Yang, R.T., 2011. CO2 capture from the atmosphere and simultaneous concentration using zeolites and amine-grafted SBA-15. Environ. Sci. Technol. 45, 10257–10264. https://doi.org/10.1021/es202647a

Sykes, A.J., Macleod, M., Eory, V., Rees, R.M., Payen, F., Myrgiotis, V., Williams, M., Sohi, S., Hillier, J., Moran, D., Manning, D.A.C., Goglio, P., Seghetta, M., Williams, A., Harris, J., Dondini, M., Walton, J., House, J., Smith, P., 2019. Characterising the biophysical, economic and social impacts of soil carbon sequestration as a greenhouse gas removal technology. Glob. Chang. Biol. 26, 1085–1108. https://doi.org/10.1111/gcb.14844

Taylor, L.L., Quirk, J., Thorley, R.M.S., Kharecha, P.A., Hansen, J., Ridgwell, A., Lomas, M.R., Banwart, S.A., Beerling, D.J., 2016. Enhanced weathering strategies for stabilizing climate and averting ocean acidification. Nat. Clim.

Chang. 6, 402–406. https://doi.org/10.1038/nclimate2882

TERC, 2020. Climate and Carbon Cycle [WWW Document]. URL https://serc.carleton.edu/earthlabs/climate_intro/index.html (accessed 5.22.20).

The Royal Society, 2018. Greenhouse Gas Removal.

Thoni, T., Beck, S., Borchers, M., Förster, J., Görl, K., Hahn, A., Mengis, N., Stevenson, A., Thrän, D., 2020. Deployment of NETs at the National Level: A Need for Holistic Feasibility Assessments. Front. Clim. 2, 12.

Tisserant, A., Cherubini, F., 2019. Potentials, limitations, co-benefits, and trade-offs of biochar applications to soils for climate change mitigation. Land 8. https://doi.org/10.3390/LAND8120179

UNFCCC, 2015. Adoption of the Paris Agreement.

Viebahn, P., Scholz, A., Zelt, O., 2019. German Energy Research Program — Results of a Multi-Dimensional Analysis. Energies.

Voskian, S., Hatton, T.A., 2019. Faradaic electro-swing reactive adsorption for CO2 capture. Energy Environ. Sci. 12, 3530–3547. https://doi.org/10.1039/c9ee02412c

Waller, L., Rayner, T., Chilvers, J., Gough, C.A., Lorenzoni, I., Jordan, A., Vaughan, N., 2020. Contested framings of greenhouse gas removal and its feasibility: Social and political dimensions. Wiley Interdiscip. Rev. Clim. Chang. 11, 1–17. https://doi.org/10.1002/wcc.649

Wang, H., Yi, H., Zhang, X., Su, W., Li, X., Zhang, Y., Gao, X., 2020. Biochar mitigates greenhouse gas emissions from an acidic tea soil. Polish J. Environ. Stud. 29, 323–330. https://doi.org/10.15244/pjoes/99837

Wang, Y., Yan, X., Wang, Z., 2014. The biogeophysical effects of extreme afforestation in modeling future climate. Theor. Appl. Climatol. 118, 511–521. https://doi.org/10.1007/s00704-013-1085-8

Whitehead, D., 2011. Forests as carbon sinks - Benefits and consequences. Tree Physiol. 31, 893–902. https://doi.org/10.1093/treephys/tpr063

Whitmore, A.P., Kirk, G.J.D., Rawlins, B.G., 2015. Technologies for increasing carbon storage in soil to mitigate climate change. Soil Use Manag. 31, 62–71. https://doi.org/10.1111/sum.12115

Woolf, D., Amonette, J.E., Street-Perrott, F.A., Lehmann, J., Joseph, S., 2010. Sustainable biochar to mitigate global climate change. Nat. Commun. 1. https://doi.org/10.1038/ncomms1053

Wurzbacher, J.A., Gebald, C., Steinfeld, A., 2011. Separation of CO 2 from air by temperature-vacuum swing adsorption using diamine-functionalized silica gel. Energy Environ. Sci. 4, 3584–3592. https://doi.org/10.1039/c1ee01681d

Yadav, M.R., Yadav, R.., Parihar, C.M., Kumar, R., Bajiya, R., Yadav, N., Meena, R.K., H. Ram, H., Yadav, B., Yadav, D.K., 2017. Role of Biochar in Mitigation of Climate Change through Carbon Sequestration. Int. J. Curr. Microbiol. Appl. Sci. 6, 859–866. https://doi.org/10.20546/ijcmas.2017.604.107

Zhang, C., Zeng, G., Huang, D., Lai, C., Chen, M., Cheng, M., Tang, W., Tang, L., Dong, H., Huang, B., Tan, X., Wang, R., 2019. Biochar for environmental management: Mitigating greenhouse gas emissions, contaminant treatment, and potential negative impacts. Chem. Eng. J. 373, 902–922. https://doi.org/10.1016/j.cej.2019.05.139

Zimmerman, A.R., Gao, B., Ahn, M.Y., 2011. Positive and negative carbon mineralization priming effects among a variety of biochar-amended soils. Soil Biol. Biochem. 43, 1169–1179. https://doi.org/10.1016/j.soilbio.2011.02.005

Zimmermann, M., Bird, M.I., Wurster, C., Saiz, G., Goodrick, I., Barta, J., Capek, P., Santruckova, H., Smernik, R., 2012. Rapid degradation of pyrogenic carbon. Glob. Chang. Biol. 18, 3306–3316. https://doi.org/10.1111/j.1365-2486.2012.02796.x

3 Methodology

3.1 Introduction

This chapter presents details of the methodology applied in achieving the objectives of this study. Given that the first objective, which has been presented in Chapter 2 is based on a review of the literature, this chapter is thus focussed on the respective methodology applied for the other three objectives or work packages, namely:

1. Categorise the global deployment suitability of GGR methods at the country-level using hierarchical clustering ML.
2. Apply supervised ML algorithms for resource mapping of GGR methods.
3. Evaluate the cumulative amount of CO_2 removable by 2100 via these GGR methods by each country using a MCDA approach, assessing sufficiency to meet quotas, and identify areas of regional competitive advantages and collaborations.

3.2 Input Data Characteristics

For each of the outlined objectives in this study, only five GGR methods were considered. These technologies which were selected based on their CDR potential and technological readiness levels include forestation, EW, DACCS, BECCS and biochar. Having identified the factors required for the deployment and performance of these technologies in Chapter 2, associated indicators of these factors were thus selected to form the input data variables for the study (Table 3-1).

These selected indicators of bio-geophysical and techno-economic factors form the primary indicators as they show the range of key resources available for the siting and deployment of these technologies. Bio-geophysical factors refers to a composite of the biological, geological and physical or ecological characteristics operating in an area such as climate, land use, vegetation and water availability. Techno-economic factors on the other hand refers to characteristics that assess the technological performance and economic feasibility of a process, system or

value chain. While the former is largely natural, the latter is man-made and includes factors such as gross national income (GNI) and availability of low carbon energy.

Table 3-1 Input variables applied for the assessment of the GGR technologies

GGR method	Input variables
Forestation	Climatic factor (temperature and precipitation)[a], land availability (FLu), water availability (WA).
EW	Rock availability, low carbon energy availability (LCEA), cost consideration (GNI), climatic factor [a], land availability (AgLu).
DACCS	Geological storage potential (GSP), LCEA, GNI and WA.
BECCS	GSP, Biomass availability (BA), WA and GNI.
Biochar	BA, climatic factor [a], GNI and AgLu

[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).

Other factors such as those within the highly dynamic socio-political environment were not considered in this study. While they are no doubt important, they are however considered as secondary factors because their impact only comes into play after the viable range of GGR technologies deployable has been identified. With this study aimed at identifying the range of GGR technologies deployable based on locational availability of needed resources, these factors are thus not required. The approach deployed in the study is apolitical and whilst final investment and deployment decisions would no doubt be influenced by the respective political and prevailing social systems; these factors, however, have no influence on the process of identifying the range of technologies deployable in a particular location.

3.3 Data Collection

Most recent available country-level data for the selected indicators were obtained for 182 countries (see **Appendix A** for list of countries). It is important to state that this study is limited to assessing the domestic potential of countries. Hence,

only data indicating domestic resource availability was applied. Resources from external sources such as energy or biomass importation, foreign financial investment were not considered in the study. Details about each indicator including data sourcing information are briefly discussed in the following sections.

3.3.1 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.

3.3.2 Land availability

The share of land use for forest and agriculture was adopted to assess land availability (CIA, 2022). For forestation, a combination of the countries' forest land use (reforestation potential) and agricultural land use (afforestation potential) was chosen as the indicator (FLu). For the latter, arable land suited for growing crops was not considered to ensure that the growing of trees did not negatively impact on food production. For EW and biochar, AgLu was adopted to indicate the availability of land

3.3.3 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.

3.3.4 Geological CO_2 storage potential (GSP)

Underground geological storage option has been generally recommended as the most viable choice because of favourable economic factors, wide geographical distribution and environmental concerns (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), combined with the sedimentary basins data reported by Kearns et al. (2017).

3.3.5 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 drive the development and deployment 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).

3.3.6 Low carbon energy availability (LCEA)

For energy availability, only low carbon energy sources were considered. This is to ensure that the deployment of energy intensive GGR methods does not result in additional 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 percentage share of each countries' energy that is generated from 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.

3.3.7 Biomass availability (BA)

Lignocellulosic feedstocks like wood, Miscanthus, switchgrass and agricultural residues have been generally recommended for dedicated planting or importation as they are less likely to compete with food supply (Royal Society, 2018; Smith et al., 2015). 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.

3.3.8 Rock availability

Country-level data for rock availability, a key indicator for deployment of EW was unavailable. A scenario in which all nations possess the needed rock resources was however assumed for the EW assessment. This assumption is confirmed by basalt's vast abundance, which makes up about 6.8 million km^2 of the earth's surface (about 4.56% of the planet's land mass) and is present in considerably greater quantities below the surface and beneath the oceans (Dessert et al., 2003).

3.4 Data Pre-processing

The obtained raw data was pre-processed into a usable form by numerical encoding of string type data and analytical determination of incomplete data. Data normalisation was also carried out between 0 and 1 for the entire dataset using equation (3-1). By doing this, any potential bias caused by variations in the range of values among the variables was eliminated. Data normalisation also ensured that the data of each country was better situated and captured within a global context. This is important given the global nature of the mitigation situation and the need to comparatively assess the role, scale and capacity of countries and to identify collaborative prospects.

$$x_{ij}^{norm} = \frac{x_{ij} - x_{min}}{x_{max} - x_{min}} \quad (3\text{-}1)$$

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.

Table 3-2 presents description of the obtained data characteristics and pre-processing applied.

Table 3-2 Description of input data characteristics and applied pre-processing

Input variables	Raw Data characteristics	Applied data pre-processing
Climatic factor	This consisted of the quarterly mean temperature (Q1T, Q2T, Q3T, Q4T) and precipitation (Q1P, Q2P, Q3P, Q4P) for each country.	Normalisation of the 182 datasets between 0 and 1 for each quarterly variable.
Land availability	Forest land use (sq.km) and agricultural land use (sq.km) for each country.	Data normalisation between 0 and 1
Water availability	Water stress level for each country was obtained in the form of categories (*no stress*, *low stress*, *medium stress*, *high stress* and *critical* categories).	Using the UN water stress level categorisation (UN Water, 2022), scores for water availability of countries were assigned as follows: *no stress* (5), *low stress* (4), *medium stress* (3), *high stress* (2), *critical* (1). These assigned scores were then normalised between 0 and 1.
Geological storage potential (GSP)	GSP for each country was obtained in the form of suitability categories (*unsuitable*, *unproven*, *possible*, *suitable* and *highly suitable*).	To apply this data in the model, they had to be converted to numbers. To do this, numbers (scores) between 0 and 4 were allocated to the categories as follows: *unsuitable* (0), *unproven* (1), *possible* (2), *suitable* (3), *highly suitable* (4). These assigned scores were then normalised between 0 and 1.
Financial capability	2019 Gross national income per capita (GNI) US$ was obtained for each country.	Using the world bank 2020 GNI per capita threshold of $12536 for high-income economies (Hamadeh et al., 2021) as maximum value, the raw data was normalised between 0 and 1.

Low carbon energy availability	The percentage share of each countries' energy that is generated from low carbon energy sources (%). These low carbon energy sources included nuclear and renewable sources.	The obtained percentages were then converted to their respective decimal equivalent.
Biomass availability	Biomass potential measured in terms of the net primary production (tC/ha/yr) was obtained for each country (IRENA, 2021).	The obtained net primary production for each country was multiplied by their respective forest and agricultural (arable) land use to obtain the current biomass potential (tC/yr). This value was then normalised between 0 and 1.

Having presented the general information regarding the data collection and pre-processing applied in this study, details on the specific methodology deployed for each of the work packages is presented in the following sections.

3.5 Categorisation of GGR Deployment Suitability of Countries Using Hierarchical Clustering ML

In this work package, the suitability of 182 countries to deploy the five selected GGR technologies was investigated using an unsupervised machine learning (ML) algorithm known as the hierarchical clustering ML technique. Figure 3-1 presents the framework of the methodology applied in this work package. With the first four steps already covered in the preceding sections 3.2 – 3.4, this section is focused on the application of the hierarchical clustering and the categorisation process.

3.5.1 Machine Learning

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. The goal of ML is to create computer programmes that can access data and use it to acquire knowledge on their own (ExpertAI, 2022). It finds widespread use in several fields of human endeavours including finance, retail,

security, healthcare, image and speech recognition, robot control and other sectors (Jordan and Mitchell, 2015; Kumar, 2019). Though constrained by elements including ethics, data quality and availability, improper application and interpretability, ML is characterised by several advantages including ease of spotting trends and patterns, automation that requires little human interaction, ability to constantly improve, and great efficiency when managing data that is multi-dimensional and multi-variety (Garbade, 2018; Jordan and Mitchell, 2015).

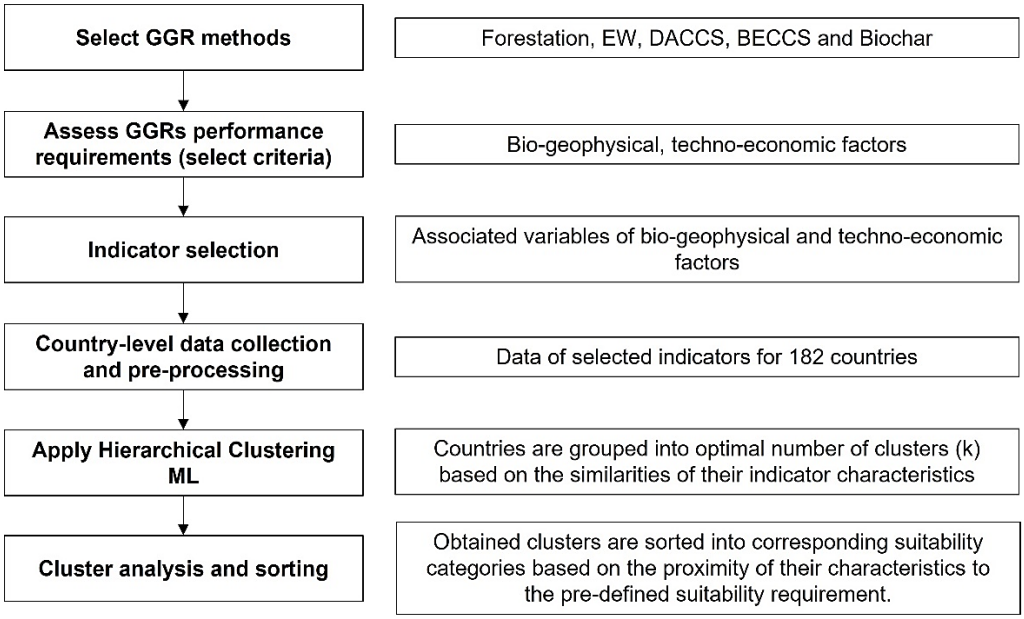


Figure 3-1 Methodology framework for the suitability categorisation of countries for GGR deployment using hierarchical clustering machine learning

There are three main types of ML: the Supervised ML, the Unsupervised ML and the Reinforcement ML. While Supervised ML creates classification and regression predictive models using both input and output data, Unsupervised ML looks for hidden patterns or structures in unlabelled input data, that is, it determines output by assessing patterns in the input data. Reinforcement ML are a trial-and-error search technique that interacts with the environment by generating actions and discovering errors or rewards (ExpertAI, 2022).

With this work package aimed at determining the suitability category of 182 countries to deploy the five selected GGR technologies based on a multidimensional assessment of their respective bio-geophysical and techno-

economic characteristics, there was need for an objective approach wholly based on the input data, that will minimise human bias and be efficient at multi-dimensional data assessment. ML was thus chosen and deployed in this study on account of its advantages and ability to meet this need. ML is dependent on available data and given the current lack of labelled data on GGR deployment suitability of countries, brought about by the fact that GGR technologies are yet to be globally deployed at scale, the Unsupervised ML technique was thus adopted. With this work package being a categorisation-kind problem in which the ML algorithm is expected to assess the input data characteristics and categorise or cluster countries with similar input characteristics, the commonly used clustering algorithms were thus assessed. They include K-means, Fuzzy K-means, Hierarchical clustering, density-based spatial clustering of applications with noise (DBSCAN) and Gaussian Mixture algorithm (McGregor, 2020; Mishra, 2017). Based on the assessment of the characteristics of these algorithms with respect to the needs of the study and data characteristics, the hierarchical clustering ML technique was selected for use in this study. This is on account of its simplicity, structured clustering process, ease of assess of the clustering process (produces a dendrogram) as well as multiple and more efficient linkage methods for assessing similarities of datapoints.

3.5.2 Hierarchical clustering ML

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). The clustering occurs either in a bottom-up (agglomerative) or a top-down (divisive) format. The agglomerative approach, which was applied in this study is one in which each data point identified as a cluster at the beginning of the clustering process. Each of this datapoint then gets joined to those of similar characteristics to form new clusters with more members. Similar clusters are combined on each iteration until one large root cluster containing all of the data

points is obtained. When the iteration is finished, the output resembles a dendrogram so that you can quickly see the clusters.

There are various hierarchical clustering algorithms depending on the type of linkage or approach deployed by the ML in assessing the similarity or dissimilarity between datapoints or clusters. These linkages which are usually specified by the user as part of the modelling code include the single link in which the algorithm considers closest datapoints (nearest neighbour) as members of same clusters, others include complete link (diameter), group average (average link), centroid method, Median method and Ward's method (Murtagh and Contreras, 2012). The Ward's linkage method which is generally considered as the most suitable for quantitative variables was adopted for this study (Hu et al., 2018). This method analyses the variance that exists between clusters. It specifies the distance between two clusters by computing the increase in the error sum of squares when the clusters are merged. The Ward's linkage thus chooses successive clustering steps that would minimise this increase in error sum of squares. According to Hu et al. (2018), for merging two clusters, A and B, the increase in the error sum of squares, Δ can be calculated using equation (3-2), while the dissimilarity between the cluster centers, d_c can be obtained using equation (3-3).

$$\Delta(A,B) = \sum_{i\in A\cup B} ||\overrightarrow{x_i} - \overrightarrow{m_{A\cup B}}||^2 - \sum_{i\in A} ||\overrightarrow{x_i} - \overrightarrow{m_A}||^2 - \sum_{i\in B} ||\overrightarrow{x_i} - \overrightarrow{m_B}||^2 \qquad (3\text{-}2)$$

$$d_c(A,B) = \frac{n_A n_B}{n_A + n_B} ||\overrightarrow{m_A} - \overrightarrow{m_B}||^2 \qquad (3\text{-}3)$$

where $\overrightarrow{m_j}$ is the center of cluster j, and n_j is the number of points within the cluster j.

For two points or objects, i and j agglomerated into cluster i∪j, the new dissimilarity, d, between the cluster and all other points (objects or clusters) can be specified using the Lance–Williams dissimilarity update formula (Murtagh and Contreras, 2012) presented in equation (3-4).

$$d(i \cup j, k) = \alpha_i d(i,k) + \alpha_j d(j,k) + \beta d(i,j) + \gamma |d(i,k) - d(j,k)| \qquad (3\text{-}4)$$

where α_i, α_j, β, and γ are the agglomerative criterion which is dependent on the type of linkage applied. For Ward's linkage, while $\gamma = 0$, the formula for obtaining α_i, α_j and β are presented in equations (3-5), (3-6) and (3-7) respectively (Murtagh and Contreras, 2012).

$$\alpha_i = \frac{n_i + n_k}{n_i + n_j + n_k} \tag{3-5}$$

$$\alpha_j = \frac{n_j + n_k}{n_i + n_j + n_k} \tag{3-6}$$

$$\beta = \frac{n_k}{n_i + n_j + n_k} \tag{3-7}$$

Where n_j is the number of points within cluster j.

In deploying the hierarchical clustering in this study, the dataset consisted of 182 datapoints representing the 182 countries studied. For the assessment of each GGR technology, each datapoint was characterised by the respective input variables specified in Table 3-1.

3.5.3 Determination of the optimal number of clusters

The agglomerative hierarchical clustering algorithm follows a bottom-up approach in clustering datapoints from the first iteration where each single point is identified as single clusters till the final iteration where all data points have been merged to become members of a single cluster. While it performs this clustering task effectively, there is however a need to specify the number of clusters required from the process. To ensure that the number of clusters specified optimally captures the similarities and dissimilarities of the dataset specified, there is thus a need to first determine the optimal number of clusters (k) that can be obtained for the particular dataset. This 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.

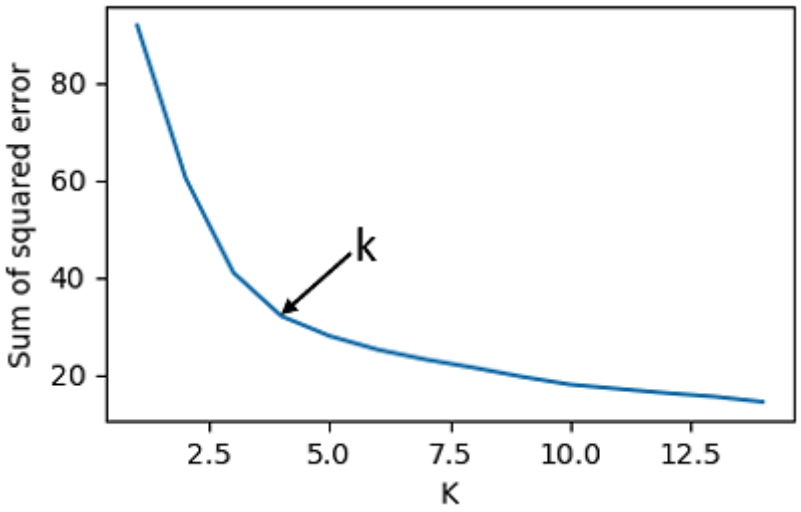


Figure 3-2 Plot to determine the optimum number of clusters (*k*) for the forestation dataset using the elbow method

To obtain the optimal number of clusters (k) for the respective dataset of each GGR, the elbow method in KMeans clustering was applied. The elbow method works by determining the sum of square error (SSE) between points within a cluster and the centroid of the cluster (within-cluster SSE) (Saji, 2021). A line graph of this SSE (y-axis) and its corresponding value of k (x-axis) is obtained. The line graph obtained typically resembles an elbow curve and the k-value that corresponds to the crux of the elbow curve (elbow point) indicates optimal number of clusters (see Figure 3-2). The elbow point is the minimum limit of significant reduction in the SSE, thus indicating maximum similarity of members in the same cluster. Increasing the value of 'k' beyond this point results in insignificant reduction in the within-cluster SSE.

With the elbow method being a graphical visualisation-based solution, there could be occasions where the elbow point cannot be clearly identified. To ensure certainty of results, a second method known as the Silhouette score method was also applied (Tomar, 2022). Figure 3-3 presents the code written in Python for determining the optimal number of clusters (k) for the forestation dataset. Similar code was applied for the other GGR methods using their respective dataset (line 7 of code), with changes made to line 14 of code (specify the input variables).

```python
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.cluster import KMeans


# #Loading locational dataset
df = pd.read_csv('Updated normalised Forestation data2.csv')

# Using the elbow method to determine the k value to be applied
k_rng = range(1, 10)
sse = []
for k in k_rng:
    km = KMeans(n_clusters=k)
    km.fit(df[['Q1T','Q2T','Q3T','Q4T','Q1P','Q2P','Q3P','Q4P','FLu','WA']])
    sse.append(km.inertia_)

# Plot to obtain elbow
plt.xlabel('K')
plt.ylabel('Sum of squared error')
plt.plot(k_rng, sse)
```

Figure 3-3 Python code for determining optimum number of clusters for the forestation dataset.

3.5.4 Clustering and cluster characteristics

Having obtained the optimum number of clusters for the dataset, the hierarchical clustering code was then written in Python. The *Agglomerative Clustering* library was imported from the sklearn.cluster module. The pandas data analysis library was applied for loading and reading the respective datasets. The seaborn visualization library from the matplotlib library was imported to generate the cluster characteristics heatmap. The *scipy.cluster.hierarchy* function was also imported for the creation and visualisation of the dendrogram. For the clustering, the linkage was set to 'ward' while the Euclidean distance method was adopted. The Euclidean distance, d_e calculates the square root of the sum of the squared differences between any two data points, p and q, in a Euclidean space (see equation (3-8)).

$$d_e(p,q) = d_e(q,p) = \sqrt{\sum_{i=1}^{k} (q_i - p_i)^2} \tag{3-8}$$

For forestation, the dataset consisted of 10 input variables for 182 countries. These 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). On running the code, the 182 datapoints (countries) was grouped optimally into four clusters (based on the obtained k value for forestation in section 3.5.2) and labelled 0 – 3. A dendrogram showing the agglomerative clustering process was generated and is presented in Figure 3-4. The obtained k-value of 4 is indicated on the dendrogram as the point at which our vertical lines are cut by the red dashed horizontal line.

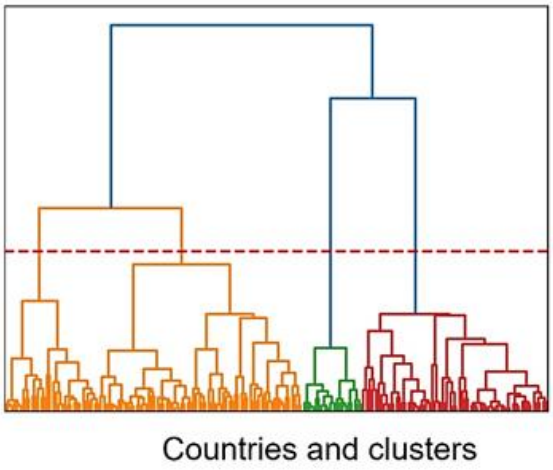


Figure 3-4 Dendrogram for the forestation dataset clustering

The characteristics of the four obtained clusters were then 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 Figure 3-5. 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).

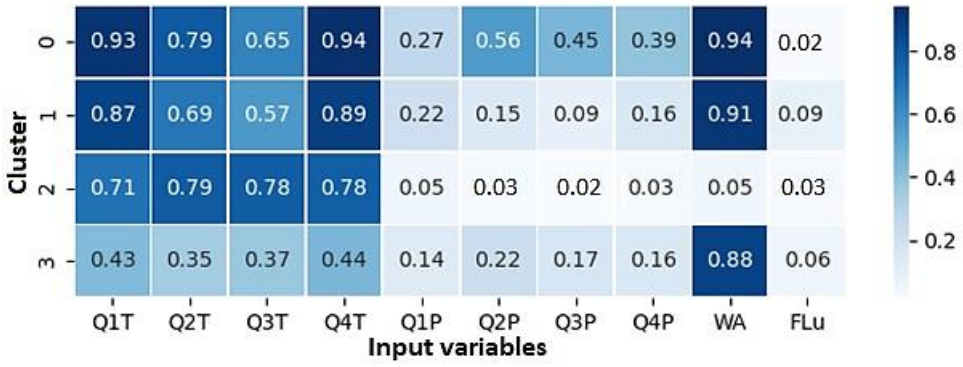


Figure 3-5 Heatmap showing the forestation cluster characteristics

3.5.5 Cluster sorting into suitability categories

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 methods.

Table 3-3 The bio-geophysical and techno-economic requirements selected for GGR deployment

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

To ensure that the sorting of the obtained ML clusters into suitability categories was done based on a consideration of the impact/importance of the various factors (Table 2-3), the deployment requirements for each GGR technology was grouped into major and minor requirements as presented in Table 3-3. Major requirements indicate high impact variables that are indispensable for the deployment of the particular GGR technology, while minor requirements indicate low impact factors without which the particular GGR technology can still be deployed.

Based on the level of similarity between the obtained cluster characteristics and those identified in Table 3-3, the clusters were then sorted into their corresponding level of deployment suitability. 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 3-3, a description of these suitability categories is presented in Table 3-4.

Table 3-4 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

3.5.6 Forestation

With reference to Figure 3-5, the similarity of the obtained cluster characteristics were assessed by comparing with those required for deployment of forestation,

as presented in Table 3-3. Based on this assessment, 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 (Figure 3-5) and their corresponding categories are presented in Table 3-5.

Table 3-5 Description of Forestation cluster characteristics

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

Having exhaustively described the hierarchical clustering methodology using the forestation dataset, the same method was applied for the other four GGR technologies under consideration, namely: EW, DACCS, BECCS and Biochar. Modelling details for these other four GGR methods are presented in the following sections. It includes information on the data variable applied for each GGR method, figures for obtaining the optimal number of clusters (k) and cluster characteristics. It also includes the tables for the description of the respective cluster characteristics and their corresponding categories (*highly suitable* (HS), *suitable* (S), *possible* (P) and *unsuitable* (U)).

3.5.7 Enhanced weathering

Data features: The mean quarterly temperature (Q1T, Q2T, Q3T, Q4T), the mean quarterly precipitation (Q1P, Q2P, Q3P, Q4P), GNI per capita, low carbon energy availability (LCEA) and agricultural land use (AgLu).

Optimal number of clusters, k = 7

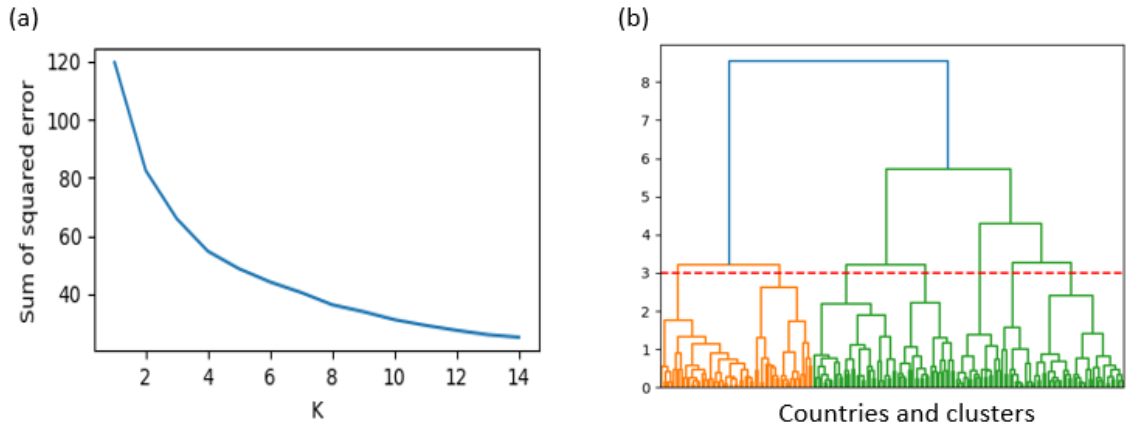


Figure 3-6 (a) Optimum number of clusters (k) determined by the elbow method for EW, (b) EW dendrogram

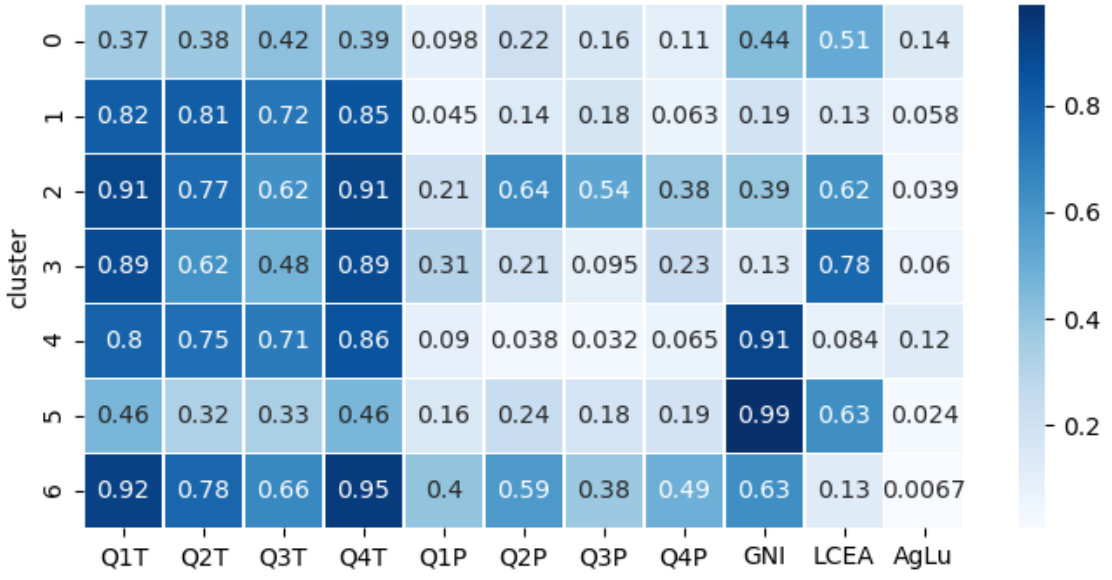


Figure 3-7 Heatmap of EW cluster characteristics

Table 3-6 Description of EW cluster characteristics

Suitability category	Characteristics	Cluster label
Highly suitable	High GNI (indicating financial capability) and high LCEA for rock crushing and logistics, medium temperature and precipitation coupled with relatively medium land availability for rock spreading.	5
Suitable	Medium GNI, high LCEA, relatively medium temperature and low precipitation coupled with high land availability.	0
	Medium GNI, high LCEA, high temperature and precipitation to enhance the weathering process coupled relatively medium land availability.	2
Possible	Low GNI per capita and high LCEA, high temperature and low precipitation coupled with relatively medium land availability.	3
	High GNI per capita and very low LCEA, high temperature and low precipitation coupled with relatively high land availability.	4
	High GNI per capita and low LCEA, high temperature and precipitation coupled with very low land availability.	6
Unsuitable	Low GNI per capita and LCEA, high temperature and low precipitation coupled with relatively low land availability.	1

3.5.8 DACCS

Data features: Water availability (WA), CO_2 storage potential (GSP), low carbon energy availability (LCEA), GNI per capita. Optimal number of clusters, k = 5

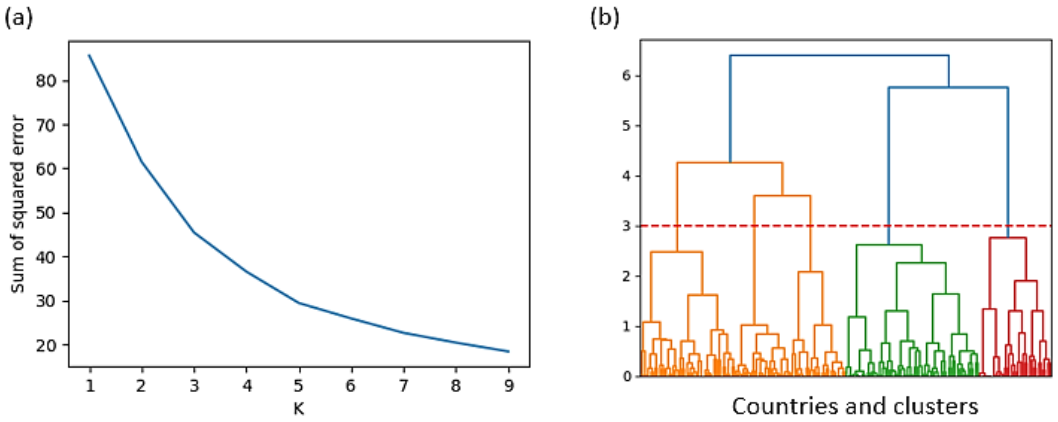


Figure 3-8 (a) Optimum number of clusters (k) determined by the elbow method for DACCS, (b) DACCS dendrogram

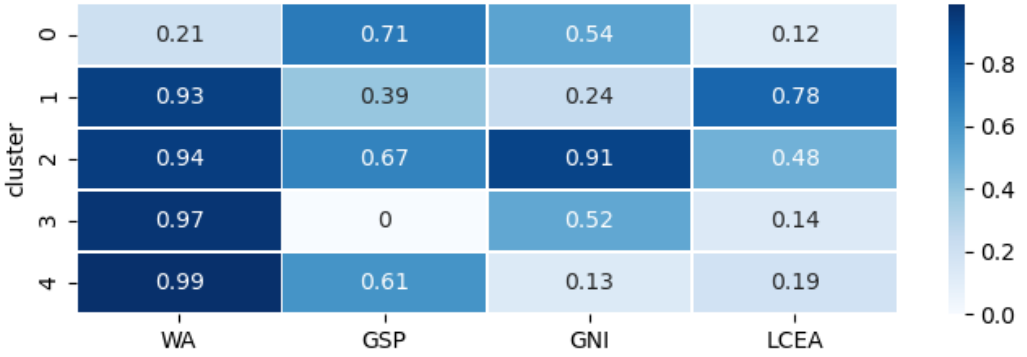


Figure 3-9 Heatmap of DACCS cluster characteristics

Table 3-7 Description of DACCS cluster characteristics

Suitability category	Characteristics	Cluster label
Highly suitable	High GSP, high GNI, relatively high LCEA and high WA.	2
Suitable	Medium GSP, low GNI, high LCEA and high WA.	1
Possible	High GSP, medium GNI, very low LCEA and low WA.	0
	High GSP, low GNI, very low LCEA and high WA.	4
Unsuitable	Highly unsuitable GSP with medium GNI, very low LCEA and high WA.	3

3.5.9 BECCS

Data features: GNI per capita, geological storage potential (GSP), water availability (WA), biomass availability (BA). Optimal number of clusters, k = 5

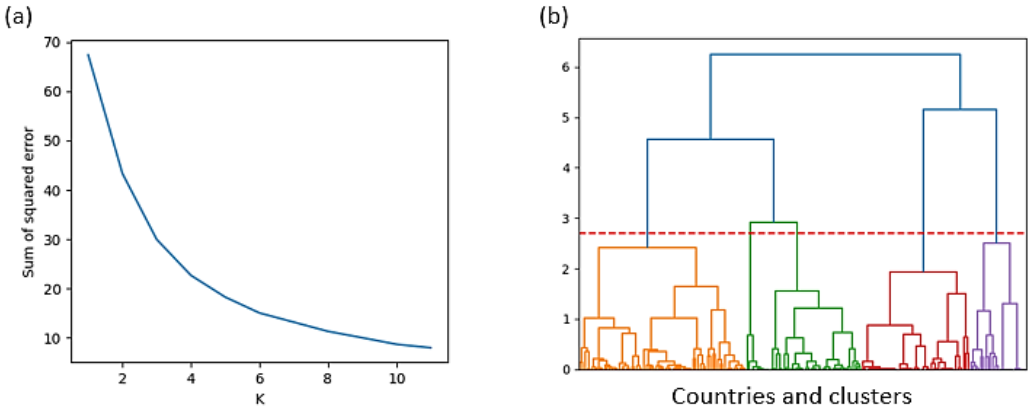


Figure 3-10 (a) Optimum number of clusters (k) determined by the elbow method for BECCS, (b) BECCS dendrogram

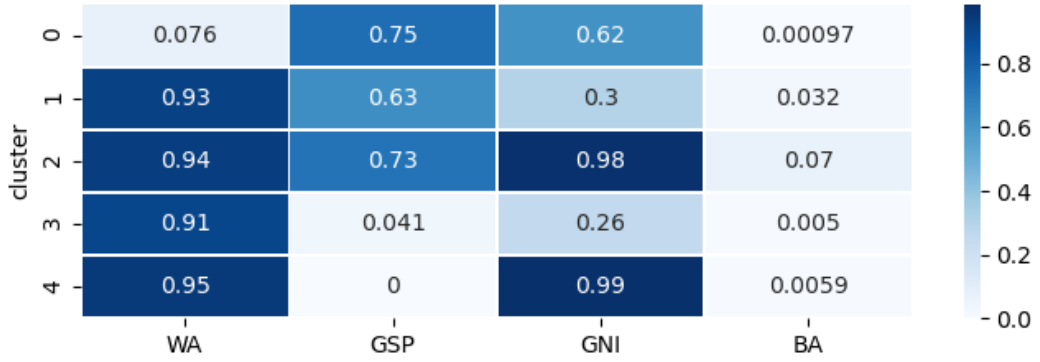


Figure 3-11 Heatmap of BECCS cluster characteristics

Table 3-8 Description of BECCS cluster characteristics

Suitability category	Characteristics	Cluster label
Highly suitable	High GSP, BA, WA and GNI.	2
Suitable	High GSP, medium BA, high WA and low GNI.	1
Possible	High GSP, very low BA, low WA and high GNI.	0
Unsuitable	Very low GSP, very low BA, high WA and low GNI.	3
	Highly unsuitable GSP, very low BA, high WA and high GNI.	4

3.5.10 Biochar

Data features: The mean quarterly temperature (Q1T, Q2T, Q3T, Q4T), the mean quarterly precipitation (Q1P, Q2P, Q3P, Q4P), GNI per capita, agricultural land use (AgLu) and biomass availability (BA). Optimal number of clusters, k = 6

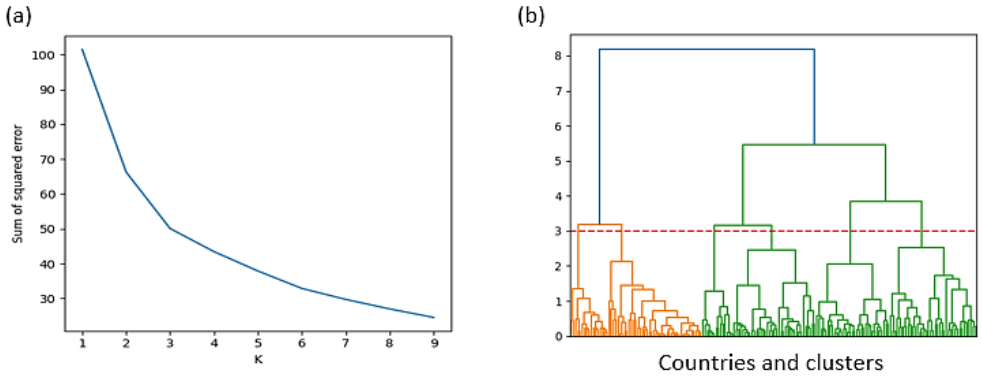


Figure 3-12 (a) Optimum number of clusters (k) determined by the elbow method for Biochar, (b) biochar dendrogram

Figure 3-13 Heatmap of Biochar cluster characteristics

Table 3-9 Description of Biochar cluster characteristics

Suitability Category	Characteristics	Cluster label
Highly suitable	High BA, AgLu for biochar application and GNI, with medium temperature and low precipitation.	2
Suitable	High BA, low AgLu for biochar application, medium GNI, with high temperature and precipitation.	0
Possible	Medium BA, high AgLu for biochar application, very low GNI, with high temperature and low precipitation.	1
	Medium BA and AgLu for biochar application, very low GNI, with high temperature and precipitation.	3
Unsuitable	Very low BA, low AgLu and low GNI, with medium temperature and precipitation.	4
	Very low BA, medium AgLu and high GNI, with high temperature and low precipitation.	5

3.6 Application of Supervised ML for Resource Mapping of GGR Methods

In this work package, supervised ML was applied to develop models that can predict the suitability of a location to deploy the five GGR technologies based on the bio-geophysical and techno-economic characteristics of the location. As

explained in section 3.5, the deployment of supervised ML for predictive modelling requires a labelled dataset consisting of both input variables and corresponding output label. The supervised ML algorithm trains the dataset to establish a relationship between the input variables and the output (Singh et al., 2016; Wilson, 2019). For this study, the same input data deployed in the hierarchical clustering (section 3.5) was applied. This input dataset consisted of data for the input variables highlighted in Table 3-1 for the 182 countries. While the output label consisted of the respective suitability category of the 182 countries to deploy the five GGR technologies which was obtained from the hierarchical clustering analysis (section 3.5). The labelled dataset for each GGR method thus consisted of the data for the respective input variables of bio-geophysical and techno-economic factors (Table 3-1) and the corresponding output labels (deployment suitability level) for the 182 countries.

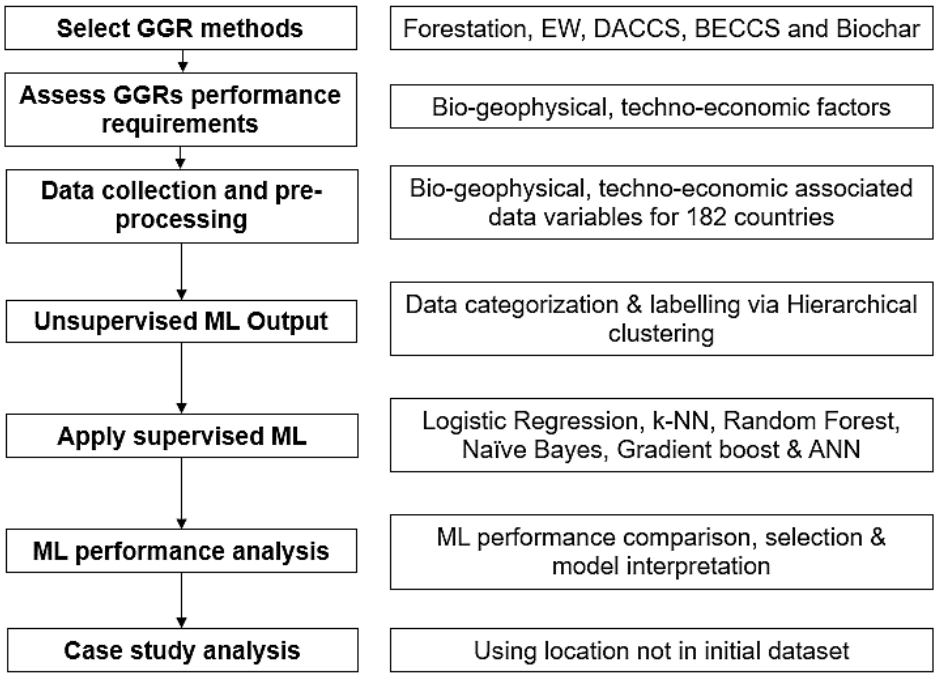


Figure 3-14 Method framework for the supervised machine learning modelling

Figure 3-14 presents the framework of the method applied in this study. With the first four steps already addressed in the preceding sections, this section is focussed on detailing the supervised ML application. Since it is a classification-type problem in which a given location's deployment suitability category is expected to be predicted by the ML model, seven of the most commonly applied

ML classification algorithm was employed in this study. These ML algorithms which include logistic regression, Decision Tree, k-NN, naïve bayes, Random Forest, gradient boost and ANN, are briefly discussed in the following sections. It is important to note that in the application of each of these algorithms, the dataset was randomly divided between training and testing groups with a ratio of 70:30. This was to get best results, minimise training and testing bias and ensure that the model's accuracy is neither overestimated nor underestimated (Gholamy et al., 2018; Güleç et al., 2022). The respective codes for each algorithm was written in Python using the corresponding ML algorithm library imported from their respective *sklearn* module (see **Appendix C**). All codes were run 30 times to minimise bias.

3.6.1 Logistic Regression

This a classification algorithm that predicts the likelihood of a dependent variable (usually binary) belonging to a category. While it is majorly used for binary classification-type problems, it also finds application in multiclass categorisation. It can return probabilities and can easily be updated and adjusted to take new data. It does not assume linear relationships between input and output variables. Though it requires large data size to achieve stable results, it is however very well suited to power terms, nonlinear effect and interaction effect (Singh et al., 2016). The governing function for the logistic regression model also known as the sigmoid function is presented in equation (3-9) (Rai, 2020).

$$F(x) = \frac{1}{1 + e^{-x}} = \frac{e^{x}}{e^{x} + 1} \tag{3-9}$$

Where x is the input data point.

Equation (3-10) presents the likelihood function, $L(\hat{y}, y)$ for its probabilities prediction, $\hat{y}$.

$$L(\hat{y}, y) = \sum_{i=0}^{n} y_i log\hat{y} + (1 - y_i)\log(1 - \hat{y}) \tag{3-10}$$

Where y is the target class.

3.6.2 Decision Tree

This interpretable algorithm performs by splitting values of data features into branches at decision nodes until a final decision output is established. It can be used for solving regression and classification tasks. It is organized hierarchically and has a root node, branches, internal or decision nodes, and leaf or terminal nodes. Figure 3-15 present the typical structure of a Decision Tree. The prediction of a class label starts from the root node which represents the entire data attributes of the test samples. By comparing the values of the root attribute with the training data attributes, the branch corresponding to that value is split to the next node. It classifies the test data by sorting them from the root node down the tree to some leaf/terminal node which provides the classification of the test data. The decision or internal node acts as a test case for evaluating some data attribute, and each branch descending from the node represents the potential solutions to the test case. Recursively, this splitting process is repeated for each subtree rooted at the new node until all or most of the test data have been assigned to distinct class labels.

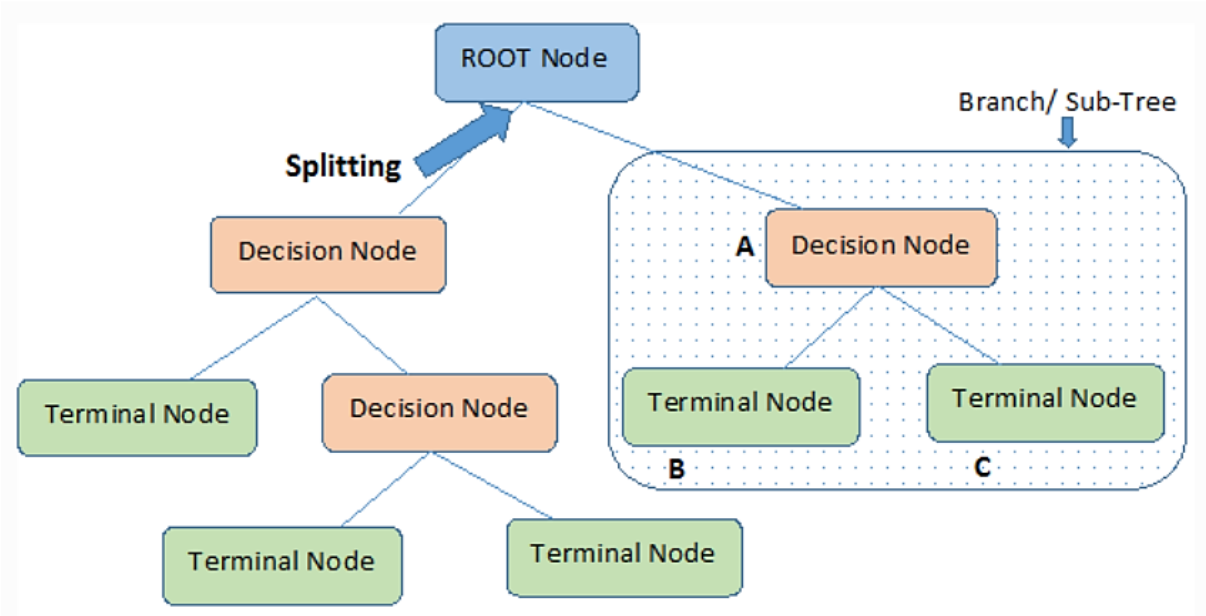


Figure 3-15 Schematic showing the structure of a Decision Tree (Chauhan, 2022a)

Multiple algorithms are deployed by Decision Trees in splitting a node into two or more sub-nodes. The splitting is usually aimed at creating sub-nodes with high

homogeneity of attributes compared to the target variable. Some common algorithms used in Decision Trees include the ID3 (Iterative Dichotomiser 3), C4.5 (successor of ID3), CART (Classification and Regression Tree), CHAID (Chi-square automatic interaction detection Performs multi-level splits when computing classification trees) and MARS (multivariate adaptive regression splines) (IBM, 2023a). The choice of attribute to be evaluated at each node by these algorithms can be determined by various methods or criteria. This includes Entropy, Information gain, Gini index, Gain Ratio, Reduction in Variance and the Chi-Square methods. For decision tree models, the information gain and Gini impurity have been identified as the most common splitting criteria. This is because of their ability to assess the effectiveness of each test condition and its corresponding capacity to categorise samples into a group (Chauhan, 2022a).

While Decision Trees is characterised by advantages of ease of interpretation, minimal data preparation requirement and more flexibility (classification and regression applications) compared to other ML classifiers, it however has some disadvantages. This include high computational cost, feature reduction, high variance estimates and susceptibility to overfitting.

3.6.3 k-Nearest Neighbour (k-NN)

This is a non-parametric algorithm requiring little to no training that makes its selection based on the proximity to other data points regardless of what feature the numerical values represent. It is a simple, supervised ML algorithm applicable to both classification and regression tasks. It's easy to implement and understand, easily adaptable with few hyperparameters requirements. It however has a major disadvantage of becoming significantly slower as the size of that data in use increases (Harrisson, 2018).

The working principle of the k-NN algorithm assumes that similar things are likely to exist in close proximity. It works by finding the distances between a test data and all the training data points. It then selects the specified number of training data points (k) that is closest to the test data. from the selected 'k' training data points, the algorithm then selects the class with the most frequent label (Christopher, 2021). Figure 3-16 presents a description of classification by k-NN.

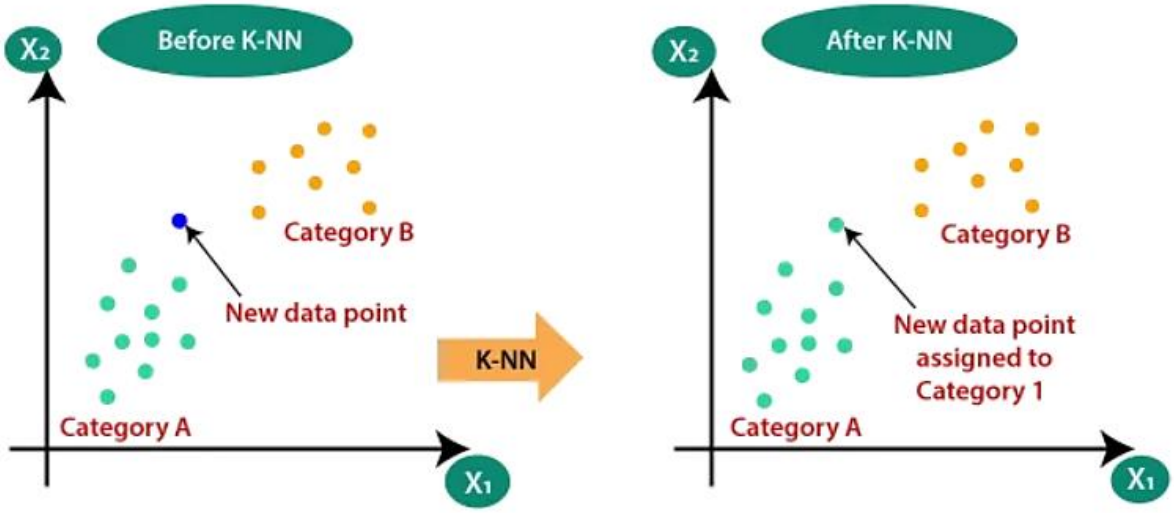


Figure 3-16 Diagram showing how a new data point is classified by k-NN (Christopher, 2021)

Different types of distance metrics that can be deployed in calculating the distance between the test data and the training data points include the Euclidean, Manhattan, Minkowski and the Hamming distances (Christopher, 2021). Since the k-value determines the number of neighbours and consequently impacts on the output, it is important to ensure that various ranges of k-values are tested before final selection to ensure accuracy of choice and prevent issues of underfitting or overfitting. While it is generally recommended that the k-value should be an odd number to prevent ties in classification, the magnitude of the selected k should be majorly dependent on the input data density and distribution characteristics. For example, higher k values are more suited for sparse data characterised by more outliers or noise.

3.6.4 Naïve Bayes

This algorithm is based on the Bayesian theorem which updates the prior knowledge of an event with the independent probability of each feature that can affect the event. It assumes that each feature or variable makes an independent and equal contribution to the classification output. It evaluates conditional probabilities which is the probability of occurrence of an event based on the assumption, evidence, assertion or presumption of occurrence of another event (Chauhan, 2022b). For a given class variable, y, and dependent feature vector

x_1 through x_n, the Bayes' theorem for the conditional probability, $P(y|x)$ can be represented mathematically as follows (Pedregosa et al., 2011):

$$P(y \mid x_i \dots, x_n) = \frac{P(y)P(\, x_i \dots, x_n|y)}{P(\, x_i \dots, x_n)} \tag{3-11}$$

Using the naive conditional independence assumption that

$$P(x_i|y, x_1, \dots, x_{i-1}, x_{i+1}, \dots, x_n) = P(x_i|y), \tag{3-12}$$

for all i, this relationship is simplified to

$$P(y \mid x_i \dots, x_n) = \frac{P(y)\prod_{i=1}^{n} P(\, x_i|y)}{P(\, x_i \dots, x_n)} \tag{3-13}$$

Since $P(\, x_i \dots, x_n)$ is constant given the input, the following classification rule can be used:

$$P(y \mid x_i \dots, x_n) \propto P(y)\prod_{i=1}^{n} P(\, x_i|y) \tag{3-14}$$

$$\hat{y} = \arg max_y \; P(y)\prod_{i=1}^{n} P(\, x_i|y) \tag{3-15}$$

$P(y)$ and $P(\, x_i|y)$ can be estimated using the maximum posteriori estimation with the former being the relative frequency of class y in the training set.

Naive Bayes classifiers have proven to be effective in a variety of real-world applications, including spam filtering, sentiment analysis, mental state predictions and document classification. Advantages include its ability to perform with small amount of training data, ease of implementation and effective handling of high-dimensional data. They however fail to perform in zero frequency scenarios where a variable does not exist in the training dataset. Another drawback of this algorithm is it's requirement of input variables to be independent.

3.6.5 Random Forest

This algorithm is an ensemble of decision trees characterised by improved accuracy. It operates by generating a multitude of decision trees and uses either

the modal vote or average prediction for classification or regression tasks, respectively. Figure 3-17 presents an example of the random forest. In this example, the random forest consisting of nine decision trees has been deployed to classify a test data into either class 1 or class 0. With class 1 having more predictions (6) compared to class 0 (3), the test data is thus classified into 1.

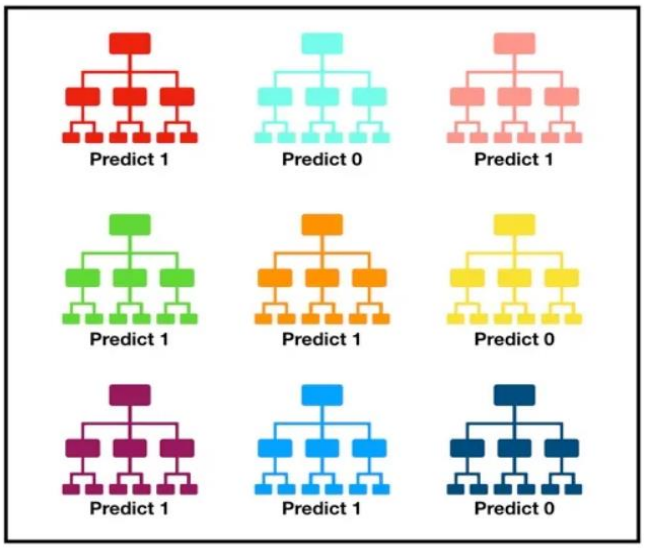


Figure 3-17 An example of a Random Forest comprising of nine decision trees (Yiu, 2019).

To make accurate class predictions, the Random Forest requires attributes that have some predictive power and decision trees whose respective predictions need to be of low correlations or uncorrelated with each other. It creates an uncorrelated forest of trees whose overall prediction is more accurate than that of any individual tree. This is done using bagging and feature randomness to generate each individual decision tree. Bagging or bootstrap aggregation is a process in which the random forest allows each individual tree to randomly sample from the training dataset with replacement, in order to obtain significantly different trees. Feature randomness aims to further increase the diversity to the dataset and lower the correlation among decision trees by generating a random subset of variables (IBM, 2023b; Yiu, 2019). This is a main distinction between Random Forests and Decision Trees. While the former only selects a subset of the variables, the latter considers all the possible feature splits. It is important to

also add that the algorithm allows each tree to grow to the largest extent possible without pruning.

Random Forest algorithm has found applications in various sectors including finance (credit checks, fraud detection), healthcare (computational biology, gene expression classification, drug response to articular medications) as well as e-commerce. Advantages of this ML algorithm include reduced risk of overfitting, high flexibility, high efficiency and predictive accuracy as well as capacity to assess impact of input variables (feature importance). A few of its drawbacks include its seemingly interpretation complexity as well as time and resource consumption requirement especially for very large datasets (IBM, 2023b).

3.6.6 Gradient Boost

This ensemble algorithm combines multiple weak algorithms to obtain an improved output. Each prediction in gradient boosting aims to outperform the one before it by lowering the errors. At each iteration, it fits the new predictor to the residual errors created by the preceding predictor, not on the data (Aliyev, 2020). The three essential parts of this algorithm are the loss function, weak learner and the additive model. While the loss function determines how well the model predicts based on the available data, the data is classified by a weak learner (e.g., decision trees), which does so while making numerous errors. The additive model is the new model that is added progressively and iteratively to improve the overall performance of the ensemble (Simplilearn, 2023).

For input training dataset $\{(x_i, y_i)\}_{i=1}^{n}$, loss function $L(y, F(x))$, number of iterations M, and additive model $h_m(x)$, the mathematical equations for the gradient boost algorithm to obtain the output $F_M(x)$, are as follows (Kurama, 2020):

The model is initiated with a constant value:

$$F_0(x) = \arg min_\gamma \sum_{i=1}^{n} L(y_i, \gamma) \tag{3-16}$$

Where y_i is the observed values and γ is the log (odds) of the target value.

For each iteration, $m = 1$ to M, the pseudo-residuals r_{im} which is the difference between the observed value and the predicted value can be obtained from equation (3-1):

$$r_{im} = -\left[\frac{\partial L(y_i, F(x_i))}{\partial F(x_i)}\right]_{F(x)=F_{m-1}(x)} for\ i = 1, \dots, n. \tag{3-17}$$

A weaker learner is then fitted to the obtained residual and trained using the training dataset $\{(x_i, r_{im})\}_{i=1}^{n}$. A multiplier or learning rate γ_m applied to scale the contribution of the additive model (or new tree) $h_m(x)$, can be obtained from using equation (3-18)

$$\gamma_m = \arg min_{\gamma} \sum_{i=1}^{n} L(y_i, F_{m-1}(x_i) + \gamma h_m(x_i)) \tag{3-18}$$

The updated model for each iteration, m is thus:

$$F_m(x) = F_{m-1}(x) + \gamma_m h_m(x) \tag{3-19}$$

i.e., previous model + learning rate * new model

At the final iteration M, The output $F_M(x)$ is obtained.

Advantages of the gradient boost ML algorithm include its remarkable predictive accuracy, high flexibility in hyperparameter adjustment and optimisation of various loss functions, minimal data pre-processing requirement and ability to work with incomplete data. Major disadvantages of this ML algorithm include susceptibility to overfitting and too much emphasis on outliers, computationally expensive and less interpretative among others (Kurama, 2020; Simplilearn, 2023).

3.6.7 Artificial Neural Network (ANN)

ANN is inspired by the biological neural networks of the human brain. It is made up of input, hidden and output layers, as well as a number of parallel-interconnected neurons in each layer. It can be trained to recognise patterns,

classify data, and predict future events. The neurons within each layer interacts with the neurons in the succeeding layer, with each output serving as an input for the next function. For every function at a neuron, the input and generated outputs are typically real numbers obtained from an internalised non-linear function consisting of the sum of its inputs and a bias term, b, that is specific to each neuron. The obtained output is then multiplied by a suitable weight, w, to create the numeric input for the function in the following layer. This process continues until the network's final output is generated (Dey, 2016; Knocklein, 2019). Figure 3-18 presents an artificial neural network showing the input layer, one hidden layer, output layer as well as weights and biases.

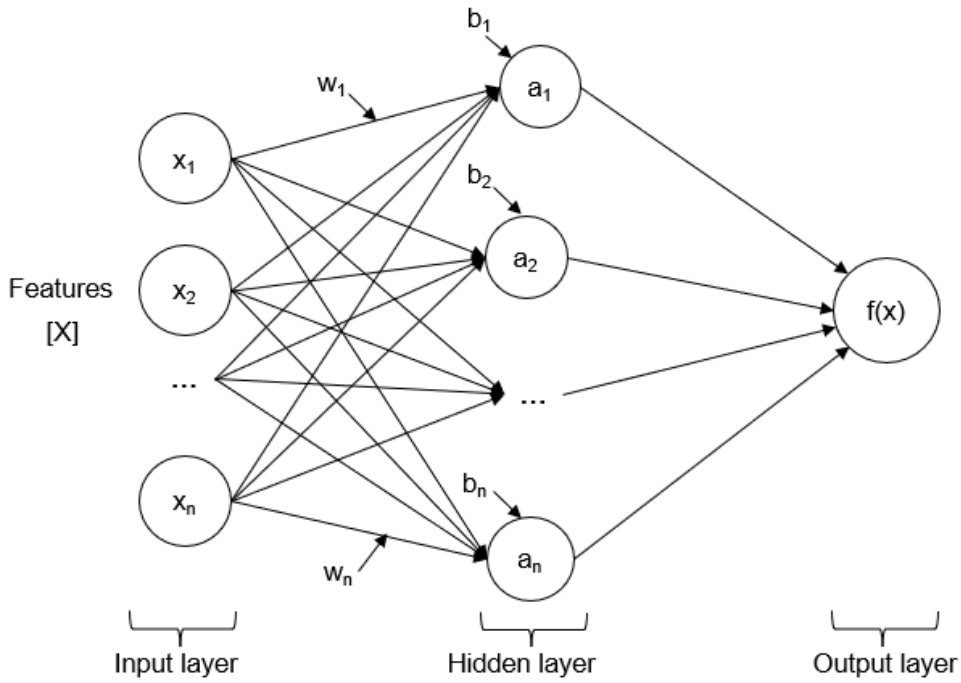


Figure 3-18 Network diagram of ANN showing the input layer, one hidden layer, output layer as well as weights and biases.

The magnitude of the weight assigned by the ML algorithm to a specific link is dependent on the cost function and the optimizing function. The cost function determines the difference between the predicted output of the network and the target output (the best possible solution). After each iteration also known as epoch, the cost function is analysed to assess the model’s performance. Based on the information obtained from the cost function, the optimizing function then

calculates new weight and bias values, to minimize that cost function. These new values are then integrated into the next epoch of the model. This process continues until further adjustments no longer improves the cost function.

According to Pedregosa et al. (2011), for a set of training dataset consisting of n training samples and m features, $(x_1, y_1), (x_2, y_2), \dots, (x_n, y_n)$ where $x_i \in R^n$ and $y_i \in \{0,1\}$, a neuron in a one hidden layer will learn the function;

$$f(x) = W_2\, g(W_1^T x + b_1) + b_2 \tag{3-20}$$

Where $W_1 \in R^m$ and $W_2, b_1, b_2 \in R$ are model parameters.

W_1, W_2 are the weights of the input and hidden layer respectively,

b_1, b_2 are the bias added to the hidden an output layers respectively.

The activation function, $g(\cdot) : R \to R$, represented as the hyperbolic tan is given by equation (3-21).

$$g(z) = \frac{e^z - e^{-z}}{e^z + e^{-z}} \tag{3-21}$$

For binary classification, the activation function takes the form of a logistic function:

$$g(z) = \frac{1}{1 + e^{-z}} \tag{3-22}$$

Obtained output values exist between 0 and 1, with the threshold set to 0.5. Outputs greater than or equal to this threshold are assigned to the positive class, while the others are assigned to the negative class.

For multi-classification, the activation function takes the form of a softmax function:

$$softmax(z)_i = \frac{\exp\,(z_i)}{\sum_{l=1}^{k} \exp\,(z_l)} \tag{3-23}$$

Where z_i is the ith element of the input to softmax corresponding to class i, and K is the number of classes. The outcome is a vector representing the probabilities

of the sample, x belonging to each class. The class with the highest probability is the output.

The loss or cost function is given by equation (3-24).

$$Loss(\hat{y}, y, W) = -\frac{1}{n}\sum_{i=0}^{n}(y_i ln\hat{y}_i + (1 - y_i)\ln(1 - \hat{y}_i)) + \frac{\alpha}{2n}||W||_2^2 \quad (3\text{-}24)$$

Where $\alpha||W||_2^2$ is the L2-regularisation (ridge regression) term or penalty, $\alpha > 0$, controls the magnitude of the penalty and $\hat{y}$ is the predicted output. By repeatedly updating the weight, the cost function is minimised to obtain the final output.

ANN finds application in many areas including system identification, process control, natural resource management, quantum chemistry, pattern and object recognition, sensor data analysis, sequence recognition, finance, data mining, visualization, social network filtering, e-mail spam filtering, healthcare, infrastructure reliability analysis, geoscience, hydrology, ocean modelling, cybersecurity, physics among others. Its advantages include its ability to learn non-linear models, ability for real-time learning using partial fit, adaptive and accurate Disadvantages include high cost and computational requirements, sensitivity to feature scaling, prone to overfitting and hyperparameter tuning requirements (Pedregosa et al., 2011; Singh et al., 2016).

3.6.8 Model interpretation

Having developed the ML predictive models, an assessment was carried out to understand the logic employed by the ML model in its predictive decision process (model interpretation). This understanding assists in verifying the correctness of the model. It provides information on the impact of each input variable (bio-geophysical and technoeconomic factors) in determining the output (GGR deployment suitability). By assessing the correlation between the ML-generated variable impact and literature expectations (Table 2.4), the extent of correctness of the ML model can be evaluated.

This was done using the *feature_importances_* tool in the Random Forest library imported from the *sklearn* module (Pedregosa et al., 2011). This tool assess the

importance of a variable based on how the variable contributes to enhancing the purity of the leaves (or terminal nodes) or decreasing the weighted impurity using the Gini importance. The higher contribution, the higher the feature importance score. This is done for each tree that make up the Random Forest. The average value of the respective contributions of each variable for all the trees is then obtained and normalized, such that the sum of the obtained importance scores is 1 (Lewinson, 2019; Malato, 2021).

For a tree consisting of two child nodes, the feature importance, can be calculated using equation (3.25) (Shin, 2021).

$$fi_j = \frac{\sum_{j:node\ j\ splits\ on\ feature\ i} ni_j}{\sum_{j \in all\ nodes} ni_j} \tag{3-25}$$

Where, ni_j is the importance of a node, j, which is evaluated using (3.26)

$$ni_j = w_j C_j - w_{left(j)} C_{left(j)} - w_{right(j)} C_{right(j)} \tag{3-26}$$

Where, w_j is the weighted number of samples reaching node j,

C_j is the impurity value of node j,

$left(j)$ and $right(j)$ are the child nodes on left and right of node j, respectively.

Figure 3-19 presents the code (written in Python) that was applied in assessing the feature importance score for the forestation dataset. Similar code was applied for the other GGR methods using their respective dataset (line 8 of code), with changes made to line 11 of code (specify the input variables).

```python
import pandas as pd
import matplotlib.pyplot as plt
plt.rcParams['figure.figsize'] = (9, 6)
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import train_test_split

# Reading data
df = pd.read_csv("Updated labelled Forestation data2.csv")

# creating input identity
sub_df = df[['Q1T','Q2T','Q3T','Q4T','Q1P','Q2P','Q3P','Q4P','WA','FLu']]

X = sub_df
y = df.Category
X_train, X_test, y_train, y_test = train_test_split(X, y, train_size=0.7, random_state=0)

# creating Model (with 100 trees)
rf = RandomForestClassifier(n_estimators=100)

# Fitting training data
rf.fit(X_train, y_train)


# Determining feature importance
feature_imp = pd.DataFrame(rf.feature_importances_,index= X_train.columns,
                           columns=['importance']).sort_values('importance',ascending=False)
print(feature_imp)

#Feature importance visualisation
feature_imp.plot(kind='barh')
```

Figure 3-19 Python code for evaluating the feature importance score for the forestation dataset.

3.7 Country-level Assessment of the Deployment Potential of GGR Technologies

In this work package, the CO_2 removal potential of the 182 countries via five selected GGR technologies was evaluated using a multi criteria decision analysis (MCDA) approach. An assessment of the sufficiency of nations to meet their respective CDR quotas was also investigated. Figure 3-20 presents the framework of the methodology applied in this work package. With the steps 1, 2 and 4 already covered in the preceding sections 3.2 – 3.4, this section is focused on the other steps including the application of the MCDA approach and the CDR quota assessment.

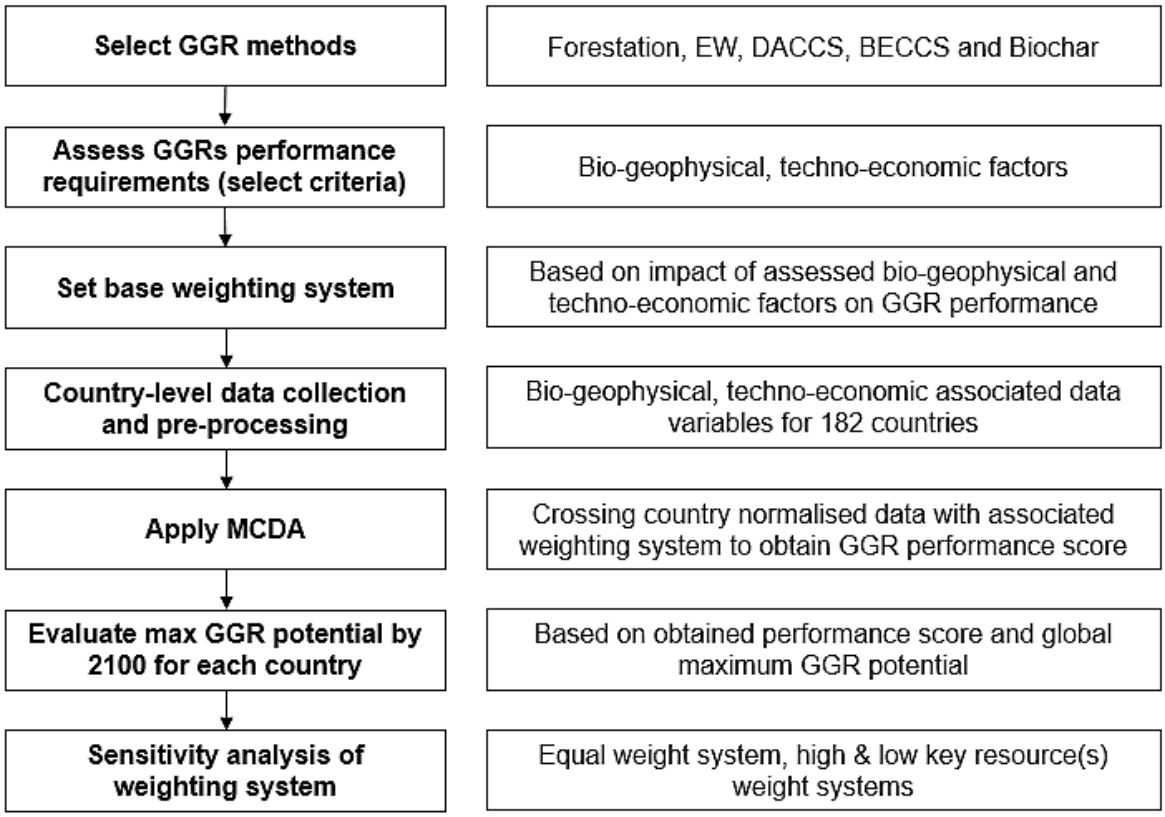


Figure 3-20 Method framework for the MCDA assessment showing the steps applied in obtaining the GGR potential of nations.

3.7.1 Multi-Criteria Decision Analysis (MCDA)

The methodology adopted in this study was based on the typical MCDA process employed in negative emissions technologies portfolio (Rueda et al., 2021) and sustainable energy (Wang et al., 2009). MCDA is an integrated operational evaluation and decision support approach that is suitable for addressing complex problems with high uncertainty, conflicting objectives, different forms of data and information, multi-interests and perspectives, and the accounting for complex and evolving biophysical and socio-economic systems (Wang et al., 2009). It provides an integrated result (performance scores) for competing alternatives (or options) based on an assessment of selected multi-criteria or attributes. For *m* alternatives (182 countries), assessed using *n* criteria (bio-geophysical and techno-econmic factors), and set criteria weights (impact weight of selected factors on respective GGR technology performance (Table 2-4)), the performance scores can be

evaluated from the decision matrix (*m*×*n*). For each GGR technology, the performance score of each country which is an indication of their ability to deploy the respective technology was obtained.

The key steps in MCDA approach is the selection of the assessment criteria and the assignment of weight to these criteria. These steps are presented in the following sections. For criteria selection, the input variables presented in Table 3-1 were also applied as the assessment criteria for the MCDA.

3.7.2 Setting the criteria weighting system

Weights were assigned to the selected criteria based on the impact of these factors on the performance of the respective GGR methods. This obtained weight system (base wt) was adapted from the impact ranking of GGR factors presented in Table 2-4. To get a unit sum of weight of criteria for each GGR method, this ranking was then scaled down proportionately using equation (3-27). For each GGR method,

$$Scaled\ criteria\ weight\ of\ a\ variable = \frac{r_i}{R_n} \qquad (3\text{-}27)$$

Where, r_i is the impact score of the variable, R_n is the sum of the impact scores of all the variables selected for that GGR method. The obtained base weight system is presented in Table 3-10.

Table 3-10 Applied criteria weights for the MCDA assessment of GGR potential

	Temp	Ppt	FLu	AgLu	BA.	WA	GSP	Cost	LCEA	Veg
Forestation	0.133	0.2	0.267	0	0	0.133	0	0.067	0	0.2
EW	0.1	0.1	0	0.134	0	0	0	0.333	0.333	0
DACCS	0	0	0	0.067	0	0.067	0.333	0.267	0.267	0
BECCS	0	0	0	0	0.333	0.134	0.333	0.2	0	0
Biochar	0.018	0.164	0	0.182	0.454	0	0	0.182	0	0

3.7.3 Evaluating the maximum cumulative GGR potential

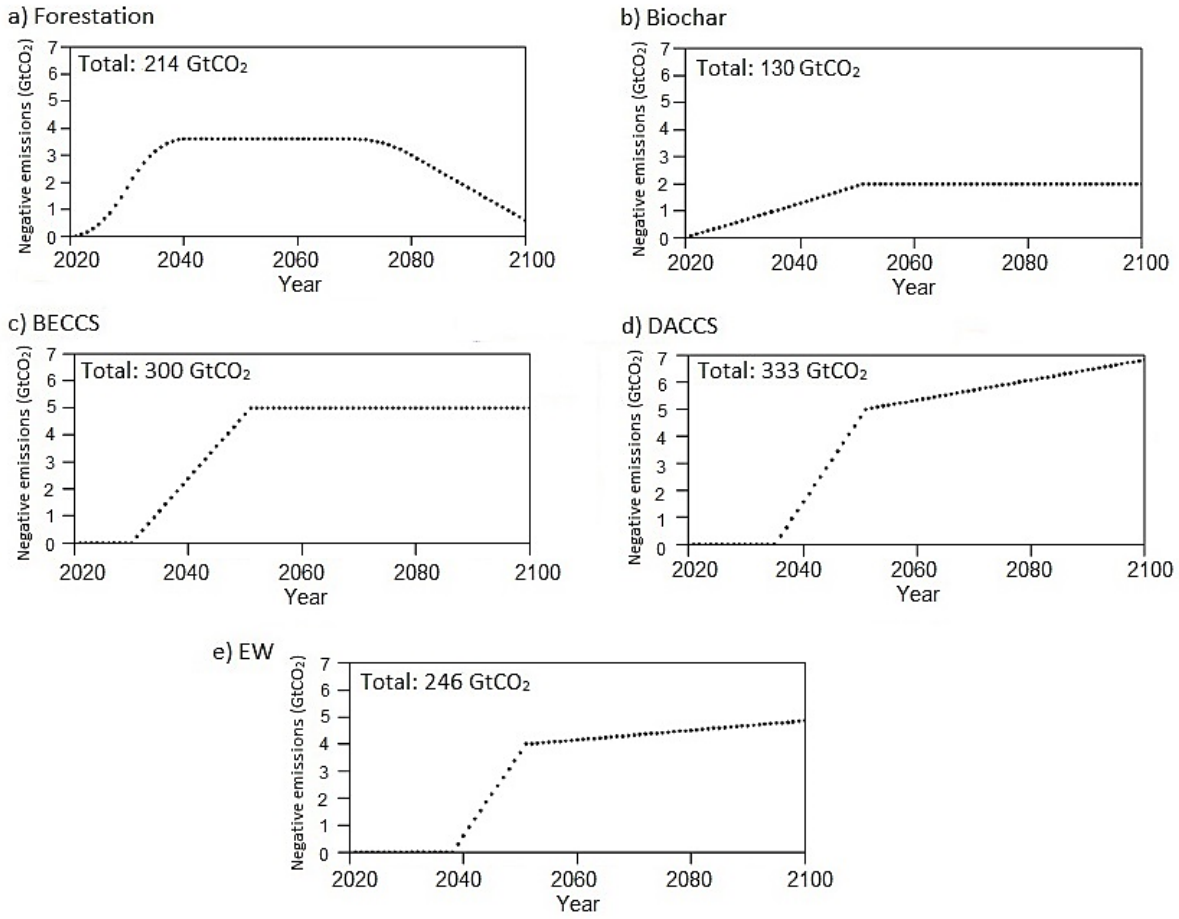


Figure 3-21 Curves of GGR technologies potential for 2020–2100. a) forestation, b) biochar, c) BECCS, d) DACCS, e) EW (reprinted with permission from Rueda et al. (2021), Copyright 2021 Elsevier).

For each GGR method, the same pre-processed input data obtained for the 182 countries (sections 3.3 and 3.4) and the criteria weight of the respective GGR method (Table 3-10) were combined using the simple additive weighting (SAW) method, to obtain the performance score for each country. For a country, with input variables $x_1, x_2 \dots x_n$, its performance score, z, in deploying a GGR technology with assessment criteria weights, $y_1, y_2 \dots y_n$, is given by equation (3-28).

$$performance\ score, z = x_1y_1 + x_2y_2 + \cdots + x_ny_n = \sum_{i=1}^{n} x_iy_i \tag{3-28}$$

This method was applied because of its convenience in calculation and the requirement of attributes (variables) to be independent. Using the obtained performance score of each country as a fraction of the total global scores, the share of each country's maximum cumulative carbon removal potential for each GGR technology was then evaluated from the projected global maximum cumulative potential by 2100 reported by Rueda et al., (2021) based on their review of the literature. Figure 3-21 presents the curves of the global potential of GGR technologies, with the area under the curve indicating the maximum cumulative potential by 2100 (total) as shown.

3.7.4 Assessing the CDR quotas

The cumulative CDR potential of the five GGR technologies obtained for each of the 182 countries considered, was assessed to ascertain if it was sufficient to meet the respective nationally assigned CDR quotas that was reported by Pozo et al. (2020). In their report, the global CDR quota of 687 $GtCO_2$, which represents amount of CO_2 expected to be removed by 2100 under the IPCC SR1.5 'middle-of-the-road' P3 scenario (IPCC, 2018), was shared to 176 countries. The sharing was done under three equity principles. The first was the Responsibility principle, in which the CDR burden was allocated based on the respective historical emission liability of countries. Under this scenario, the more industrialised nations with high historic emissions were assigned higher share of the CDR burden, in comparison to the less-industrialised nations. For the second principle, termed, the Capability principle, the allocation was done based on the respective financial ability of countries. Under this scenario, richer countries were assigned higher CDR burdens than poorer countries. And the third, termed the Equality principle, was based on the population size of countries. Under this scenario, countries with high populations received a higher CDR quota than countries with comparatively lower population. Using their findings, we compared the MCDA-obtained domestic CDR potential for each country with the respective quotas allocated to them under the three equity sharing principles. Through this assessment, countries that will be able to meet up with their allocated quotas domestically using these five GGR methods will be identified. This comparative assessment

will also highlight areas of surplus CDR potential as well as areas that will require regional partnerships and collaborations to offset deficits.

3.7.5 Sensitivity analysis of weight

A sensitivity analysis was carried out to evaluate the robustness and stability of the obtained output (CDR potential and regional share) by assessing the impact of other weighting systems. This was done to minimise the impact of probable subjectivity and account for uncertainties in the applied criteria weighting system (base wt). For each GGR method, four criteria weight allocation scenarios (weighting systems) were considered: Equal weight scenario and three dominant variables scenarios (50%, 60%, 70%). While the same weights were assigned to all the variables under the Equal weight scenario, the dominant variables scenario involved assessing the impact of assigned weights (50%, 60%, 70%) on key factors (criteria) that influence the performance of the respective GGR methods. For forestation, land availability & vegetation type (LV) was considered; for EW, cost and low carbon energy availability (CE); for DACCS, cost and geological storage potential (CS); for BECCS, geological storage potential and biomass availability (SB); and for biochar, biomass availability (B). Details of the various weighting systems applied for the five GGR methods are presented in Table 3-11 to Table 3-15.

Table 3-11 Forestation criteria weighting scenarios

Scenarios	Temp	Ppt	FLu	WA.	Cost	Veg
Base wt	0.133	0.2	0.267	0.133	0.067	0.2
Equal wt.	0.167	0.167	0.167	0.167	0.167	0.167
50% (LV)	0.125	0.125	0.25	0.125	0.125	0.25
60% (LV)	0.1	0.1	0.3	0.1	0.1	0.3
70% (LV)	0.075	0.075	0.35	0.075	0.075	0.35

Table 3-12 EW criteria weighting scenarios

Scenarios	Temp	Ppt	AgLu	Cost	LCEA
Base wt	0.1	0.1	0.134	0.333	0.333
Equal wt.	0.2	0.2	0.2	0.2	0.2
50% (CE)	0.167	0.167	0.167	0.25	0.25
60% (CE)	0.133	0.133	0.133	0.3	0.3
70% (CE)	0.1	0.1	0.1	0.35	0.35

Table 3-13 DACCS criteria weighting scenarios

Scenarios	AgLu	WA	GSP	Cost	LCEA
Base wt	0.067	0.067	0.333	0.267	0.267
Equal wt.	0.2	0.2	0.2	0.2	0.2
50% (SC)	0.167	0.167	0.25	0.25	0.167
60% (SC)	0.133	0.133	0.3	0.3	0.133
70% (SC)	0.1	0.1	0.35	0.35	0.1

Table 3-14 BECCS criteria weighting scenarios

Scenarios	BA	WA	GSP	Cost
Base wt	0.333	0.134	0.333	0.2
Equal wt.	0.25	0.25	0.25	0.25
50% (SB)	0.25	0.25	0.25	0.25
60% (SB)	0.3	0.2	0.3	0.2
70% (SB)	0.35	0.15	0.35	0.15

Table 3-15 Biochar criteria weighting scenarios

Scenarios	Temp	Ppt	AgLu	BA	Cost
Biochar	0.018	0.164	0.182	0.454	0.182
Equal wt.	0.2	0.2	0.2	0.2	0.2
50% (B)	0.125	0.125	0.125	0.5	0.125
60% (B)	0.1	0.1	0.1	0.6	0.1
70% (B)	0.075	0.075	0.075	0.7	0.075

References

Aliyev, V., 2020. Gradient Boosting Classification explained through Python [WWW Document]. Towar. Data Sci. URL https://towardsdatascience.com/gradient-boosting-classification-explained-through-python-60cc980eeb3d (accessed 4.17.23).

Aminu, M.D., Nabavi, S.A., Rochelle, C.A., Manovic, V., 2017. A review of developments in carbon dioxide storage. Appl. Energy 208, 1389–1419. https://doi.org/10.1016/j.apenergy.2017.09.015

Bui, M., Adjiman, C.S., Bardow, A., Anthony, E.J., Boston, A., Brown, S., Fennell, P.S., Fuss, S., Galindo, A., Hackett, L.A., Hallett, J.P., Herzog, H.J., Jackson, G., Kemper, J., Krevor, S., Maitland, G.C., Matuszewski, M., Metcalfe, I.S., Petit, C., Puxty, G., Reimer, J., Reiner, D.M., Rubin, E.S., Scott, S.A., Shah, N., Smit, B., Trusler, J.P.M., Webley, P., Wilcox, J., Mac Dowell, N., 2018. Carbon capture and storage (CCS): The way forward. Energy Environ. Sci. 11, 1062–1176. https://doi.org/10.1039/c7ee02342a

Chauhan, N.S., 2022a. Decision Tree Algorithm Explained [WWW Document]. KDnuggets. URL https://www.kdnuggets.com/2020/01/decision-tree-algorithm-explained.html (accessed 4.14.23).

Chauhan, N.S., 2022b. Naïve Bayes Algorithm: Everything You Need to Know [WWW Document]. KDnuggets. URL https://www.kdnuggets.com/2020/06/naive-bayes-algorithm-everything.html (accessed 4.14.23).

Christopher, A., 2021. K-Nearest Neighbor [WWW Document]. The Startup. URL https://medium.com/swlh/k-nearest-neighbor-ca2593d7a3c4 (accessed 4.14.23).

CIA, 2022. The World Factbook [WWW Document]. URL https://www.cia.gov/the-world-factbook/field/land-use (accessed 6.10.20).

Dessert, C., Dupré, B., Gaillardet, J., François, L.M., Allègre, C.J., 2003. Basalt weathering laws and the impact of basalt weathering on the global carbon cycle. Chem. Geol. 202, 257–273. https://doi.org/10.1016/j.chemgeo.2002.10.001

Dey, A., 2016. Machine Learning Algorithms: A Review. Int. J. Comput. Sci. Inf. Technol. 7, 1174–1179.

ExpertAI, 2022. What Is the Definition of Machine Learning? [WWW Document]. URL https://www.expert.ai/blog/machine-learning-definition/ (accessed 4.10.23).

FAO, 2022. FAO-AQUASTAT database [WWW Document]. URL http://www.fao.org/nr/water/aquastat/data/query/results.html (accessed 7.15.20).

Garbade, M.J., 2018. Clearing the Confusion: AI vs Machine Learning vs Deep

Learning Differences [WWW Document]. Towar. Data Sci. URL https://towardsdatascience.com/clearing-the-confusion-ai-vs-machine-learning-vs-deep-learning-differences-fce69b21d5eb (accessed 2.8.21).

Gholamy, A., Kreinovich, V., Kosheleva, O., 2018. Why 70/30 or 80/20 Relation Between Training and Testing Sets : A Pedagogical Explanation. Dep. Tech. Reports 1–6.

Güleç, F., Pekaslan, D., Williams, O., Lester, E., 2022. Predictability of higher heating value of biomass feedstocks via proximate and ultimate analyses – A comprehensive study of artificial neural network applications. Fuel 320, 123944. https://doi.org/10.1016/j.fuel.2022.123944

Hamadeh, N., Van Rompaey, C., Metreau, E., 2021. New World Bank country classifications by income level: 2021-2022 [WWW Document]. World Bank Blogs. URL https://blogs.worldbank.org/opendata/new-world-bank-country-classifications-income-level-2021-2022 (accessed 9.18.22).

Harrisson, O., 2018. Machine Learning Basics with the K-Nearest Neighbors Algorithm [WWW Document]. Towar. Data Sci. URL https://towardsdatascience.com/machine-learning-basics-with-the-k-nearest-neighbors-algorithm-6a6e71d01761 (accessed 4.14.23).

Hu, Y., Li, K., Meng, A., 2018. Agglomerative Hierarchical Clustering using Ward Linkage [WWW Document]. URL https://jbhender.github.io/Stats506/F18/GP/Group10.html (accessed 4.10.23).

IBM, 2023a. Decision Trees [WWW Document]. IBM. URL https://www.ibm.com/uk-en/topics/decision-trees (accessed 4.14.23).

IBM, 2023b. What is random forest? IBM Cloud Educ.

IEA, 2020. IEA Energy Atlas [WWW Document]. URL http://energyatlas.iea.org/#!/tellmap/-1118783123/1 (accessed 9.15.20).

IEAGHG, 2011. Global Storage Resources Gap Analysis for Policy Makers.

IPCC, 2018. Global warming of 1.5°C An IPCC Special Report on the impacts of global warming of 1.5°C above pre-industrial levels and related global greenhouse gas emission pathways, in the context of strengthening the global response to the threat of climate change,.

IRENA, 2021. Statistical Profiles [WWW Document]. URL https://www.irena.org/Statistics/Statistical-Profiles (accessed 12.10.20).

Jordan, M.I., Mitchell, T.M., 2015. Machine learning: Trends, perspectives, and prospects. Science (80-.). 349, 255–260.

Kearns, J., Teletzke, G., Palmer, J., Thomann, H., Kheshgi, H., Chen, H., Paltsev, S., Herzog, H., 2017. Developing a Consistent Database for Regional Geologic CO2 Storage Capacity Worldwide. Energy Procedia 114, 4697–4709. https://doi.org/10.1016/j.egypro.2017.03.1603

Knocklein, O., 2019. Classification Using Neural Networks [WWW Document]. Towar. Data Sci. URL https://towardsdatascience.com/classification-using-neural-networks-b8e98f3a904f (accessed 4.20.23).

Kumar, S., 2019. Advantages and Disadvantages of Artificial Intelligence [WWW Document]. Towar. Data Sci. URL https://towardsdatascience.com/advantages-and-disadvantages-of-artificial-intelligence-182a5ef6588c (accessed 2.8.21).

Kurama, V., 2020. Gradient Boosting for Classification [WWW Document]. Pap. Blog. URL https://blog.paperspace.com/gradient-boosting-for-classification/ (accessed 4.17.23).

Lewinson, E., 2019. Explaining Feature Importance by example of a Random Forest [WWW Document]. Towar. Data Sci. URL Explaining Feature Importance by example of a Random Forest

Malato, G., 2021. Feature selection with Random Forest [WWW Document]. Your Data Teach. URL https://www.yourdatateacher.com/2021/10/11/feature-selection-with-random-forest/#:~:text=Each tree of the random,the importance of the feature.

McGregor, M., 2020. 8 Clustering Algorithms in Machine Learning that All Data Scientists Should Know [WWW Document]. Free Code Camp. URL https://www.freecodecamp.org/news/8-clustering-algorithms-in-machine-learning-that-all-data-scientists-should-know/ (accessed 4.10.23).

Mishra, S., 2017. Unsupervised Learning and Data Clustering [WWW Document]. Towar. Data Sci. URL https://towardsdatascience.com/unsupervised-learning-and-data-clustering-eeecb78b422a (accessed 4.10.23).

Murtagh, F., Contreras, P., 2012. Algorithms for hierarchical clustering : an overview. Wiley Interdiscip. Rev. Data Min. Knowl. Discov. 2, 86–97. https://doi.org/10.1002/widm.53

Pedregosa, F., Michel, V., Grisel, O., Blondel, M., Prettenhofer, P., Weiss, R., Vanderplas, J., Cournapeau, D., Pedregosa, F., Varoquaux, G., Gramfort, A., Thirion, B., Grisel, O., Dubourg, V., Passos, A., Brucher, M., Perrot, M., Duchesnay, É., 2011. Scikit-learn: Machine Learning in Python. J. Mach. Learn. Res. 12, 2825–2830.

Pozo, C., Galán-martín, Á., Reiner, D.M., Dowell, N. Mac, Guillén-gosálbez, G., 2020. Equity in allocating carbon dioxide removal quotas. Nat. Clim. Chang. https://doi.org/10.1038/s41558-020-0802-4

Rai, K., 2020. The Math behind Logistic Regression | Medium [WWW Document]. Anal. Vidhya. URL https://medium.com/analytics-vidhya/the-math-behind-logistic-regression-c2f04ca27bca (accessed 4.13.23).

Ritchie, H., Roser, M., Rosado, P., 2020. Renewable Energy - Our World in Data [WWW Document]. URL https://ourworldindata.org/renewable-energy (accessed 6.14.22).

Royal Society, 2018. Options for producing low-carbon hydrogen at scale, The Royal Society.

Rueda, O., Mogollón, J.M., Tukker, A., Scherer, L., 2021. Negative-emissions technology portfolios to meet the 1.5 °C target. Glob. Environ. Chang. 67. https://doi.org/10.1016/j.gloenvcha.2021.102238

Saji, B., 2021. Elbow Method for Finding the Optimal Number of Clusters in K-Means [WWW Document]. Anal. Vidhya. URL https://www.analyticsvidhya.com/blog/2021/01/in-depth-intuition-of-k-means-clustering-algorithm-in-machine-learning/

Shin, T., 2021. Understanding Feature Importance and How to Implement it in Python [WWW Document]. Towar. Data Sci. URL https://towardsdatascience.com/understanding-feature-importance-and-how-to-implement-it-in-python-ff0287b20285

Simplilearn, 2023. Gradient Boosting Algorithm in Python with Scikit-Learn [WWW Document]. Simplilearn. URL https://www.simplilearn.com/gradient-boosting-algorithm-in-python-article (accessed 4.17.23).

Singh, A., Thakur, N., Sharma, A., 2016. A review of supervised machine learning algorithms, in: 2016 3rd International Conference on Computing for Sustainable Global Development, (INDIACom). Bharati Vidyapeeth, New Delhi as the Organizer of INDIACom - 2016, pp. 1310–1315.

Smith, P., Davis, S.J., Creutzig, F., Fuss, S., Minx, J., Gabrielle, B., Kato, E., Jackson, R.B., Cowie, A., Kriegler, E., Van Vuuren, D.P., Rogelj, J., Ciais, P., Milne, J., Canadell, J.G., McCollum, D., Peters, G., Andrew, R., Krey, V., Shrestha, G., Friedlingstein, P., Gasser, T., Grübler, A., Heidug, W.K., Jonas, M., Jones, C.D., Kraxner, F., Littleton, E., Lowe, J., Moreira, J.R., Nakicenovic, N., Obersteiner, M., Patwardhan, A., Rogner, M., Rubin, E., Sharifi, A., Torvanger, A., Yamagata, Y., Edmonds, J., Yongsung, C., 2015. Biophysical and economic limits to negative CO2 emissions. Nat. Clim. Chang. 6, 42–50. https://doi.org/10.1038/nclimate2870

Tomar, A., 2022. Stop Using Elbow Method in K-means Clustering, Instead, Use this! [WWW Document]. Towar. Data Sci. URL https://towardsdatascience.com/elbow-method-is-not-sufficient-to-find-best-k-in-k-means-clustering-fc820da0631d (accessed 4.11.23).

UN Water, 2022. Progress on Level of Water Stress [WWW Document]. URL https://sdg6data.org/indicator/6.4.2 (accessed 6.12.22).

Usama, M., Qadir, J., Raza, A., Arif, H., Yau, K.A., Elkhatib, Y., Hussain, A., Al-fuqaha, A., 2019. Unsupervised Machine Learning for Networking : Techniques , Applications and Research Challenges. IEEE Access 7, 1–37.

Wang, J.J., Jing, Y.Y., Zhang, C.F., Zhao, J.H., 2009. Review on multi-criteria decision analysis aid in sustainable energy decision-making. Renew. Sustain. Energy Rev. 13, 2263–2278. https://doi.org/10.1016/j.rser.2009.06.021

Wilson, A., 2019. A Brief Introduction to Supervised Learning [WWW Document]. Towar. Data Sci. URL https://towardsdatascience.com/a-brief-introduction-to-supervised-learning-54a3e3932590 (accessed 5.3.21).

World Bank, 2022. World Bank Climate Change Knowledge Portal [WWW Document]. URL https://climateknowledgeportal.worldbank.org/ (accessed 7.21.20).

World Bank, 2021. GNI per capita, Atlas method (current US$) | Data [WWW Document]. URL https://data.worldbank.org/indicator/NY.GNP.PCAP.CD (accessed 10.9.21).

Yiu, T., 2019. Understanding Random Forest [WWW Document]. Towar. Data Sci. URL https://towardsdatascience.com/understanding-random-forest-58381e0602d2 (accessed 4.17.23).

4 A Machine Learning Approach for Country-level Deployment of Greenhouse Gas Removal Technologies

Jude O. Asibor, Peter T. Clough, Seyed Ali Nabavi, Vasilije Manovic

School of Water, Energy and Environment, Cranfield University, Bedfordshire, MK43 0AL, UK.

Submitted 12 October 2022.

Under Review in the International Journal of Greenhouse Gas Control.

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 65-98%. 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.

Keywords

Greenhouse gas removal, BECCS, DACCS, Machine learning, Climate change mitigation.

4.1 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 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.

4.2 Methodology

Figure 4-1. 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.

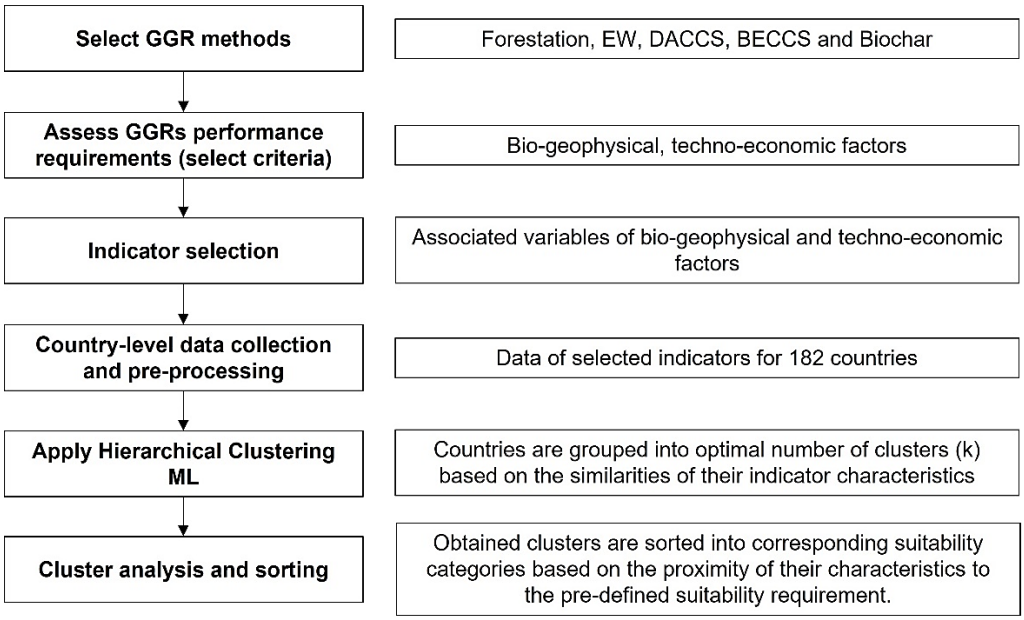


Figure 4-1 Methodology framework for the suitability categorisation of countries for GGR deployment using hierarchical clustering machine learning

4.2.1 GGR Methods

4.2.1.1 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 0.03–0.16 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 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.

4.2.1.2 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).

4.2.1.3 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 pa (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/tCO2 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).

4.2.1.4 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 – 0.5 ha/tCO_2 (Smith et al., 2015; The Royal Society, 2018). Water requirement for this GGR method is high ranging from 60 – 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 $100–200/tCO2 by 2050 with actual cost dependent on choice of biomass source and adopted technology (Fuss et al., 2018).

4.2.1.5 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$30–120/t$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 3-1. 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.

4.2.2 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 4-1. 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.

4.2.2.1 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.

4.2.2.2 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 land use and agricultural land use of each country was thus adopted as the indicator for land availability (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, AgLu was adopted to indicate the availability of land for spreading their respective materials.

Table 4-1 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

4.2.2.3 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.

4.2.2.4 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), combined with the sedimentary basins data reported by Kearns et al. (2017).

4.2.2.5 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).

4.2.2.6 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.

4.2.2.7 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 (Royal Society, 2018; Smith et al., 2015). 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.

4.2.3 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 Section 3.4). Equation (4-1) 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 4-2 presents the applied input data variable for assessment of each GGR method based on the selected indicators.

$$x_{ij}^{norm} = \frac{x_{ij} - x_{min}}{x_{max} - x_{min}} \quad (4\text{-}1)$$

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.

4.2.4 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.

Table 4-2 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).

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 3-1, 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 4-1. Availability of major requirements were thus 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 4-1, a description of these suitability categories is presented in Table 4-3.

Table 4-3 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

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 Sections 3.5.6 – 3.5.9.

4.2.5 Determination of the optimal number of clusters

For the forestation deployment suitability analysis, ten input data variables, as shown in Table 4-2, 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 (Figure 4-2(a)) and indicated on the dendrogram shown in Figure 4-2(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, 2021). As shown in Figure 4-2(a), the optimum number of clusters (*k*) for the forestation dataset is approximately 4. This value is indicated on the dendrogram in Figure 4-2(b) as the point at which six vertical lines are cut by the red dashed horizontal line.

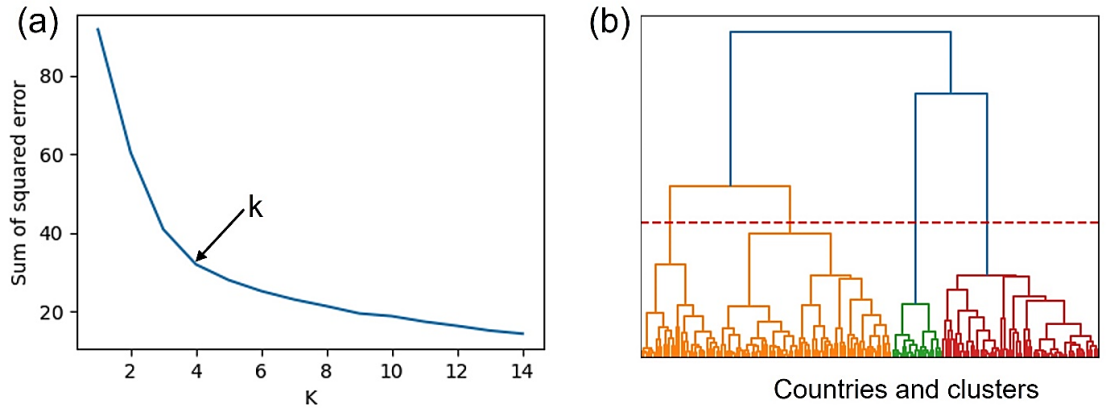


Figure 4-2 Plots showing (a) Optimum number of clusters (*k*) determined by the elbow method for the forestation dataset, (b) Dendrogram for the forestation dataset.

4.2.6 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 Figure 4-3. 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).

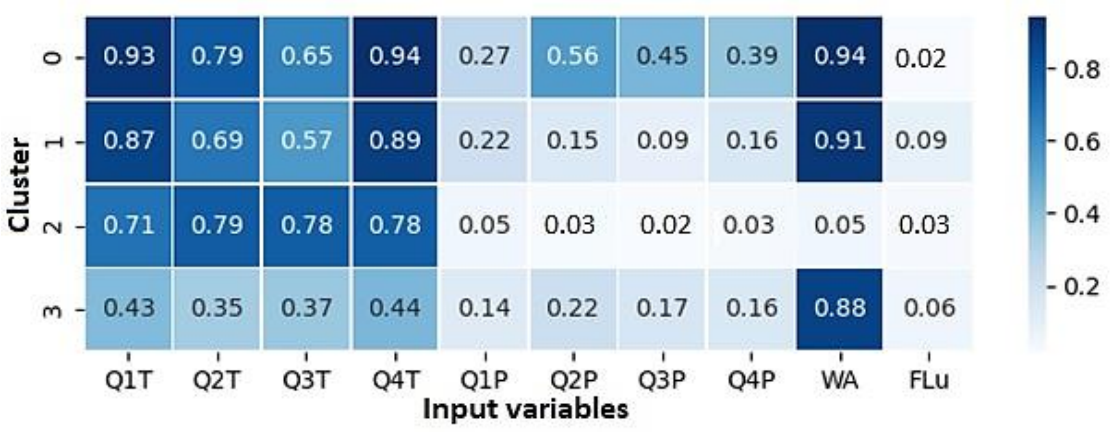


Figure 4-3 Heat map showing the cluster characteristics for forestation

Based on the similarity of the provided cluster characteristics in Figure 4-3 with those required for deployment of forestation, as presented in Table 4-1, 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 (Figure 4-3) and their corresponding categories are presented in Table 4-4.

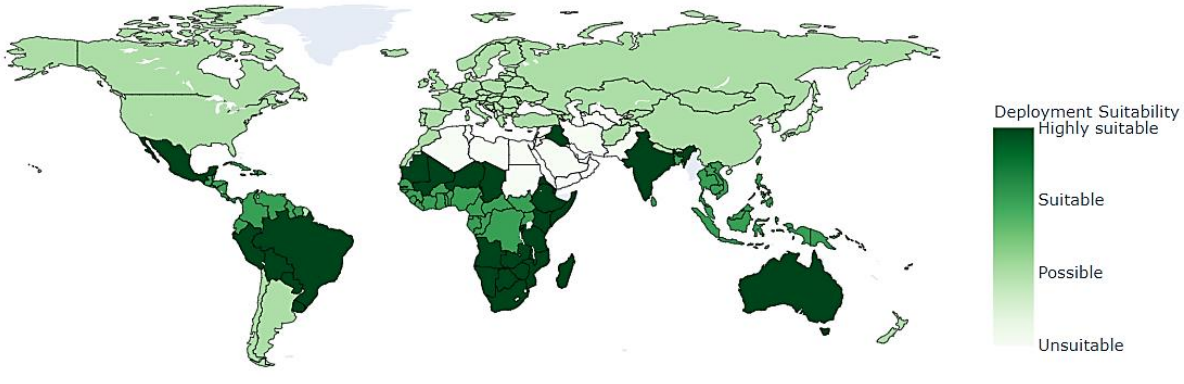
Table 4-4 Description of Forestation cluster characteristics

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

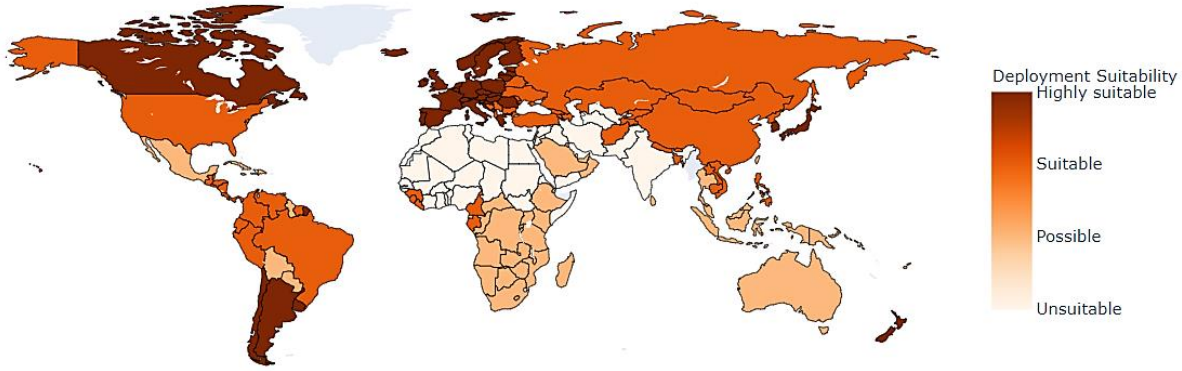
4.3 Results and Discussions

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. Figure 4-4 presents the obtained global maps showing the suitability categorisation of countries to deploy these GGR methods.

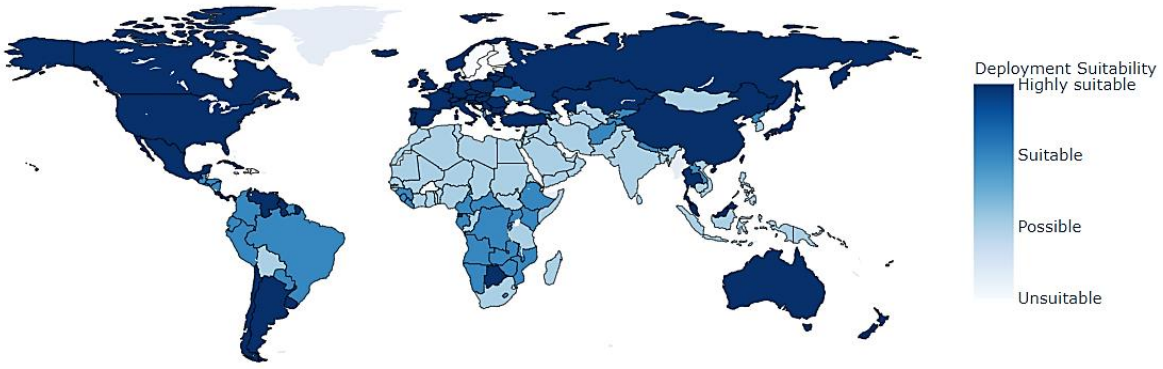
(a) Forestation



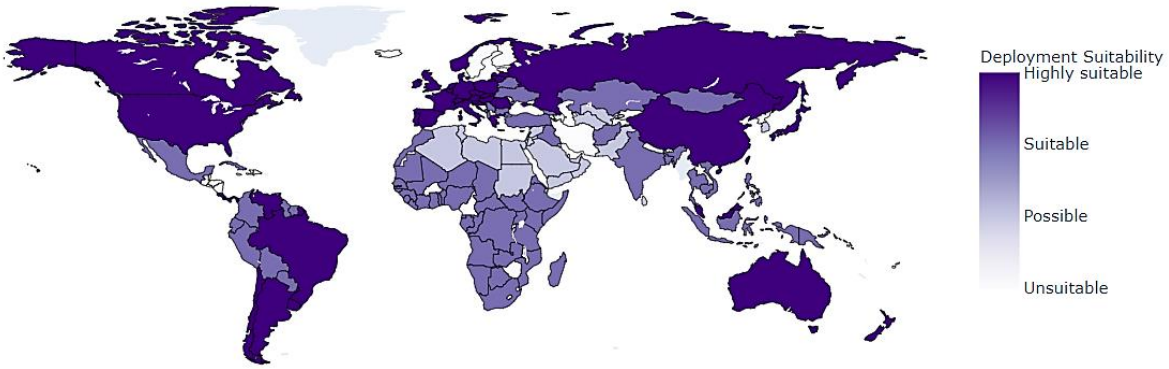
(b) Enhanced weathering



(c) DACCS



(d) BECCS



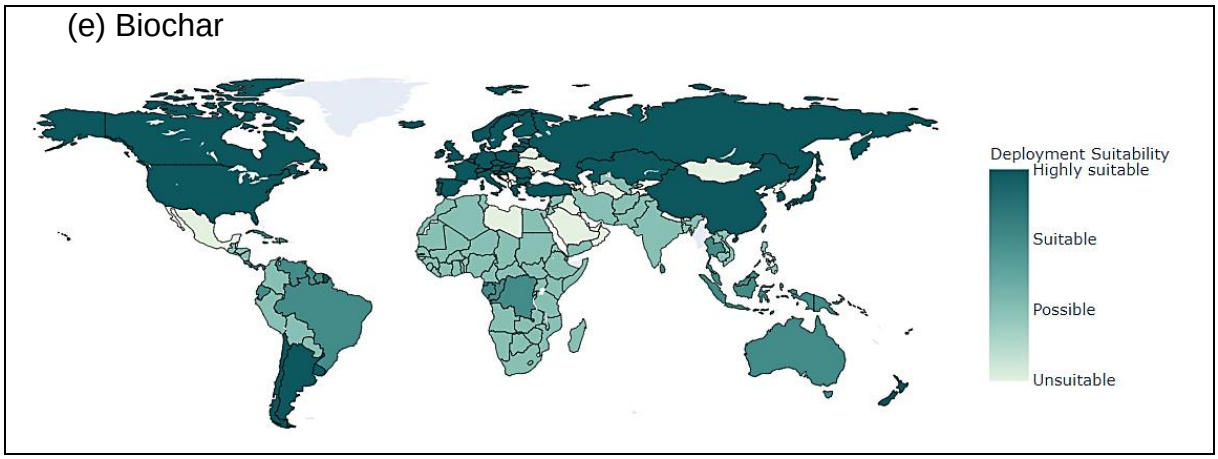


Figure 4-4 Global maps showing the suitability of countries to deploy five GGR methods: Forestation (a), Enhanced weathering (b), DACCS (c), BECCS (d) and Biochar (e).

According to Figure 4-4(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 Figure 4-4(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 Figure 4-4(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).

The availability of biomass and suitable geological storage locations 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 (Figure 4-4(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 Figure 4-4(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.

4.4 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 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). These resources were assessed under optimistic (+50%) and pessimistic (-50%) scenarios of availability (Pozo et al., 2020). Figure 4-5 presents the changes in the obtained membership of categories (represented by the error bars) 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 **Appendix B.**

Figure 4-5(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 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 (20%) moving from S to the HS category under optimistic scenario and 31 countries (17%) moving from HS to S category under the pessimistic scenario.

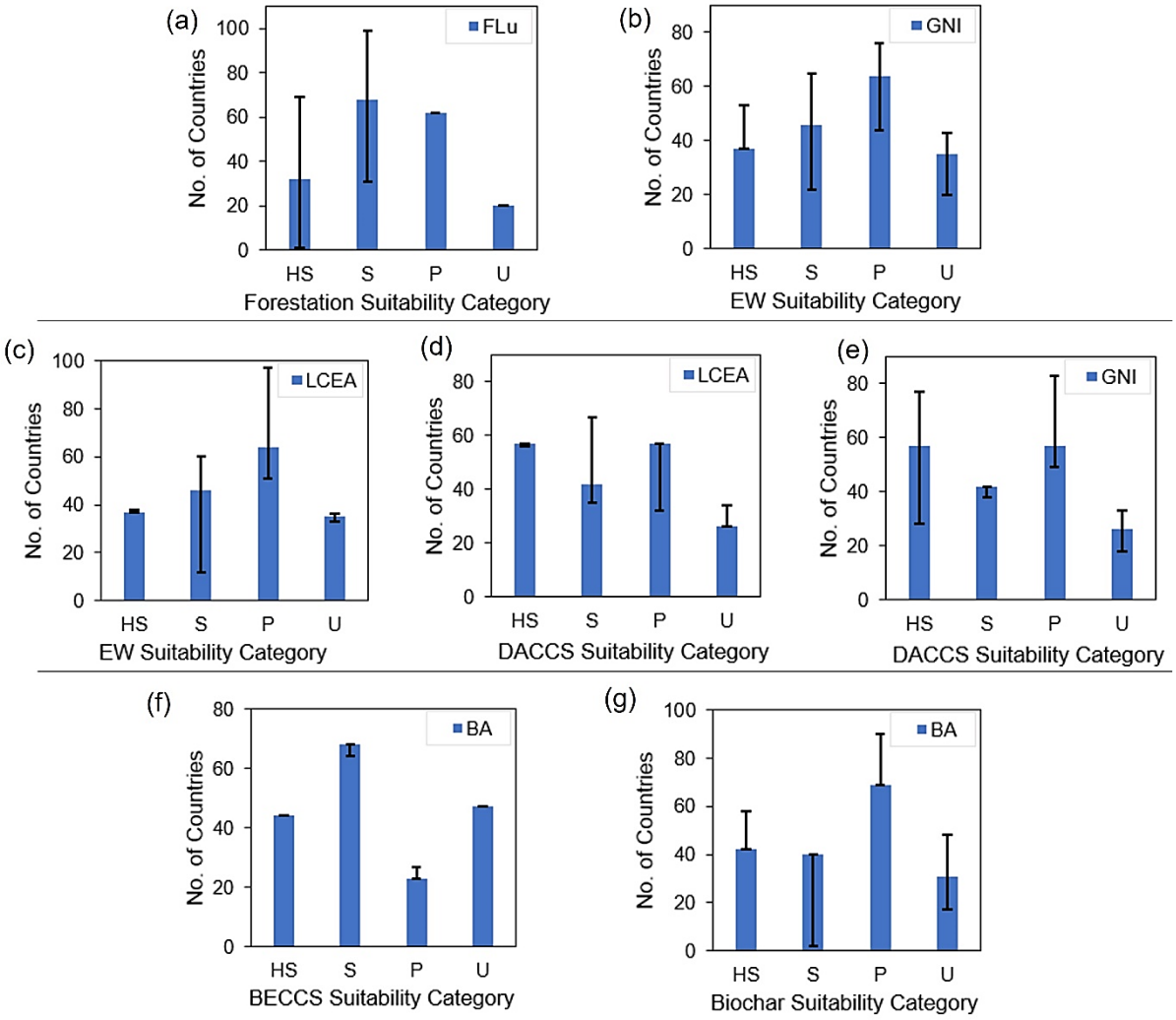


Figure 4-5 Impact of resource availability on obtained suitability categorisation (a) FLu on Forestation, (b) GNI on EW, (c) LCEA on EW, (d) LCEA on DACCS, (e) GNI on DACCS, (f) BA on BECCS and (g) BA on Biochar.

The blue bar charts indicate the number of countries in the obtained categories. The error bars indicate the increased or decreased number of countries in each category under pessimistic and optimistic resource availability scenario. Optimistic scenario is indicated by positive error bars (for categories HS and S) and negative error bars (for categories P and U). Pessimistic scenario on the other hand is indicated by negative error bars (for categories HS and S) and positive error bars (for categories P and U).

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 (Figure 4-5(c)); while a 14% change (25 countries) was observed for DACCS (Figure 4-5(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 requirement for deployment. For EW (Figure 4-5(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 (Figure 4-5(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 (Figure 4-5(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 (Figure 3-5(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 for the obtained categorisation results (Figure 4-4) is set as follows: Forestation, DACCS and Biochar (20%), EW (35%) and BECCS (2%).

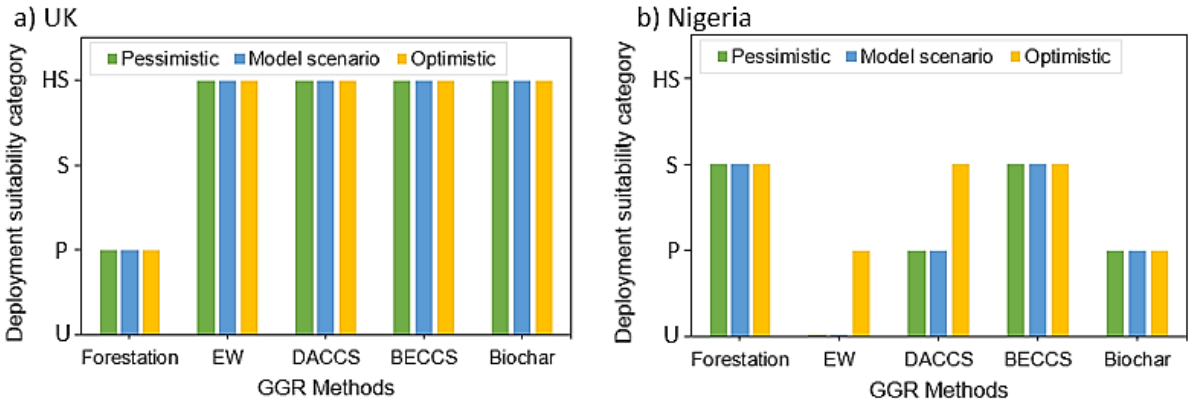


Figure 4-6 Impact of model input variation (pessimistic and optimistic scenarios) on the deployment suitability categorisation of the UK and Nigeria.

Figure 3-6 presents two case studies (the UK and Nigeria) to illustrate the discussed sensitivity analysis. For the UK (Figure 3-6(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 (Figure 3-6(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.

4.5 Limitations and recommendations

The suitability category of 182 countries to deployment 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.

Another limitation which is commonly associated with categorisation-based study is the lack of consideration for individual variations, 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.

4.6 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 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 - 98%. It is advised, thus, to update the categorization results whenever fresh estimates become available.

Data availability statement

Data underlying this study can be accessed through the Cranfield University repository (CORD) at: https://figshare.com/s/6cf5797db17ff4530ed2. Data are available under the terms of the [Creative Commons Attribution 4.0 International (CC BY 4.0)].

4.7 References

Abbas, F., Hammad, H.M., Fahad, S., Cerdà, A., Rizwan, M., Farhad, W., Ehsan, S., Bakhat, H.F., 2017. Agroforestry: a sustainable environmental practice for carbon sequestration under the climate change scenarios—a review. Environ. Sci. Pollut. Res. 24, 11177–11191. https://doi.org/10.1007/s11356-017-8687-0

Alabdrabalnabi, A., Gautam, R., Mani Sarathy, S., 2022. Machine learning to predict biochar and bio-oil yields from co-pyrolysis of biomass and plastics. Fuel 328, 125303. https://doi.org/10.1016/j.fuel.2022.125303

Alcalde, J., Smith, P., Haszeldine, R.S., Bond, C.E., 2018. The potential for implementation of Negative Emission Technologies in Scotland. Int. J. Greenh. Gas Control 76, 85–91. https://doi.org/10.1016/j.ijggc.2018.06.021

Aminu, M.D., Nabavi, S.A., Rochelle, C.A., Manovic, V., 2017. A review of developments in carbon dioxide storage. Appl. Energy 208, 1389–1419. https://doi.org/10.1016/j.apenergy.2017.09.015

Andrews, M., Taylor, L., 2019. Combating Climate Change Through Enhanced Weathering of Agricultural Soils. Elements 15, 325–330. https://doi.org/10.2138/gselements.15.4.253

Asibor, J.O., Clough, P.T., Nabavi, S.A., Manovic, V., 2021. Assessment of optimal conditions for the performance of greenhouse gas removal methods. J. Environ. Manage. 294, 113039. https://doi.org/10.1016/j.jenvman.2021.113039

Baik, E., Sanchez, D.L., Turner, P.A., Mach, K.J., Field, C.B., Benson, S.M., 2018. Geospatial analysis of near-term potential for carbon-negative bioenergy in the United States. Proc. Natl. Acad. Sci. U. S. A. 115, 3290–3295. https://doi.org/10.1073/pnas.1720338115

Brassard, P., Godbout, S., Raghavan, V., 2016. Soil biochar amendment as a climate change mitigation tool: Key parameters and mechanisms involved. J. Environ. Manage. 181, 484–497. https://doi.org/10.1016/j.jenvman.2016.06.063

Bui, M., Adjiman, C.S., Bardow, A., Anthony, E.J., Boston, A., Brown, S., Fennell, P.S., Fuss, S., Galindo, A., Hackett, L.A., Hallett, J.P., Herzog, H.J., Jackson, G., Kemper, J., Krevor, S., Maitland, G.C., Matuszewski, M., Metcalfe, I.S., Petit, C., Puxty, G., Reimer, J., Reiner, D.M., Rubin, E.S., Scott, S.A., Shah, N., Smit, B., Trusler, J.P.M., Webley, P., Wilcox, J., Mac Dowell, N., 2018. Carbon capture and storage (CCS): The way forward. Energy Environ. Sci. 11, 1062–1176. https://doi.org/10.1039/c7ee02342a

Chen, Y., Wu, B., Chen, D., Qi, Y., 2019. Using machine learning to assess site suitability for afforestation with particular species. Forests 10, 1–22. https://doi.org/10.3390/f10090739

Christopher, A., 2021. K-Nearest Neighbor [WWW Document]. The Startup. URL

https://medium.com/swlh/k-nearest-neighbor-ca2593d7a3c4 (accessed 4.14.23).

CIA, 2022. The World Factbook [WWW Document]. URL https://www.cia.gov/the-world-factbook/field/land-use (accessed 6.10.20).

Dessert, C., Dupré, B., Gaillardet, J., François, L.M., Allègre, C.J., 2003. Basalt weathering laws and the impact of basalt weathering on the global carbon cycle. Chem. Geol. 202, 257–273. https://doi.org/10.1016/j.chemgeo.2002.10.001

Donnison, C., Holland, R.A., Hastings, A., Armstrong, L.M., Eigenbrod, F., Taylor, G., 2020. Bioenergy with Carbon Capture and Storage (BECCS): Finding the win–wins for energy, negative emissions and ecosystem services—size matters. GCB Bioenergy 12, 586–604. https://doi.org/10.1111/gcbb.12695

ExpertAI, 2022. What Is the Definition of Machine Learning? [WWW Document]. URL https://www.expert.ai/blog/machine-learning-definition/ (accessed 4.10.23).

Fajardy, M., Patrizio, P., Daggash, H.A., Mac Dowell, N., 2019. Negative Emissions: Priorities for Research and Policy Design. Front. Clim. 1, 1–7. https://doi.org/10.3389/fclim.2019.00006

FAO, 2022. FAO-AQUASTAT database [WWW Document]. URL http://www.fao.org/nr/water/aquastat/data/query/results.html (accessed 7.15.20).

Fasihi, M., Efimova, O., Breyer, C., 2019. Techno-economic assessment of CO 2 direct air capture plants. J. Clean. Prod. 224, 957–980. https://doi.org/10.1016/j.jclepro.2019.03.086

Favero, A., Sohngen, B., Huang, Y., Jin, Y., 2018. Global cost estimates of forest climate mitigation with albedo: A new integrative policy approach. Environ. Res. Lett. 13. https://doi.org/10.1088/1748-9326/aaeaa2

Fuss, S., Lamb, W.F., Callaghan, M.W., Hilaire, J., Creutzig, F., Amann, T., Beringer, T., De Oliveira Garcia, W., Hartmann, J., Khanna, T., Luderer, G., Nemet, G.F., Rogelj, J., Smith, P., Vicente, J.V., Wilcox, J., Del Mar Zamora Dominguez, M., Minx, J.C., 2018. Negative emissions - Part 2: Costs, potentials and side effects. Environ. Res. Lett. 13. https://doi.org/10.1088/1748-9326/aabf9f

Garbade, M.J., 2018. Clearing the Confusion: AI vs Machine Learning vs Deep Learning Differences [WWW Document]. Towar. Data Sci. URL https://towardsdatascience.com/clearing-the-confusion-ai-vs-machine-learning-vs-deep-learning-differences-fce69b21d5eb (accessed 2.8.21).

Griscom, B.W., Busch, J., Cook-Patton, S.C., Ellis, P.W., Funk, J., Leavitt, S.M., Lomax, G., Turner, W.R., Chapman, M., Engelmann, J., Gurwick, N.P., Landis, E., Lawrence, D., Malhi, Y., Murray, L.S., Navarrete, D., Roe, S., Scull, S., Smith, P., Streck, C., Walker, W.S., Worthington, T., 2020. National

mitigation potential from natural climate solutions in the tropics. Philos. Trans. R. Soc. B Biol. Sci. 375. https://doi.org/10.1098/rstb.2019.0126

Hartman, P.J., 2017. Reviews of Science for Science Librarians: Forestry as a Climate Change Mitigation Tool. Sci. Technol. Libr. 36, 219–234. https://doi.org/10.1080/0194262X.2017.1337541

Haszeldine, S., Cavanagh, A., Scott, V., Sohi, S., Mašek, O., Renforth, P., 2019. Greenhouse Gas Removal Technologies-approaches and implementation pathways in Scotland Executive summary. ClimateXChange.

Hepburn, C., Adlen, E., Beddington, J., Carter, E.A., Fuss, S., Mac Dowell, N., Minx, J.C., Smith, P., Williams, C.K., 2019. The technological and economic prospects for CO2 utilization and removal. Nature 575, 87–97. https://doi.org/10.1038/s41586-019-1681-6

Hu, Y., Li, K., Meng, A., 2018. Agglomerative Hierarchical Clustering using Ward Linkage [WWW Document]. URL https://jbhender.github.io/Stats506/F18/GP/Group10.html (accessed 4.10.23).

IEA, 2020. IEA Energy Atlas [WWW Document]. URL http://energyatlas.iea.org/#!/tellmap/-1118783123/1 (accessed 9.15.20).

IEAGHG, 2011. Global Storage Resources Gap Analysis for Policy Makers.

IPCC, 2022. Summary for Policymakers, in: Shukla, P.R., Skea, J., Slade, R., Al Khourdajie, A., van Diemen, R., McCollum, D., Pathak, M., Some, S., Vyas, P., Fradera, R., Belkacemi, M., Hasija, A., Lisboa, G., Luz, S., Malley, J. (Eds.), Climate Change 2022: Mitigation of Climate Change. Cambridge University Press, Cambridge, UK, pp. 1–30.

IPCC, 2018. Global warming of 1.5°C An IPCC Special Report on the impacts of global warming of 1.5°C above pre-industrial levels and related global greenhouse gas emission pathways, in the context of strengthening the global response to the threat of climate change,.

IRENA, 2021. Statistical Profiles [WWW Document]. URL https://www.irena.org/Statistics/Statistical-Profiles (accessed 12.10.20).

Jiang, K., He, C., Dai, H., Liu, J., Xu, X., 2018. Emission scenario analysis for China under the global 1.5 °C target. Carbon Manag. 9, 481–491. https://doi.org/10.1080/17583004.2018.1477835

Jordan, M.I., Mitchell, T.M., 2015. Machine learning: Trends, perspectives, and prospects. Science (80-.). 349, 255–260.

Kantola, I.B., Masters, M.D., Beerling, D.J., Long, S.P., DeLucia, E.H., 2017. Potential of global croplands and bioenergy crops for climate change mitigation through deployment for enhanced weathering. Biol. Lett. 13. https://doi.org/10.1098/rsbl.2016.0714

Karlsson, H., Delahaye, T., Johnsson, F., Rootzén, J., 2017. Immediate

deployment opportunities for negative emissions with BECCS : a Swedish case study. arXiv Prepr. arXiv1705.07894. 1–16.

Kearns, J., Teletzke, G., Palmer, J., Thomann, H., Kheshgi, H., Chen, H., Paltsev, S., Herzog, H., 2017. Developing a Consistent Database for Regional Geologic CO2 Storage Capacity Worldwide. Energy Procedia 114, 4697–4709. https://doi.org/10.1016/j.egypro.2017.03.1603

Kumar, S., 2019. Advantages and Disadvantages of Artificial Intelligence [WWW Document]. Towar. Data Sci. URL https://towardsdatascience.com/advantages-and-disadvantages-of-artificial-intelligence-182a5ef6588c (accessed 2.8.21).

Li, Y., Gupta, R., You, S., 2022. Machine learning assisted prediction of biochar yield and composition via pyrolysis of biomass. Bioresour. Technol. 359, 127511. https://doi.org/10.1016/j.biortech.2022.127511

Li, Yongfu, Hu, S., Chen, J., Müller, K., Li, Yongchun, Fu, W., Lin, Z., Wang, H., 2018. Effects of biochar application in forest ecosystems on soil properties and greenhouse gas emissions: a review. J. Soils Sediments 18, 546–563. https://doi.org/10.1007/s11368-017-1906-y

Lorenz, K., Lal, R., 2014. Biochar application to soil for climate change mitigation by soil organic carbon sequestration. J. Plant Nutr. Soil Sci. 177, 651–670. https://doi.org/10.1002/jpln.201400058

Madhulatha, T.S., 2012. An Overview of Clustering Methods. IOSR J. Eng. 2, 719–725.

Meysman, F.J.R., Montserrat, F., 2017. Negative CO2 emissions via enhanced silicate weathering in coastal environments. Biol. Lett. 13. https://doi.org/10.1098/rsbl.2016.0905

Moreira, J.R., Romeiro, V., Fuss, S., Kraxner, F., Pacca, S.A., 2016. BECCS potential in Brazil : Achieving negative emissions in ethanol and electricity production based on sugar cane bagasse and other residues. Appl. Energy 179, 55–63. https://doi.org/10.1016/j.apenergy.2016.06.044

Mulligan, J., Rudee, A., Lebling, K., Levin, K., Anderson, J., Christensen, B., 2020. CarbonShot: Federal Policy Options for Carbon Removal in the United States, World Resources Institute.

Murtagh, F., Contreras, P., 2012. Algorithms for hierarchical clustering : an overview. Wiley Interdiscip. Rev. Data Min. Knowl. Discov. 2, 86–97. https://doi.org/10.1002/widm.53

Nair, V.D., Nair, P.K.R., Dari, B., Freitas, A.M., Chatterjee, N., Pinheiro, F.M., 2017. Biochar in the agroecosystem-climate-change-sustainability Nexus. Front. Plant Sci. 8. https://doi.org/10.3389/fpls.2017.02051

Ordóñez Galán, C., Matías, J.M., Rivas, T., Bastante, F.G., 2009. Reforestation planning using Bayesian networks. Environ. Model. Softw. 24, 1285–1292.

https://doi.org/10.1016/j.envsoft.2009.05.009

Pour, N., Webley, P.A., Cook, P.J., 2018. Opportunities for application of BECCS in the Australian power sector. Appl. Energy 224, 615–635. https://doi.org/10.1016/j.apenergy.2018.04.117

Pozo, C., Galán-martín, Á., Reiner, D.M., Dowell, N. Mac, Guillén-gosálbez, G., 2020. Equity in allocating carbon dioxide removal quotas. Nat. Clim. Chang. https://doi.org/10.1038/s41558-020-0802-4

Psarras, P., Krutka, H., Fajardy, M., Zhang, Z., Liguori, S., Dowell, N. Mac, Wilcox, J., 2017. Slicing the pie: how big could carbon dioxide removal be? Wiley Interdiscip. Rev. Energy Environ. 6, 1–21. https://doi.org/10.1002/wene.253

Raihan, A., Begum, R.A., Mohd Said, M.N., Abdullah, S.M.S., 2019. A Review of Emission Reduction Potential and Cost Savings through Forest Carbon Sequestration. Asian J. Water, Environ. Pollut. 16, 1–7. https://doi.org/10.3233/AJW190027

Renforth, P., 2012. The potential of enhanced weathering in the UK. Int. J. Greenh. Gas Control 10, 229–243. https://doi.org/10.1016/j.ijggc.2012.06.011

Ritchie, H., Roser, M., Rosado, P., 2020. Renewable Energy - Our World in Data [WWW Document]. URL https://ourworldindata.org/renewable-energy (accessed 6.14.22).

Roe, S., Streck, C., Beach, R., Busch, J., Chapman, M., Daioglou, V., Deppermann, A., Doelman, J., Emmet-Booth, J., Engelmann, J., Fricko, O., Frischmann, C., Funk, J., Grassi, G., Griscom, B., Havlik, P., Hanssen, S., Humpenöder, F., Landholm, D., Lomax, G., Lehmann, J., Mesnildrey, L., Nabuurs, G.J., Popp, A., Rivard, C., Sanderman, J., Sohngen, B., Smith, P., Stehfest, E., Woolf, D., Lawrence, D., 2021. Land-based measures to mitigate climate change: Potential and feasibility by country. Glob. Chang. Biol. 1–34. https://doi.org/10.1111/gcb.15873

Roe, S., Streck, C., Obersteiner, M., Frank, S., Griscom, B., Drouet, L., Fricko, O., Gusti, M., Harris, N., Hasegawa, T., Hausfather, Z., Havlík, P., House, J., Nabuurs, G.J., Popp, A., Sánchez, M.J.S., Sanderman, J., Smith, P., Stehfest, E., Lawrence, D., 2019. Contribution of the land sector to a 1.5 °C world. Nat. Clim. Chang. 9, 817–828. https://doi.org/10.1038/s41558-019-0591-9

Rogelj, J., Elzen, M. Den, Höhne, N., Fransen, T., Fekete, H., Winkler, H., Schaeffer, R., Sha, F., 2016. Paris Agreement climate proposals need a boost to keep warming well below 2 ° C. Nature 534. https://doi.org/10.1038/nature18307

Rolnick, D., Donti, P.L., Kaack, L.H., Kochanski, K., Lacoste, A., Sankaran, K., Ross, A.S., Milojevic-Dupont, N., Jaques, N., Waldman-Brown, A., Luccioni, A.S., Maharaj, T., Sherwin, E.D., Mukkavilli, S.K., Kording, K.P., Gomes,

C.P., Ng, A.Y., Hassabis, D., Platt, J.C., Creutzig, F., Chayes, J., Bengio, Y., 2022. Tackling Climate Change with Machine Learning. ACM Comput. Surv. 55. https://doi.org/10.1145/3485128

Royal Society, 2018. Options for producing low-carbon hydrogen at scale, The Royal Society.

Rueda, O., Mogollón, J.M., Tukker, A., Scherer, L., 2021. Negative-emissions technology portfolios to meet the 1.5 °C target. Glob. Environ. Chang. 67. https://doi.org/10.1016/j.gloenvcha.2021.102238

Saji, B., 2021. Elbow Method for Finding the Optimal Number of Clusters in K-Means [WWW Document]. Anal. Vidhya. URL https://www.analyticsvidhya.com/blog/2021/01/in-depth-intuition-of-k-means-clustering-algorithm-in-machine-learning/

Schiermeier, Q., 2015. Combined climate pledges of 146 nations fall short of 2 ° C target. Nature 2–4. https://doi.org/10.1038/nature.2015.18693

Schuiling, R.D., 2017. Olivine Weathering against Climate Change. Nat. Sci. 09, 21–26. https://doi.org/10.4236/ns.2017.91002

Smith, P., Davis, S.J., Creutzig, F., Fuss, S., Minx, J., Gabrielle, B., Kato, E., Jackson, R.B., Cowie, A., Kriegler, E., Van Vuuren, D.P., Rogelj, J., Ciais, P., Milne, J., Canadell, J.G., McCollum, D., Peters, G., Andrew, R., Krey, V., Shrestha, G., Friedlingstein, P., Gasser, T., Grübler, A., Heidug, W.K., Jonas, M., Jones, C.D., Kraxner, F., Littleton, E., Lowe, J., Moreira, J.R., Nakicenovic, N., Obersteiner, M., Patwardhan, A., Rogner, M., Rubin, E., Sharifi, A., Torvanger, A., Yamagata, Y., Edmonds, J., Yongsung, C., 2015. Biophysical and economic limits to negative CO2 emissions. Nat. Clim. Chang. 6, 42–50. https://doi.org/10.1038/nclimate2870

Stewart, M., 2019. The Limitations of Machine Learning [WWW Document]. Towar. Data Sci. URL https://towardsdatascience.com/the-limitations-of-machine-learning-a00e0c3040c6 (accessed 2.8.21).

Strefler, J., Amann, T., Bauer, N., Kriegler, E., Hartmann, J., 2018. Potential and costs of carbon dioxide removal by enhanced weathering of rocks. Environ. Res. Lett. 13. https://doi.org/10.1088/1748-9326/aaa9c4

Sultana, S.I., 2020. How the Hierarchical Clustering Algorithm Works [WWW Document]. Dataaspirant. URL https://dataaspirant.com/hierarchical-clustering-algorithm/ (accessed 9.13.22).

The Royal Society, 2018. Greenhouse Gas Removal.

Thoni, T., Beck, S., Borchers, M., Förster, J., Görl, K., Hahn, A., Mengis, N., Stevenson, A., Thrän, D., 2020. Deployment of NETs at the National Level: A Need for Holistic Feasibility Assessments. Front. Clim. 2, 12.

Tisserant, A., Cherubini, F., 2019. Potentials, limitations, co-benefits, and trade-offs of biochar applications to soils for climate change mitigation. Land 8.

https://doi.org/10.3390/LAND8120179

Usama, M., Qadir, J., Raza, A., Arif, H., Yau, K.A., Elkhatib, Y., Hussain, A., Al-fuqaha, A., 2019. Unsupervised Machine Learning for Networking : Techniques , Applications and Research Challenges. IEEE Access 7, 1–37.

Viebahn, P., Scholz, A., Zelt, O., 2019. German Energy Research Program — Results of a Multi-Dimensional Analysis. Energies.

Woolf, D., Amonette, J.E., Street-Perrott, F.A., Lehmann, J., Joseph, S., 2010. Sustainable biochar to mitigate global climate change. Nat. Commun. 1. https://doi.org/10.1038/ncomms1053

World Bank, 2022. World Bank Climate Change Knowledge Portal [WWW Document]. URL https://climateknowledgeportal.worldbank.org/ (accessed 7.21.20).

World Bank, 2021. GNI per capita, Atlas method (current US$) | Data [WWW Document]. URL https://data.worldbank.org/indicator/NY.GNP.PCAP.CD (accessed 10.9.21).

Yan, Yongliang, Borhani, T.N., Subraveti, S.G., Pai, K.N., Prasad, V., Rajendran, A., Nkulikiyinka, P., Asibor, J.O., Zhang, Z., Shao, D., Wang, L., Zhang, W., Yan, Yong, Ampomah, W., You, J., Wang, M., Anthony, E.J., Manovic, V., Clough, P.T., 2021. Harnessing the power of machine learning for carbon capture, utilisation, and storage (CCUS)-a state-of-the-art review. Energy Environ. Sci. 14, 6122–6157. https://doi.org/10.1039/d1ee02395k

Yousefi, S., Avand, M., Yariyan, P., Jahanbazi Goujani, H., Costache, R., Tavangar, S., Tiefenbacher, J.P., 2021. Identification of the most suitable afforestation sites by Juniperus excels specie using machine learning models: Firuzkuh semi-arid region, Iran. Ecol. Inform. 65, 101427. https://doi.org/10.1016/j.ecoinf.2021.101427

Zhu, X., Li, Y., Wang, X., 2019. Machine learning prediction of biochar yield and carbon contents in biochar based on biomass characteristics and pyrolysis conditions. Bioresour. Technol. 288, 121527. https://doi.org/10.1016/j.biortech.2019.121527

Zimmermann, M., Bird, M.I., Wurster, C., Saiz, G., Goodrick, I., Barta, J., Capek, P., Santruckova, H., Smernik, R., 2012. Rapid degradation of pyrogenic carbon. Glob. Chang. Biol. 18, 3306–3316. https://doi.org/10.1111/j.1365-2486.2012.02796.x

5 A Machine Learning Approach for Resource Mapping Analysis of Greenhouse Gas Removal Technologies

Jude O. Asibor, Peter T. Clough, Seyed Ali Nabavi, Vasilije Manovic

School of Water, Energy and Environment, Cranfield University, Bedfordshire, MK43 0AL, UK.

Submitted 8 November 2022; Accepted 17 July 2023

Published in Energy and Climate Change 4 (2023) 100112

DOI: https://doi.org/10.1016/j.egycc.2023.100112

Abstract

In this study, machine learning (ML) was applied to investigate the suitability of a location to deploy five greenhouse gas removal (GGR) methods within a global context, based on a location's bio-geophysical and techno-economic characteristics. The GGR methods considered are forestation, enhanced weathering (EW), direct air carbon capture and storage (DACCS), bioenergy with carbon capture and storage (BECCS) and biochar. An unsupervised ML (hierarchical clustering) technique was applied to label the dataset. Seven supervised ML algorithms were applied in training and testing the labelled dataset with the k-Nearest neighbour (k-NN), Artificial Neural Network (ANN) and Random Forest algorithms having the highest performance accuracies of 96%, 98% and 100% respectively. A case study of Scotland's suitability to deploy these GGR methods was carried out with obtained results indicating a high correlation between the ML model results and information in the available literature. While the performance accuracy of the ML models was typically high (76 – 100%), an assessment of its decision-making logic (model interpretation) revealed some limitations regarding the impact of the various input variables on the outputs.

Keywords: Machine learning; climate change mitigation; carbon capture and storage; negative emission technologies; random forest; BECCS.

5.1 Introduction

Limiting the average global temperature rise to 1.5 °C as stated in the Paris Agreement requires a combination of a proactive emission reduction technological approach and an indispensable option to remove greenhouse gases (especially carbon dioxide) currently present in the atmosphere (IPCC, 2022; Rogelj et al., 2018; Smith, 2016). A number of greenhouse gas removal (GGR) methods have been proposed and assessed for the potential of large-scale deployment (Fuss et al., 2018; Minx et al., 2018; Nemet et al., 2018; Smith et al., 2015; The Royal Society, 2018). These methods include forestation, enhanced weathering (EW), soil carbon sequestration (SCS), biochar, direct air carbon capture and storage (DACCS), bioenergy with carbon capture and storage (BECCS), ocean fertilisation and wetland restoration among others. With the performance of these methods very much dependent on a complex interaction of bio-geophysical, techno-economic and socio-political factors, there is need to evaluate the GGR method(s) that are most suitable for deployment in a given location based on the location's characteristics. Such a system is expected to provide unbiased information that will guide and enhance the decision-making process of concerned stakeholders on the choice of GGR methods that can be sustainably and efficiently deployed in a given location. Accordingly, this study aims to utilise machine learning to provide an unbiased prediction of suitable GGR technology deployment worldwide.

Efforts to ascertain the suitability of deployment of GGR methods at local/national levels have been reported in the literature. While some addressed portfolio of GGR methods by analytically assessing the local availability of required resources (Alcalde et al., 2018; Haszeldine et al., 2019; Mulligan et al., 2020; The Royal Society, 2018), others employed various forms of optimisation modelling and decision-making techniques. Donnison et al. (IPCC, 2018) applied a land-use spatial optimisation algorithm to determine the favourability of six potential UK locations to deploy BECCS from local biomass resources. By assessing indicators such as bioenergy crop yield, agricultural output, soil organic carbon, flood management, water stress level and land availability, the algorithm generated land-use scenarios for domestic bioenergy crop resources and

compared the socio-environmental implications at each location quantitatively. In another study, Forster et al. (Förster et al., 2022) developed a traffic light system-based framework for feasibility assessment of GGR options within a national context. While it offers a flexible tool to guide participatory, multi-disciplinary, iterative decision making, it is however limited by its susceptibility to subjective interpretation with consequent likelihood of biased outcomes.

While these models and frameworks are largely localised and case-specific, Fajardy and Mac Dowell (Fajardy and Mac Dowell, 2017), developed a linear optimisation model, so-called MONET framework which is applicable in multiple locations though with focus on evaluating optimal deployment conditions for BECCS. This spatio-temporal explicit model has now been updated (known as the MONET-EU) to include other GGR methods, specifically forestation, DACCS and EW. Based on a variety of sustainability and bio-geophysical constraints, it aims to provide whole-system analysis of least-cost portfolio of GGR pathways, in ten-year time-steps (NEGEM Project, 2022). Its application is however limited to regional and country-level assessment of the European Union (EU). Thus far, within the limits of the assessed literature, no effort has yet been made to apply Machine Learning (ML) in assessing the suitability of deployment of GGR methods for any location. Herein lies the novelty in this study. The use of ML minimises human bias, offers flexibility to adapt to the ever-changing bio-geophysical and techno-economic factors while ensuring that the model is applicable globally.

ML which is a subset of artificial intelligence (AI) involves the study of statistical computer algorithms that allow computer programs to automatically improve through experience (Garbade, 2018; Jordan and Mitchell, 2015). With advantages including ease of trends and pattern identification, minimal human intervention (automation), ability to improve continuously as well as high efficiency in the handling of multi-dimensional and multi-variety data, ML finds wide application in several fields of human endeavours (Jordan and Mitchell, 2015; Kumar, 2019). Its application is, however, limited by factors such as ethics,

data availability and quality, misapplication as well as interpretability (Stewart, 2019).

With regards to climate change mitigation, ML is expected to play a key role in diverse areas ranging from smart grids to disaster management (Rolnick et al., 2022). This has also been corroborated by Yan et al. (Yan et al., 2021) who reviewed and highlighted areas of ML deployment and prospects in carbon capture, utilisation and storage (CCUS). Efforts at ML application in the advancement of other GGR methods, though limited, have also been reported in the literature. This includes prediction of biochar yield and carbon content from the pyrolysis of various materials such as lignocellulosic biomass (Zhu et al., 2019), organic waste (Li et al., 2022) and plastics (Alabdrabalnabi et al., 2022). ML has also been applied for reforestation planning (Ordóñez Galán et al., 2009) and afforestation site selection based on particular local tree species (Chen et al., 2019; Yousefi et al., 2021).

In this study, we apply ML to predict the suitability of deployment of 5 GGR methods (forestation, EW, DACCS, BECCS and biochar) based on a location's biophysical and techno-economic characteristics. The study will involve the application of unsupervised ML for data labelling and supervised ML for predictive analysis. In addition, a case study analysis to test and validate the ML predictive outcome will also be carried out.

5.2 Methods

Figure 5-1. presents the framework of the method applied in this study. The five GGR methods considered in this study, namely forestation, EW, DACCS, BECCS and biochar, were selected on the basis of their carbon dioxide removal potential and technological readiness levels (Fuss et al., 2018; Haszeldine et al., 2019). Major biophysical and techno-economic factors necessary for the sustainable and efficient performance of these GGR methods were identified from the literature (Asibor et al., 2021). This include climatic factor (temperature and precipitation), land availability, water availability (WA), Low carbon energy

availability (LCEA), geological storage potential (GSP), biomass availability (BA) and financial capability represented by the gross national income per capita (GNI).

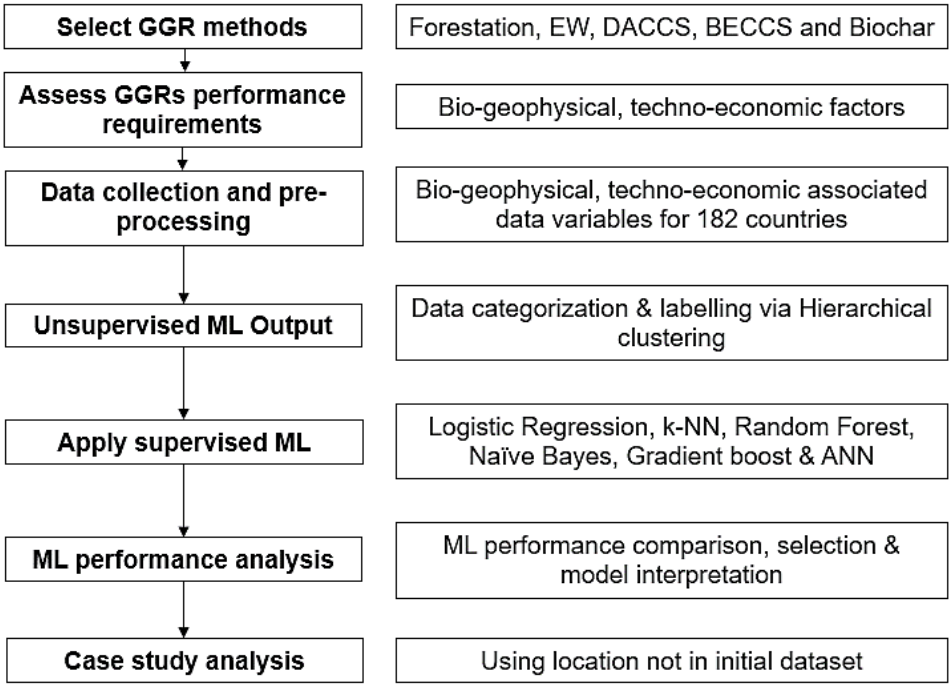


Figure 5-1 Method framework for the supervised machine learning modelling

Associated input variables of these factors which will be applied in the ML modelling were then identified as presented in Table 5-1. While the climate variable was explicitly indicated for forestation, it wasn't explicitly indicated for BECCS and biochar. This was done to avoid double-counting as its impact on biomass availability is already captured in the indicator applied for assessing biomass availability (the net primary production). However, in the case of biochar, there was need to also assess the impact of weather on the applied biochar. Hence the additional inclusion of climate variables for this GGR method.

5.2.1 Data collection and pre-processing

Most recent data for these identified variables were obtained for 182 countries from diverse sources as follows; for climatic factor, quarterly mean temperature and precipitation covering a 30-year period from 1991 to 2020 sourced from the World Bank climate knowledge portal was used (World Bank, 2022).

Table 5-1 Data variables for the GGR methods

GGR method	Deployment requirement	
	Major	**Minor**
Forestation	Climatic factor (average quarterly temperature and precipitation*), Forest land use (FLu)	WA
EW	LCEA, GNI	Average quarterly temperature and precipitation*, Agricultural land use (AgLu).
DACCS	GSP, LCEA, GNI	WA
BECCS	GSP, BA	WA, GNI
Biochar	BA	Average quarterly temperature and precipitation*, GNI, AgLu

*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).

For water availability, water stress level data soured from the Food and Agriculture Organisation was used (FAO, 2022). This indicator measures the amount of freshwater used in relation to the total amount of accessible renewable freshwater resources. Geological CO_2 storage potential was obtained from the IEAGHG world geological suitability map (IEAGHG, 2011; Kearns et al., 2017). The share of forest land use and agricultural land use sourced from the CIA's World factbook (CIA, 2022) was applied for assessing land availability. Gross national income per capita (GNI) sourced from the World Bank was adopted to measure financial capability of countries (World Bank, 2021). For energy availability, data for the percentage share of low carbon energy in each countries' energy mix sourced from the International Energy Agency was adopted (IEA, 2020; Ritchie et al., 2020). Biomass availability data, measured in terms of the net primary production (tC/ha/yr) was sourced from the International Renewable Energy Agency (IRENA, 2021). The net primary production, 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). It is important to note that other potential biomass sources such as imports and municipal wastes were not considered on account of data availability.

The raw data was pre-processed into a usable form by the numerical encoding of string type data and analytical determination of incomplete data. Data normalisation was also carried out between 0 and 1 for the entire dataset to eliminate differences in scale/range of values among the variables. In addition to eliminating bias of scale that exist across variables, normalisation also ensured that each country's data was better situated within a global context. This is very important given the global nature of the mitigation situation and the need to comparatively assess the role, scale and potential of nations as well as collaborative opportunities.

The development or training of a ML predictive model or supervised ML requires the availability of labelled dataset (input and corresponding output data). Given that these GGR methods are yet to be deployed on a large scale globally, the obtained locational dataset was unlabelled in regard to the suitability of these countries to deploy GGR methods. In order to develop the ML predictive model, the modelling in this study was thus, done in two stages. Firstly, the obtained pre-processed input dataset was labelled (derive the output – determine the deployment suitability category of the 182 countries based on their respective variables). This was done using the hierarchical clustering technique which is an unsupervised ML method (section 5.2.2). In the second stage, supervised ML was then applied to train the now labelled dataset comprising of the same input variables and the outputs obtained in stage 1 (section 5.2.3). This second stage is the focus of this paper. It is aimed at exploring the extent of ML as an innovative approach in assessing the suitability of GGR methods, which is free of human bias.

5.2.2 Hierarchical clustering

The hierarchical clustering technique is a bottom to top unsupervised machine learning 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 possible number of clusters (*k*) for the particular dataset. The optimal number of clusters 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. For each GGR method, the applied ML algorithm (Hierarchical clustering) assessed all the 182 datapoints simultaneously and clusters them based on the similarity of their characteristics. It is important to state that the clustering was wholly done by the ML model based on the data characteristics, and no specific human-defined cut-off levels was set for each variable as threshold for the categorisation. The code was written in Python using the *Agglomerative Clustering* library imported from the *sklearn.cluster* module. The linkage was set to 'ward' while the Euclidean distance method was adopted.

The obtained clusters were then sorted into four levels of deployment suitability (or categories); *highly suitable* (HS)*, suitable* (S)*, possible* (P) and *unsuitable* (U). A description of these suitability levels is presented in Table 5-2 with reference to the classification of deployment requirements in Table 5-1. This sorting of clusters into their respective suitability categories was based on a comparative assessment of their ML-generated cluster characteristics (mean cluster value for each variable) against the requirements highlighted in Tables 5-1 and 5-2. The higher the mean cluster value for a variable, the higher the availability of that factor in the countries that make up that cluster. For example, considering BECCS, with GSP and BA as major requirements and WA and GNI as minor requirements (Table 5-1), the cluster with the highest mean values for all requirements will be sorted into the Highly Suitable category (Table 5-2).

Table 5-2 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

5.2.3 Supervised ML modelling

The labelled dataset for each GGR method obtained from the hierarchical clustering consist of the data for the input variables presented in Table 5-1 and the corresponding output labels (deployment suitability level) for the 182 countries. These datasets were then trained using supervised ML algorithms. The supervised ML, the most commonly applied type of ML involves training the data to learn the relationship between the given inputs and associated output values (Singh et al., 2016; Wilson, 2019). Since the ML model is expected to predict the deployment suitability category of a given location (a classification-type problem), seven of the most commonly applied ML classification algorithm was employed in this study. These ML algorithms including logistic regression, Decision Trees, k-NN, naïve bayes, Random Forest, gradient boost and ANN, are briefly discussed in Table 5-3.

Table 5-3 Description of the applied supervised ML algorithms (Dey, 2016; Pareek, 2019; Singh et al., 2016)

Algorithm name	Description
Logistic regression	A classification algorithm that predicts the likelihood of a dependent variable (usually binary) belonging to a category.
Decision trees	This interpretable algorithm performs by splitting values of data features into branches at decision nodes until a final decision output is established.
K-Nearest neighbour	KNN is a non-parametric algorithm requiring little to no training that makes its selection based on the proximity to other data points regardless of what feature the numerical values represent.
Naïve Bayes	This algorithm is based on the Bayesian theorem which updates the prior knowledge of an event with the independent probability of each feature that can affect the event.
Random forest	The algorithm is an ensemble of decision trees characterised by improved accuracy. It operates by generating a multitude of decision trees and uses either the modal vote or average prediction for classification or regression tasks, respectively.
Gradient Boost	This ensemble algorithm combines multiple weak algorithms to obtain an improved output.
Artificial Neural Network	ANN inspired by the biological neural networks of the human brain, is made up of input, hidden and output layers, as well as a number of parallel-interconnected neurons in each layer. It can be trained to recognise patterns, classify data, and predict future events.

For all algorithms considered, the dataset was split into training and testing groups in a ratio of 70:30 respectively and randomly. This was done to minimise training and testing bias, obtain best results and ensure that the accuracy of the model is neither overestimated nor underestimated (Gholamy et al., 2018; Güleç et al., 2022). The code was written in Python using the corresponding ML algorithm library imported from their respective *sklearn* module. For each algorithm, the code was run 30 times to minimise bias.

5.3 Results and discussion

5.3.1 Supervised ML modelling

The results of the performance accuracy (R^2) of the applied seven ML algorithms in the prediction of the suitability of deployment of the five GGR methods are presented in Figure 5-2. The performance accuracy, which also refers to the coefficient of determination, or R^2, is a measure that provides information about how close the predicted model results are to the observed data values. It refers to the goodness of fit of a model, that is, how well the regression line approximates the actual data. The overall performance accuracy of all the ML algorithms for the five GGR methods was high ranging from 0.76 – 1.00. Being a classification kind of problem in which the ML models were expected to predict one out of four categories, the performance accuracy obtained for multiple runs of the various ML algorithms were typically constant with minor variations.

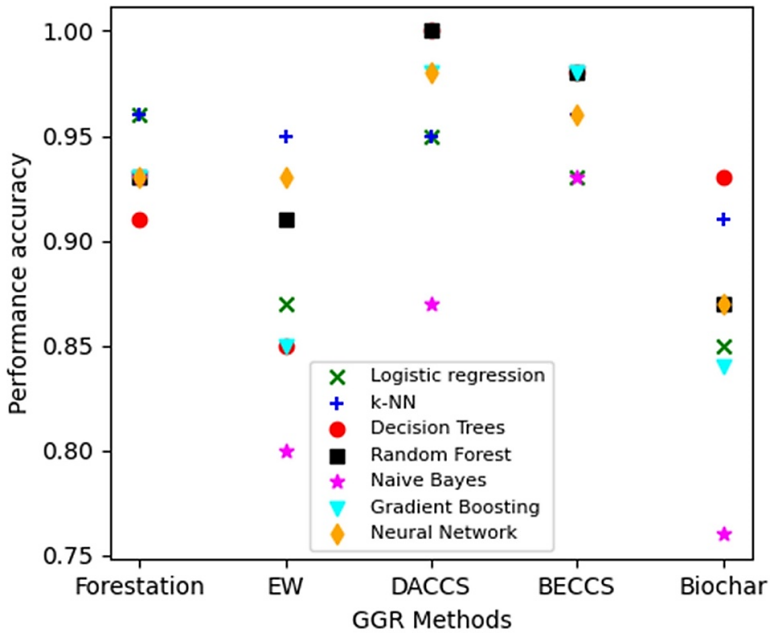


Figure 5-2 Comparison of ML algorithms performance for the suitability categorisation of 5 GGR methods

Overall, a 99% confidence interval of ±0.01 was evaluated for the performance accuracies. The Random Forest, k-NN and ANN had the highest performance accuracies of 96%, 98% and 100% respectively while the Naïve Bayes had the

lowest accuracy (76%). Given the black box nature of ML process, it is difficult to specify the particular reason for the variation in performance of the algorithms across the various GGR methods. This discrepancy in performance by the various ML algorithms is linked to multiple factors ranging from the inherent characteristics of each algorithm (operating principle, strengths and weaknesses) as well as the data characteristics (quantity, shape, dimension and distribution). The average performance accuracy of all the ML algorithms was highest for DACCS deployment suitability prediction, because it had the least number of input variables.

5.3.2 Modelling case study – Scotland

In order to validate the performance accuracy of the ML model, data for Scotland, a case study location which was not part of the initial training and testing dataset was used. Data for the input variables were sourced as follows. 10-year mean (2011-2020) weather data (mean quarterly temperature and rainfall) was obtained for Braemar station, Scotland from the Met office historical data (Met Office, 2020). This station was chosen on account of its relative central location in comparison to the other data stations in Scotland. Agricultural land use data were obtained from the Scottish Agricultural Census report (Scottish Government, 2020a). Forest land use data from the Scotland Forestry Strategy report (Scottish Government, 2019). GDP per capita data was obtained from Scottish Quarterly GDP National Accounts report (Scottish Government, 2020b), water availability (FAO, 2022), geological CO_2 storage potential (IEAGHG, 2011; Kearns et al., 2017), energy availability (BEIS, 2021) and biomass availability (IRENA, 2021).

The Random Forest ML model was applied to the obtained Scotland normalised dataset. Figure 5-3 presents the model results showing the suitability of Scotland to deploy the five GGR methods. While the ML model predicted forestation as *possible* (P), the other four were found to be *highly suitable* (HS). This ML model outcome is in good agreement with the existing literature reports concerning the probable deployment pathways for GGR methods in Scotland (Alcalde et al., 2018; Haszeldine et al., 2019).

The deployment of forestation in Scotland will involve reforestation which is already underway (Haszeldine et al., 2019) and afforestation which is expected to deliver the smallest NET contribution (1.24 $MtCO_2$/yr) of all the GGR methods on account of land use constraints (Alcalde et al., 2018). The removal potential of this GGR method is estimated to range from 2.5 – 5.3 $MtCO_2$/yr if the Scottish Government strategy on tree planting is sustained into the 2040s (Haszeldine et al., 2019). In the case of EW, the literature indicates high suitability of deployment (HS), which is in total agreement with the ML predicted outcome. This high suitability stems from Scotland's natural abundance of volcanic rocks and alkaline materials. The feasible removal potential of this GGR method is expected to range from 5-10 $MtCO_2$/yr, with the application rate expected to be dependent on the quality of the land (Haszeldine et al., 2019).

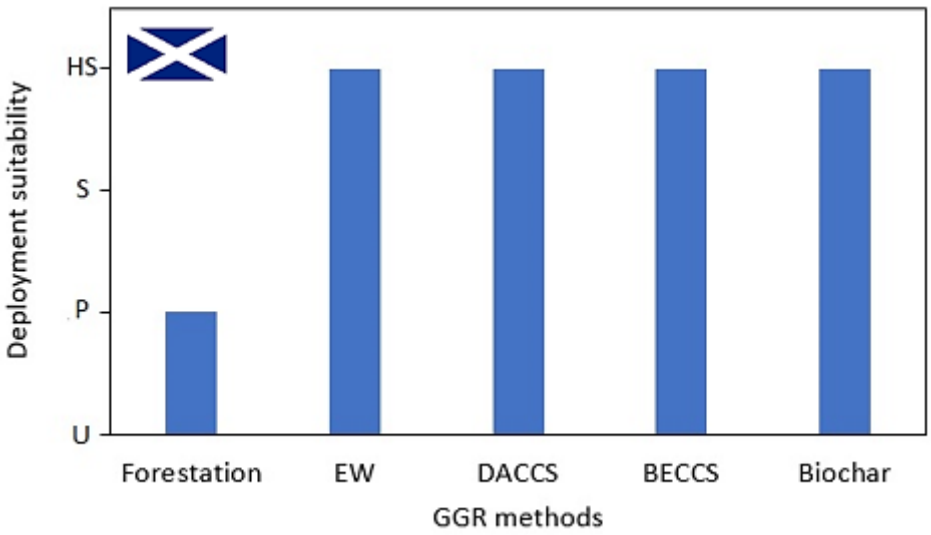


Figure 5-3 Bar chart showing the suitability of Scotland to deploy five GGR methods

With a surplus capacity of accessible CO_2 storage well beyond its needs, coupled with abundant renewable energy options, Scotland is a highly suitable location for deploying DACCS (Alcalde et al., 2018; Haszeldine et al., 2019). This agrees with the obtained ML model output for DACCS. Feasible deployment potential of this GGR method has been estimated to result in removal of 1-10 $MtCO_2$/yr based on input energy and storage availability (Haszeldine et al., 2019). Though specific locations within Scotland are yet to be identified for deploying this technology, it

is important to consider cost optimal sites that will minimise CO_2 transport and energy costs.

The negative emissions potential for BECCS and biochar if implemented on the 0.52 Mha of highly suitable land in Scotland, has been estimated to range from 5.7 – 23 $MtCO_2$/yr and 2.2 - 14.3 MtCO2 per year respectively (Alcalde et al., 2018). With an initial BECCS deployment potential estimate of 3.59 $MtCO_2$/yr using existing bioenergy installations with no additional land requirements (Brownsort, 2018) coupled with a projected 80% increase in available biomass by 2030 (Ricardo, 2019), Scotland qualifies as a highly suitable location for the deployment of these GGR methods. This suitability categorisation agrees with the obtained ML model output detailed in Figure 5-3.

Overall, with Scotland showing significant potential as a very suitable location for deploying these five GGR methods based on the ML model output and the existing literature reports, a major challenge in the particular choice of GGR methods to be eventually developed and deployed still exists. While Alcalde et al. (2018) reported that a combination of the maximum potential of BECCS, soil carbon sequestration (SCS) and EW coupled with a small contribution from DACCS could abate over 100% of Scotland's annual CO_2 emissions, Haszeldine et al. (2019) highlighted the need to ensure that chosen GGR methods are deployable at acceptable cost with minimal disruption while enhancing the development of new skills, jobs and value in Scottish supply chains.

5.3.3 Model interpretation and limitation

Model interpretation was carried out to understand the logic employed by the ML model in its predictive decision process. This understanding assists in verifying the correctness of the model regarding to how well it correlates with literature expectations on the relationship between input variables (bio-geophysical and technoeconomic factors) and outputs (GGR deployment suitability). In order to do this, the impact of the associated ML input variables (represented by the feature importance score) of the five GGR methods on their respective suitability of deployment (output) was evaluated. This was done using the *feature_importances_* tool in the Random Forest library imported from the *sklearn*

module. The feature importance score is a numerical representation of how much each input variable contributes or impacts on the ML model output. The sum of the importance scores of all the input variables in a model is usually equal to 1. The obtained result of this analysis showing the impact of the ML input variables on the deployment suitability of the GGR methods is presented in Figure 5-4.

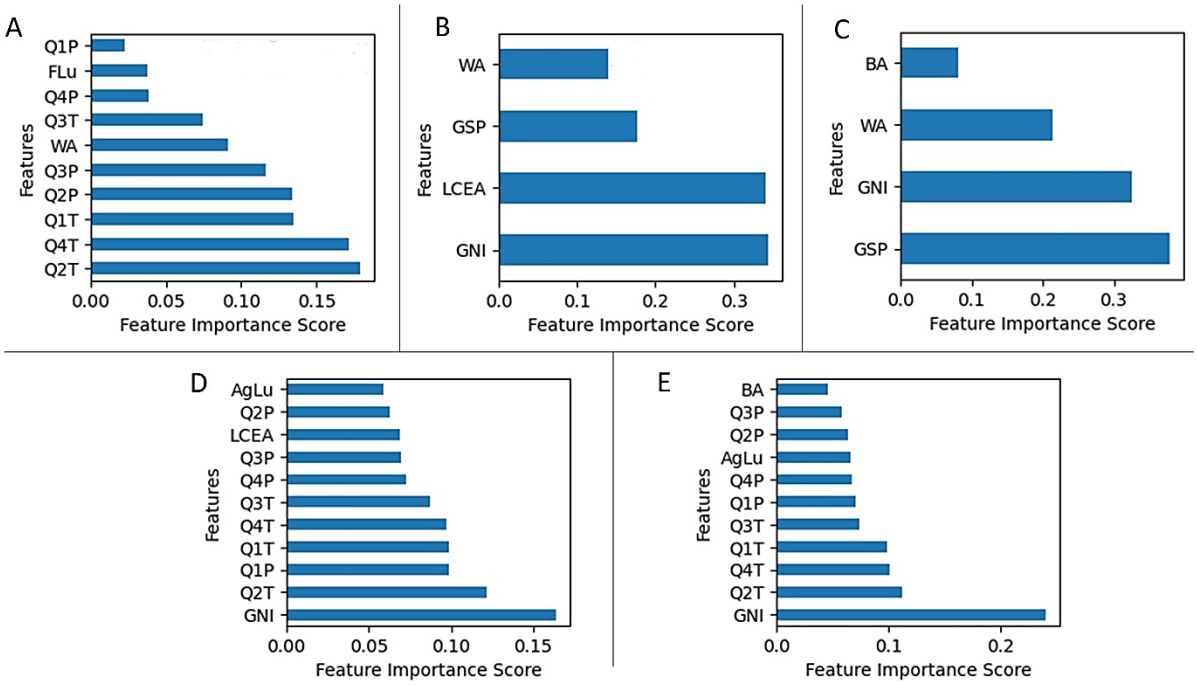


Figure 5-4 Plots of the feature importance score showing the impact of the ML input variables on the deployment suitability of the GGR methods. A) Forestation, B) DACCS, C) BECCS, D) EW and E) Biochar.

For forestation (Figure 5-4A), climatic factors (quarterly temperature and precipitation) had the highest feature importance score. Thus, indicating that these variables have the highest impact in the ML model's decision of determining the suitability of deploying this GGR method. This highly correlates with the work of Asibor et al. (Asibor et al., 2021) that ranks climatic factors as the highest impacting variable for forestation deployment. The tropical region which is characterised by high temperatures and precipitation has been generally identified as the most suitable location for forestation (Favero et al., 2018; Raihan et al., 2019). The relative importance of land availability (FLu) on the other hand, has been underestimated by the ML model in its decision making. This outcome

poorly agrees with the literature, which generally identifies land availability as a major and the next important factor (after climate) for the deployment of this GGR method (Fuss et al., 2018; The Royal Society, 2018).

In the case of DACCS (Figure 5-4B), the obtained feature importance score indicates that LCEA and GNI had the highest impact in the ML modelling outcome. Though these two factors are no doubt major requirements for deployment of DACCS, this importance ranking is however not in agreement with literature expectations. This is because geological storage potential (GSP) has been generally identified as the most important factor for DACCS deployment (Asibor et al., 2021; Fasihi et al., 2019; Viebahn et al., 2019). The ML prediction for DACCS deployment is thus, majorly influenced by the financial capability (GNI) and availability of low-carbon energy in a location with relatively lesser consideration given to the (GSP). On the other hand, water availability (WA) requirement had the lowest feature score which correlates with the literature as this requirement is dependent on the type of DAC technology employed.

For EW (Figure 5-4D), similar outcome of a high correlation between the ML variable impact ranking and literature expectations was also obtained for GNI and AgLu. This is because of the high capital requirement and low land requirement associated with the deployment of this GGR method (Renforth, 2012; Smith et al., 2015; Strefler et al., 2018). Given that EW is also energy intensive, the impact of LCEA was however underestimated by the ML model.

The importance of the availability of biomass in the deployment of BECCS (Figure 5-4C) and biochar (Figure 5-4E) was largely underestimated by the ML model and does not correlate with literature expectations (Fuss et al., 2018; Smith, 2016). These outcomes can be linked to the characteristics of the available data such as the density or distribution of the input data. Variables with dense data distribution (fewer differences in data such as the GNI of countries) were more dominant than variables with sparse distribution, such as the biomass availability. The ML model, however, has a fairly good correlation for the impact of water availability, geological storage potential and climatic condition (in the case of biochar).

While the performance accuracy of the ML model is high, coupled with a reasonable correlation with literature expectations on the impact of its input variables, its overall performance is however limited by quantitative and qualitative factors associated with the available data. This is especially so given that these GGR methods are at various levels of technological readiness (Haszeldine et al., 2019; The Royal Society, 2018) and are mostly yet to be deployed at a large scale. Thus, it is expected that the large-scale deployment of these technologies in the near future will enhance the availability of labelled data. This will eliminate the need to apply unsupervised ML (hierarchical clustering algorithm) and its attendant data-density dependency limitations in labelling the data.

Another aspect closely linked to the limitation of data availability is the use of single data point (national data) to represent the characteristics of countries. While this is a valid approach for country-level assessments, it however fails to capture the spatial variations in characteristics that exists, especially in large countries. While it is recommended that multiple data points at regional or local levels be explored when globally available, it is important to add that this factor does not impact on the correctness of the categorisation. This is because the concept of suitability in this study does not indicate that every part of a country (irrespective of size) is suitable or not. Instead, it indicates the relative possibilities/ potentials of countries (or a location) to deploy the GGR technologies with respect to other countries (or locations) within a global context, based on their characteristics.

5.4 Conclusions

In this study, ML has been applied in determining the suitability of a location to deploy five GGR methods within a global context. The use of ML minimises human bias and ensures that the outcomes are based on applicable data. The GGR methods considered are forestation, EW, DACCS, BECCS and biochar. An unsupervised ML (hierarchical clustering) technique was applied to label the dataset consisting of bio-geophysical and technoeconomic variables for 182

countries. Seven supervised ML algorithms were applied in training and testing the labelled dataset with the Artificial Neural Network (ANN), k-Nearest neighbour (k-NN) and Random Forest algorithms having the highest performance accuracy. The performance accuracy of the ML model was validated using a case study assessment of Scotland's suitability to deploy these GGR methods. While the performance accuracy of the ML models was typically high (76 – 100%), an assessment of its decision-making logic (model interpretation) revealed some limitations regarding the impact of the various input variables on the outputs. This is in addition to the use of single data point for country-level input data, which does not fully represent the spatial variations in characteristics that exists, especially in large countries. The availability of labelled data brought about by expected large-scale deployment of these GGR technologies in the near future will greatly enhance the performance and role of ML in achieving the 1.5 °C warming target.

Data availability statement

Data and codes underlying this study can be accessed through the Cranfield University repository (CORD) at: https://figshare.com/s/32e11d6ce96378bc45c1. Data are available under the terms of the [Creative Commons Attribution 4.0 International (CC BY 4.0)].

5.5 References

Alabdrabalnabi, A., Gautam, R., Mani Sarathy, S., 2022. Machine learning to predict biochar and bio-oil yields from co-pyrolysis of biomass and plastics. Fuel 328, 125303. https://doi.org/10.1016/j.fuel.2022.125303

Alcalde, J., Smith, P., Haszeldine, R.S., Bond, C.E., 2018. The potential for implementation of Negative Emission Technologies in Scotland. Int. J. Greenh. Gas Control 76, 85–91. https://doi.org/10.1016/j.ijggc.2018.06.021

Asibor, J.O., Clough, P.T., Nabavi, S.A., Manovic, V., 2021. Assessment of

optimal conditions for the performance of greenhouse gas removal methods. J. Environ. Manage. 294, 113039. https://doi.org/10.1016/j.jenvman.2021.113039

BEIS, 2021. Electricity generation and supply in Scotland, Wales, Northern Ireland and England, 2016 to 2020 [WWW Document]. BEIS Energy Trends. URL https://www.gov.uk/government/statistics/energy-trends-december-2021-special-feature-article-electricity-generation-and-supply-in-scotland-wales-northern-ireland-and-england-2016-to-20 (accessed 6.30.22).

Brownsort, P., 2018. Negative Emission Technology in Scotland: carbon capture and storage for biogenic CO2 emissions. Scottish Carbon Capture & Storage 44, 1–54.

Chen, Y., Wu, B., Chen, D., Qi, Y., 2019. Using machine learning to assess site suitability for afforestation with particular species. Forests 10, 1–22. https://doi.org/10.3390/f10090739

CIA, 2022. The World Factbook [WWW Document]. URL https://www.cia.gov/the-world-factbook/field/land-use (accessed 6.10.20).

Dey, A., 2016. Machine Learning Algorithms: A Review. Int. J. Comput. Sci. Inf. Technol. 7, 1174–1179.

Fajardy, M., Mac Dowell, N., 2017. Can BECCS deliver sustainable and resource efficient negative emissions? Energy Environ. Sci. 10, 1389–1426. https://doi.org/10.1039/c7ee00465f

FAO, 2022. FAO-AQUASTAT database [WWW Document]. URL http://www.fao.org/nr/water/aquastat/data/query/results.html (accessed 7.15.20).

Fasihi, M., Efimova, O., Breyer, C., 2019. Techno-economic assessment of CO 2 direct air capture plants. J. Clean. Prod. 224, 957–980. https://doi.org/10.1016/j.jclepro.2019.03.086

Favero, A., Sohngen, B., Huang, Y., Jin, Y., 2018. Global cost estimates of forest

climate mitigation with albedo: A new integrative policy approach. Environ. Res. Lett. 13. https://doi.org/10.1088/1748-9326/aaeaa2

Förster, J., Beck, S., Borchers, M., Gawel, E., Korte, K., Markus, T., Mengis, N., Oschlies, A., Schaller, R., Stevenson, A., Thoni, T., Thrän, D., 2022. Framework for Assessing the Feasibility of Carbon Dioxide Removal Options Within the National Context of Germany. Front. Clim. 4. https://doi.org/10.3389/fclim.2022.758628

Fuss, S., Lamb, W.F., Callaghan, M.W., Hilaire, J., Creutzig, F., Amann, T., Beringer, T., De Oliveira Garcia, W., Hartmann, J., Khanna, T., Luderer, G., Nemet, G.F., Rogelj, J., Smith, P., Vicente, J.V., Wilcox, J., Del Mar Zamora Dominguez, M., Minx, J.C., 2018. Negative emissions - Part 2: Costs, potentials and side effects. Environ. Res. Lett. 13. https://doi.org/10.1088/1748-9326/aabf9f

Garbade, M.J., 2018. Clearing the Confusion: AI vs Machine Learning vs Deep Learning Differences [WWW Document]. Towar. Data Sci. URL https://towardsdatascience.com/clearing-the-confusion-ai-vs-machine-learning-vs-deep-learning-differences-fce69b21d5eb (accessed 2.8.21).

Gholamy, A., Kreinovich, V., Kosheleva, O., 2018. Why 70/30 or 80/20 Relation Between Training and Testing Sets : A Pedagogical Explanation. Dep. Tech. Reports 1–6.

Güleç, F., Pekaslan, D., Williams, O., Lester, E., 2022. Predictability of higher heating value of biomass feedstocks via proximate and ultimate analyses – A comprehensive study of artificial neural network applications. Fuel 320, 123944. https://doi.org/10.1016/j.fuel.2022.123944

Haszeldine, S., Cavanagh, A., Scott, V., Sohi, S., Mašek, O., Renforth, P., 2019. Greenhouse Gas Removal Technologies-approaches and implementation pathways in Scotland Executive summary. ClimateXChange.

IEA, 2020. IEA Energy Atlas [WWW Document]. URL http://energyatlas.iea.org/#!/tellmap/-1118783123/1 (accessed 9.15.20).

IEAGHG, 2011. Global Storage Resources Gap Analysis for Policy Makers.

IPCC, 2022. Summary for Policymakers, in: Shukla, P.R., Skea, J., Slade, R., Al Khourdajie, A., van Diemen, R., McCollum, D., Pathak, M., Some, S., Vyas, P., Fradera, R., Belkacemi, M., Hasija, A., Lisboa, G., Luz, S., Malley, J. (Eds.), Climate Change 2022: Mitigation of Climate Change. Cambridge University Press, Cambridge, UK, pp. 1–30.

IPCC, 2018. Global warming of 1.5°C An IPCC Special Report on the impacts of global warming of 1.5°C above pre-industrial levels and related global greenhouse gas emission pathways, in the context of strengthening the global response to the threat of climate change,.

IRENA, 2021. Statistical Profiles [WWW Document]. URL https://www.irena.org/Statistics/Statistical-Profiles (accessed 12.10.20).

Jordan, M.I., Mitchell, T.M., 2015. Machine learning: Trends, perspectives, and prospects. Science (80-.). 349, 255–260.

Kearns, J., Teletzke, G., Palmer, J., Thomann, H., Kheshgi, H., Chen, H., Paltsev, S., Herzog, H., 2017. Developing a Consistent Database for Regional Geologic CO2 Storage Capacity Worldwide. Energy Procedia 114, 4697–4709. https://doi.org/10.1016/j.egypro.2017.03.1603

Kumar, S., 2019. Advantages and Disadvantages of Artificial Intelligence [WWW Document]. Towar. Data Sci. URL https://towardsdatascience.com/advantages-and-disadvantages-of-artificial-intelligence-182a5ef6588c (accessed 2.8.21).

Li, Y., Gupta, R., You, S., 2022. Machine learning assisted prediction of biochar yield and composition via pyrolysis of biomass. Bioresour. Technol. 359, 127511. https://doi.org/10.1016/j.biortech.2022.127511

Met Office, 2020. Climate data for Braemar station [WWW Document]. Met Off. URL https://www.metoffice.gov.uk/pub/data/weather/uk/climate/stationdata/braemardata.txt (accessed 5.3.21).

Minx, J.C., Lamb, W.F., Callaghan, M.W., Fuss, S., Hilaire, J., Creutzig, F., Amann, T., Beringer, T., De Oliveira Garcia, W., Hartmann, J., Khanna, T., Lenzi, D., Luderer, G., Nemet, G.F., Rogelj, J., Smith, P., Vicente Vicente, J.L., Wilcox, J., Del Mar Zamora Dominguez, M., 2018. Negative emissions - Part 1: Research landscape and synthesis. Environ. Res. Lett. 13. https://doi.org/10.1088/1748-9326/aabf9b

Mulligan, J., Rudee, A., Lebling, K., Levin, K., Anderson, J., Christensen, B., 2020. CarbonShot: Federal Policy Options for Carbon Removal in the United States, World Resources Institute.

Murtagh, F., Contreras, P., 2012. Algorithms for hierarchical clustering : an overview. Wiley Interdiscip. Rev. Data Min. Knowl. Discov. 2, 86–97. https://doi.org/10.1002/widm.53

NEGEM Project, 2022. A software tool to generate Negative Emissions deployment pathways [WWW Document]. NEGEM. URL https://www.negemproject.eu/news/a-software-tool-to-generate-negative-emissions-deployment-pathways/ (accessed 10.26.22).

Nemet, G.F., Callaghan, M.W., Creutzig, F., Fuss, S., Hartmann, J., Hilaire, J., Lamb, W.F., Minx, J.C., Rogers, S., Smith, P., 2018. Negative emissions - Part 3: Innovation and upscaling. Environ. Res. Lett. 13. https://doi.org/10.1088/1748-9326/aabff4

Ordóñez Galán, C., Matías, J.M., Rivas, T., Bastante, F.G., 2009. Reforestation planning using Bayesian networks. Environ. Model. Softw. 24, 1285–1292. https://doi.org/10.1016/j.envsoft.2009.05.009

Pareek, P., 2019. Machine learning Algorithms and where they are used? [WWW Document]. Samurai's Sakura. URL https://techsavvypriya.wordpress.com/2019/12/19/machine-learning-algorithms-and-where-they-are-used/ (accessed 2.8.21).

Raihan, A., Begum, R.A., Mohd Said, M.N., Abdullah, S.M.S., 2019. A Review of Emission Reduction Potential and Cost Savings through Forest Carbon

Sequestration. Asian J. Water, Environ. Pollut. 16, 1–7. https://doi.org/10.3233/AJW190027

Renforth, P., 2012. The potential of enhanced weathering in the UK. Int. J. Greenh. Gas Control 10, 229–243. https://doi.org/10.1016/j.ijggc.2012.06.011

Ricardo, 2019. The potential contribution of bioenergy to Scotland's energy system. ClimateXChange.

Ritchie, H., Roser, M., Rosado, P., 2020. Renewable Energy - Our World in Data [WWW Document]. URL https://ourworldindata.org/renewable-energy (accessed 6.14.22).

Rogelj, J., Popp, A., Calvin, K. V., Luderer, G., Emmerling, J., Gernaat, D., Fujimori, S., Strefler, J., Hasegawa, T., Marangoni, G., Krey, V., Kriegler, E., Riahi, K., Van Vuuren, D.P., Doelman, J., Drouet, L., Edmonds, J., Fricko, O., Harmsen, M., Havlík, P., Humpenöder, F., Stehfest, E., Tavoni, M., 2018. Scenarios towards limiting global mean temperature increase below 1.5 °c. Nat. Clim. Chang. 8, 325–332. https://doi.org/10.1038/s41558-018-0091-3

Rolnick, D., Donti, P.L., Kaack, L.H., Kochanski, K., Lacoste, A., Sankaran, K., Ross, A.S., Milojevic-Dupont, N., Jaques, N., Waldman-Brown, A., Luccioni, A.S., Maharaj, T., Sherwin, E.D., Mukkavilli, S.K., Kording, K.P., Gomes, C.P., Ng, A.Y., Hassabis, D., Platt, J.C., Creutzig, F., Chayes, J., Bengio, Y., 2022. Tackling Climate Change with Machine Learning. ACM Comput. Surv. 55. https://doi.org/10.1145/3485128

Scottish Government, 2020a. Scottish Agricultural Census [WWW Document]. URL https://www.gov.scot/collections/june-scottish-agricultural-census/ (accessed 5.3.21).

Scottish Government, 2020b. GDP Quarterly National Accounts for Scotland: 2019 Q4 [WWW Document]. URL https://www.gov.scot/publications/gdp-quarterly-national-accounts-for-scotland-2019-q4/ (accessed 5.4.21).

Scottish Government, 2019. Scotland's Forestry Strategy 2019–2029 [WWW

Document]. URL https://www.gov.scot/publications/scotlands-forestry-strategy-20192029/pages/4/ (accessed 5.3.21).

Singh, A., Thakur, N., Sharma, A., 2016. A review of supervised machine learning algorithms, in: 2016 3rd International Conference on Computing for Sustainable Global Development, (INDIACom). Bharati Vidyapeeth, New Delhi as the Organizer of INDIACom - 2016, pp. 1310–1315.

Smith, P., 2016. Soil carbon sequestration and biochar as negative emission technologies. Glob. Chang. Biol. 22, 1315–1324. https://doi.org/10.1111/gcb.13178

Smith, P., Davis, S.J., Creutzig, F., Fuss, S., Minx, J., Gabrielle, B., Kato, E., Jackson, R.B., Cowie, A., Kriegler, E., Van Vuuren, D.P., Rogelj, J., Ciais, P., Milne, J., Canadell, J.G., McCollum, D., Peters, G., Andrew, R., Krey, V., Shrestha, G., Friedlingstein, P., Gasser, T., Grübler, A., Heidug, W.K., Jonas, M., Jones, C.D., Kraxner, F., Littleton, E., Lowe, J., Moreira, J.R., Nakicenovic, N., Obersteiner, M., Patwardhan, A., Rogner, M., Rubin, E., Sharifi, A., Torvanger, A., Yamagata, Y., Edmonds, J., Yongsung, C., 2015. Biophysical and economic limits to negative CO2 emissions. Nat. Clim. Chang. 6, 42–50. https://doi.org/10.1038/nclimate2870

Stewart, M., 2019. The Limitations of Machine Learning [WWW Document]. Towar. Data Sci. URL https://towardsdatascience.com/the-limitations-of-machine-learning-a00e0c3040c6 (accessed 2.8.21).

Strefler, J., Amann, T., Bauer, N., Kriegler, E., Hartmann, J., 2018. Potential and costs of carbon dioxide removal by enhanced weathering of rocks. Environ. Res. Lett. 13. https://doi.org/10.1088/1748-9326/aaa9c4

The Royal Society, 2018. Greenhouse Gas Removal.

Usama, M., Qadir, J., Raza, A., Arif, H., Yau, K.A., Elkhatib, Y., Hussain, A., Al-fuqaha, A., 2019. Unsupervised Machine Learning for Networking : Techniques , Applications and Research Challenges. IEEE Access 7, 1–37.

Viebahn, P., Scholz, A., Zelt, O., 2019. German Energy Research Program —

Results of a Multi-Dimensional Analysis. Energies.

Wilson, A., 2019. A Brief Introduction to Supervised Learning [WWW Document]. Towar. Data Sci. URL https://towardsdatascience.com/a-brief-introduction-to-supervised-learning-54a3e3932590 (accessed 5.3.21).

World Bank, 2022. World Bank Climate Change Knowledge Portal [WWW Document]. URL https://climateknowledgeportal.worldbank.org/ (accessed 7.21.20).

World Bank, 2021. GNI per capita, Atlas method (current US$) | Data [WWW Document]. URL https://data.worldbank.org/indicator/NY.GNP.PCAP.CD (accessed 10.9.21).

Yan, Yongliang, Borhani, T.N., Subraveti, S.G., Pai, K.N., Prasad, V., Rajendran, A., Nkulikiyinka, P., Asibor, J.O., Zhang, Z., Shao, D., Wang, L., Zhang, W., Yan, Yong, Ampomah, W., You, J., Wang, M., Anthony, E.J., Manovic, V., Clough, P.T., 2021. Harnessing the power of machine learning for carbon capture, utilisation, and storage (CCUS)-a state-of-the-art review. Energy Environ. Sci. 14, 6122–6157. https://doi.org/10.1039/d1ee02395k

Yousefi, S., Avand, M., Yariyan, P., Jahanbazi Goujani, H., Costache, R., Tavangar, S., Tiefenbacher, J.P., 2021. Identification of the most suitable afforestation sites by Juniperus excels specie using machine learning models: Firuzkuh semi-arid region, Iran. Ecol. Inform. 65, 101427. https://doi.org/10.1016/j.ecoinf.2021.101427

Zhu, X., Li, Y., Wang, X., 2019. Machine learning prediction of biochar yield and carbon contents in biochar based on biomass characteristics and pyrolysis conditions. Bioresour. Technol. 288, 121527. https://doi.org/10.1016/j.biortech.2019.121527

6 A Country-level Assessment of the Deployment Potential of Greenhouse Gas Removal Technologies

Jude O. Asibor, Peter T. Cough, Seyed Ali Nabavi, Vasilije Manovic

Energy and Sustainability Theme, School of Water, Energy and Environment, Cranfield University, Bedford, Bedfordshire MK43 0AL, UK.

Submitted 29 April 2022; Accepted 5 September 2022.

Published in the Journal of Environmental Management 323 (2022) 116211

DOI: https://doi.org/10.1016/j.jenvman.2022.116211

Abstract

The deployment of greenhouse gas removal (GGR) technologies has been identified as an indispensable option in limiting global warming to 1.5 °C by the end of the century. Despite this, many countries are yet to include and promote this option in their long-term plans owing to factors such as uncertainty in technical potential, deployment feasibility and economic impact. This work presents a country-level assessment of the deployment potential of five GGR technologies, including forestation, enhanced weathering (EW), direct air carbon capture and storage (DACCS), bioenergy with carbon capture and storage (BECCS) and biochar. Using a multi criteria decision analysis (MCDA) approach consisting of bio-geophysical and techno-economic factors, priority regions for the deployment of these GGR technologies were identified. The extent of carbon dioxide removable by 2100 via these technologies was also estimated for each of the 182 countries considered. While the obtained results indicate the need for regional cooperation among countries, it also provides useful evidence on the need for countries to include and prioritise GGR technologies in their revised nationally determined contributions (NDCs).

Keywords

Greenhouse gas removal; GGR; BECCS; DACCS; Climate change mitigation.

6.1 Introduction

The deployment of greenhouse gas removal (GGR) technologies is a major requirement in limiting global warming to 1.5 °C by the end of the century (IPCC, 2022, 2018). Under this mitigation scenario, between 100 and 1000 Gigatonnes of global net anthropogenic CO_2 emissions is expected to be removed from the atmosphere before 2100 (Maher and Symons, 2022). Despite the importance of this pathway, the nationally determined contributions (NDCs) submitted to the United Nations Framework Convention on Climate Change (UNFCCC) by countries indicate a low intent to deploy these technologies, with the exclusion of forestation measures (Pozo et al., 2020), thus falling short of the 1.5 °C target (Roe et al., 2019; Rogelj et al., 2016; Schiermeier, 2015). This low level of inclusion is on account of several factors such as uncertainty about the technical potential, especially with some of the technologies at low-to-mid levels of technological readiness (Haszeldine et al., 2019; The Royal Society, 2018), uncertainty about socio-political factors (Buylova et al., 2021; Maher and Symons, 2022). Another major factor is the lack of robust country-level bio-geophysical and techno-economic feasibility assessments to ascertain national GGR deployment potential. It is this latter factor that this study aims to address.

Thus far, only a handful of countries, majorly of the Organisation of Economic Co-operation and Development (OECD) bloc, have carried out local assessments to ascertain the deployment potential of these technologies in their respective territories by considering their bio-geophysical, technical and socio-economic resources (Alcalde et al., 2018; Baik et al., 2018; Donnison et al., 2020; Element Energy and UKCEH, 2021; Haszeldine et al., 2019; Jiang et al., 2018; Mulligan et al., 2020; Pour et al., 2018; Thoni et al., 2020). Given the global nature of the emission mitigation challenge, there is, therefore, a great need for assessment of the GGR deployment potential of the other countries.

On the global country-level front, some major efforts have also been reported. Griscom et al. (2020) assessed the country-level potential of natural climate solutions for countries in the tropical region. Roe et al. (2019) and Roe et al. (2021) assessed the contribution of the land-based activities (agriculture,

forestry, land use change and BECCS) to attaining the mitigation target and identified priority regions/countries with high mitigation potentials using a combined review of modelled pathways and literature on mitigation strategies. In another study, Pozo et al. (2020) allocated carbon dioxide removal (CDR) quotas globally based on responsibility, capability and equality principles. Country-level analysis on the mitigation potential was however only carried out for the European Union on account of data availability, with the GGR technology options limited to BECCS, reforestation and DACCS.

With options ranging from the natural climate solutions to the engineered options, GGR methods not only present an opportunity to address historical and current emissions, but they also confer other co-benefits if efficiently deployed. Forestation which collectively refers to afforestation and reforestation is associated with co-benefits such as food and fuels production, air quality regulation, habitat for biodiversity and erosion control among others. Though constrained by environmental factors, it is one of the cheapest carbon sequestration options. Enhanced Weathering (EW) involves the grinding of rocks of calcium or magnesium content and spreading the resulting small grain sized rock over land or ocean surfaces to serve as storage sites for the CO_2 removed from the atmosphere. Though a capital and energy intensive option, its co-benefits include soil productivity improvement, ocean acidity reduction and reduced usage of fertilisers. In DACCS, atmospheric CO_2 is removed by exposing sorbents with a high CO_2 affinity to air. While DACCS is also characterised by high energy requirement, it enjoys advantages of minimal competition for land, water, and nutrients. BECCS which has featured in many Integrated Assessment Models (IAMs) scenarios (IPCC, 2022) has the co-benefit of generating bioenergy while simultaneously removing atmospheric CO_2. Biochar is produced when organic material such as biomass is thermally decomposed in the absence of oxygen. It is more stable than soil organic matter and thus ensures a longer sequestration time of carbon. Co-benefits of biochar deployment include energy production from the pyrolysis process (syngas), soil improvement and waste treatment. Robust reviews on the operation, impact, and potential of these GGR

technologies have been reported in the literature (Asibor et al., 2021; Fuss et al., 2018).

This study assessed the deployment potential of five GGR technologies for 182 countries using a multi-criteria decision analysis (MCDA) approach. This was carried out to estimate the maximum cumulative amount of carbon dioxide removable by 2100 via these technologies. The five GGR technologies considered are forestation, enhanced weathering (EW), direct air carbon capture and storage (DACCS), bioenergy with carbon capture and storage (BECCS) and biochar. The criteria for assessment were based on associated variables of the bio-geophysical and techno-economic factors that affect the performance of these technologies (Asibor et al., 2021; Fuss et al., 2018; Hepburn et al., 2019; Rueda et al., 2021). A sensitivity analysis was also carried out to assess the uncertainties of the applied weighting system.

6.2 Methods

6.2.1 Multi-Criteria Decision Analysis (MCDA)

Figure 6-1 presents the framework of the method applied in this study. The method was based on the typical MCDA process employed in negative emissions technologies portfolio (Rueda et al., 2021) and sustainable energy (Wang et al., 2009). MCDA is an integrated operational evaluation and decision support approach that is suitable for addressing complex problems with high uncertainty, conflicting objectives, different forms of data and information, multi-interests and perspectives, and the accounting for complex and evolving biophysical and socio-economic systems (Wang et al., 2009). It provides an integrated result (performance scores) for competing alternatives (or options) based on an assessment of selected multi-criteria or attributes. It typically involves; alternatives *m* (182 countries), criteria *n* (bio-geophysical and techno-econmic factors), criteria weights (impact weight of selected factors on respective GGR technology performance) and the evaluating result (performance scores) from the decision matrix (*m*×*n*). For each GGR technology, the performance score of each

country which is an indication of their ability to deploy the respective technology was obtained.

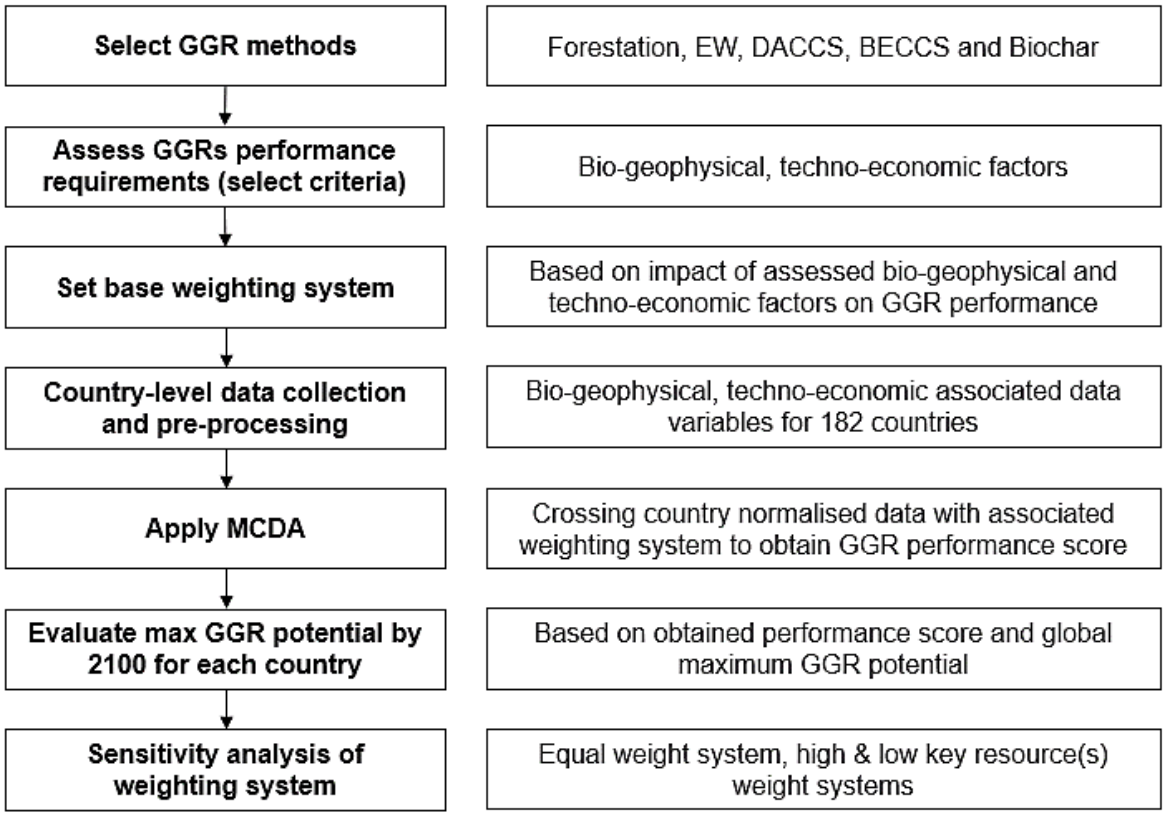


Figure 6-1 Method framework for MCDA analysis showing the steps applied in obtaining the GGR potential of nations.

6.2.2 Criteria selection

The five GGR methods considered in this study (forestation, EW, DACCS, BECCS and biochar) were selected based on their carbon dioxide removal potential and technological readiness levels (Fuss et al., 2018; Haszeldine et al., 2019). In addition, major bio-geophysical and techno-economic factors necessary for the sustainable and efficient performance of these GGR methods were identified from the literature (Asibor et al., 2021). These identified factors which formed the criteria upon which the MCDA assessment was carried out is presented in Table 6-1.

Table 6-1 Selected criteria for the MCDA assessment of GGR potential

GGR technologies	Selected criteria
Forestation	Temperature (temp) and precipitation (ppt), Forestation land availability (FLu), Water availability, Vegetation type.
EW	Temperature and precipitation, Cost, Energy requirement, Agricultural land availability (AgLu).
DACCS	Cost, Geological storage potential, Water availability, Energy requirement.
BECCS	Biomass availability, Cost, Geological storage potential, Water availability.
Biochar	Biomass availability, Temperature and precipitation, AgLu, Cost.

6.2.3 Setting the criteria weighting system

Weights were assigned to the selected criteria based on the impact of these factors on the performance of the respective GGR methods. This obtained weight system (base wt) was adapted from the impact ranking of GGR factors developed by Asibor et al., (2021). This ranking which was done on a scale of 0 – 5, was based on a comprehensive assessment of the impact of bio-geophysical and techno-economic factors on the performance of various GGR methods. To get a unit sum of weight of criteria for each GGR method, this ranking was then scaled down proportionately. The obtained base weight system is presented in Table 6-2.

Table 6-2 Applied weights for the selected criteria for the MCDA assessment of GGR potential

	Temp	**Ppt**	**FLu**	**AgLu**	**BA**	**WA.**	**GSP**	**Cost**	**LCEA**	**Veg**
Forestation	0.133	0.2	0.267	0	0	0.133	0	0.067	0	0.2
EW	0.1	0.1	0	0.134	0	0	0	0.333	0.333	0
DACCS	0	0	0	0.067	0	0.067	0.333	0.267	0.267	0
BECCS	0	0	0	0	0.333	0.134	0.333	0.2	0	0
Biochar	0.018	0.164	0	0.182	0.454	0	0	0.182	0	0

6.2.4 Country-level data collection and pre-processing

Country-level data of associated indicators for the selected criteria were obtained for 182 countries. For climate, average monthly temperature and precipitation (World Bank, 2022) was adopted. For land use (CIA, 2022), land availability for forestation (FLu) consisted of a combination of the countries' forest land use (reforestation potential) and agricultural land use (afforestation potential). For the latter, arable land suited for growing crops was not considered to ensure that the growing of trees did not negatively impact on food production. For water availability, the level of water stress (FAO, 2022a) was adopted. Cost factor was indicated by GNI per capita (World Bank, 2021). For energy availability, the percentage share of each countries' energy that is generated from low carbon energy sources (IEA, 2020; Ritchie et al., 2020) was adopted. This is to ensure that the deployment of energy-dependent GGR methods does not result in additional CO_2 emissions. Data for the other selected criteria were obtained as follows; geological CO_2 storage potential (IEAGHG, 2011; Kearns et al., 2017), biomass availability (IRENA, 2021) and Vegetation type (FAO, 2022b).

The obtained raw data was pre-processed into a usable form by numerical encoding of string type data and analytical determination of incomplete data. Data normalisation was also carried out between 0 and 1 for the entire dataset to eliminate any potential bias brought about by differences in range of values among the variables.

6.2.5 Maximum Cumulative GGR potential

Using the simple additive weighting (SAW), the performance score for each country in deploying each of the five GGR technologies was obtained. This method was applied because of its convenience in calculation and the requirement of attributes (variables) to be independent. Using the obtained performance score as a fraction of the total scores, the share of each country's maximum cumulative carbon removal potential for each GGR technology was then evaluated from the projected global maximum cumulative potential by 2100 reported by Rueda et al., (2021) based on their review of the literature. Figure 6-2 presents the curves of the global potential of GGR technologies, with the area

under the curve indicating the maximum cumulative potential by 2100 (total) as shown.

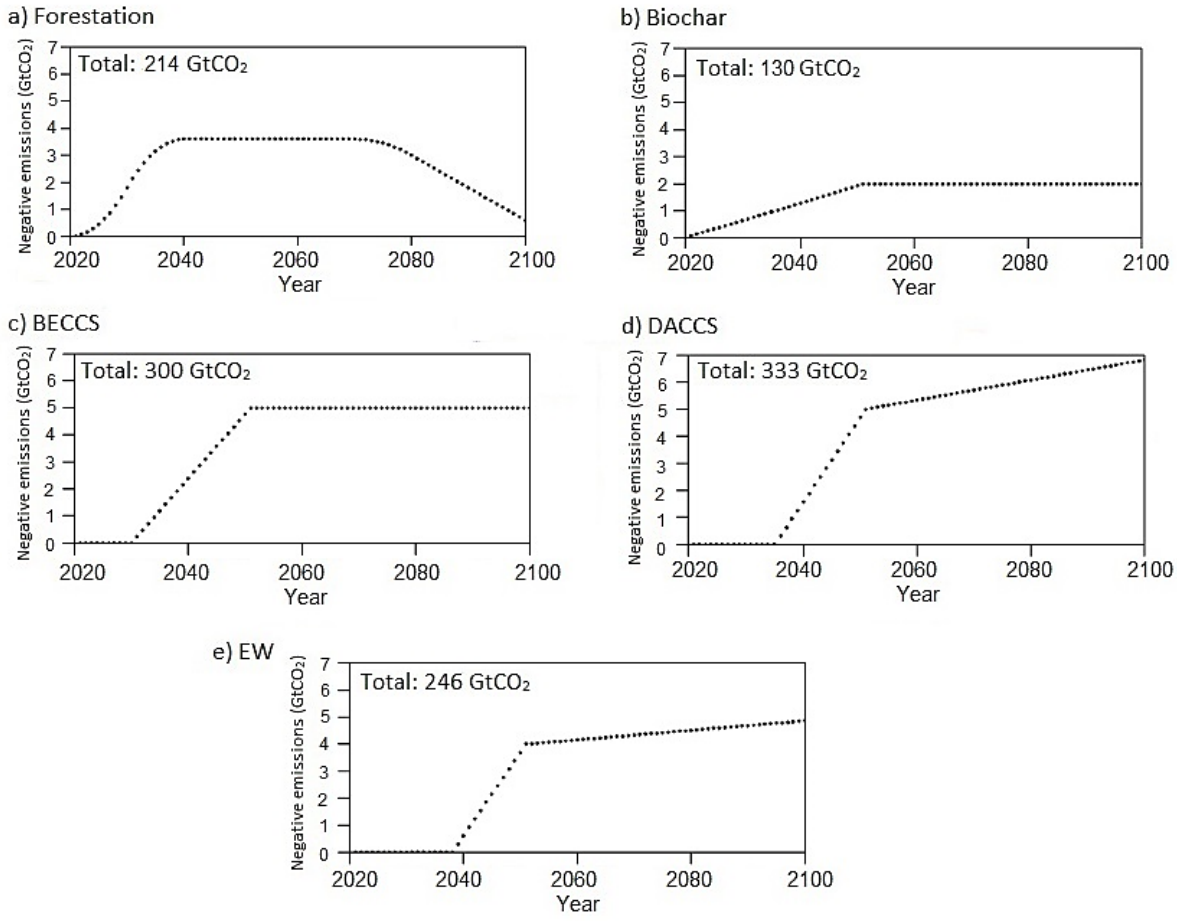


Figure 6-2 Curves of GGR technologies potential for 2020–2100. a) forestation, b) biochar, c) BECCS, d) DACCS, e) EW (reprinted with permission from Rueda et al. (2021), Copyright 2021 Elsevier).

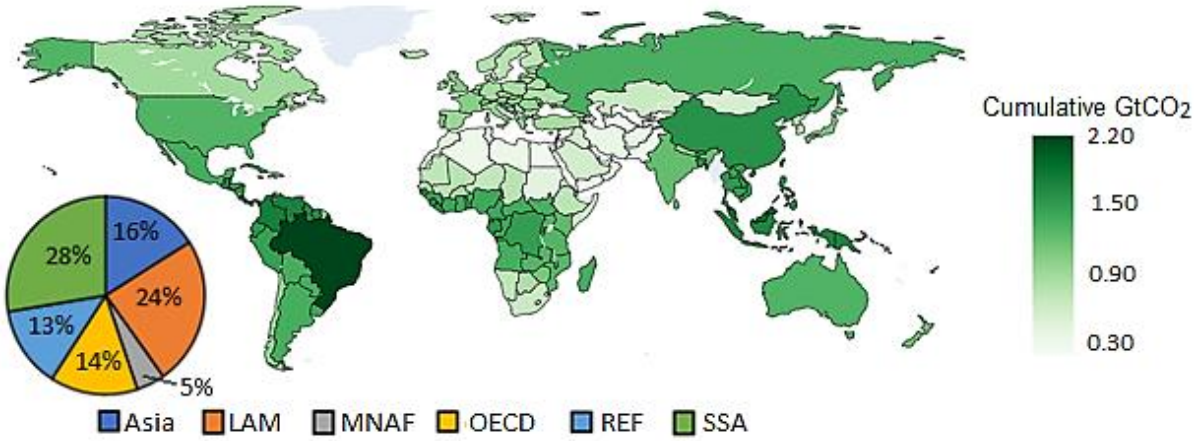
6.3 Results and discussion

6.3.1 Global GGR potential

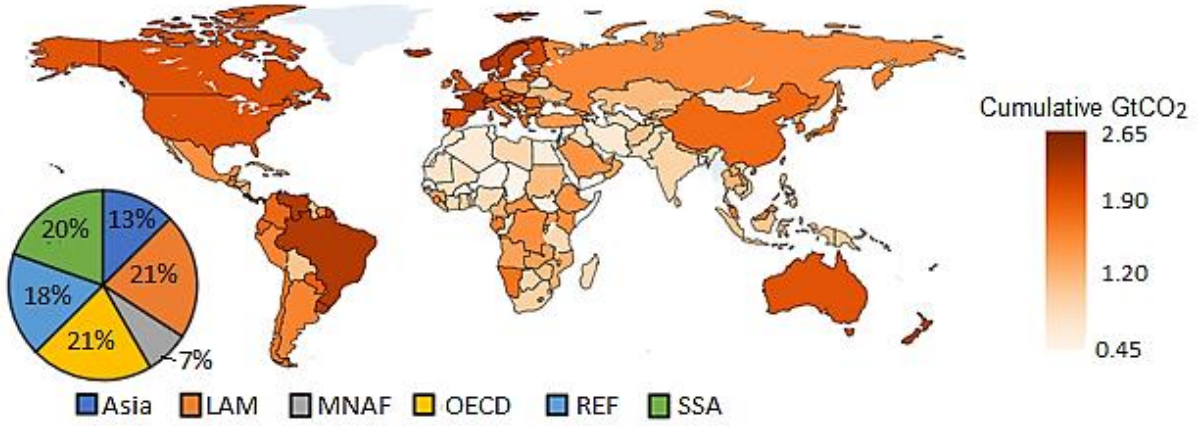
Using the MCDA approach, the maximum cumulative CDR potential by 2100 via five technologies was obtained for 182 countries on the basis of their bio-geophysical and techno-economic characteristics. The GGR technologies considered are forestation, EW, DACCS, BECCS and Biochar. Figure 6-3

presents global maps showing the CDR potential of these countries for the five GGR methods considered.

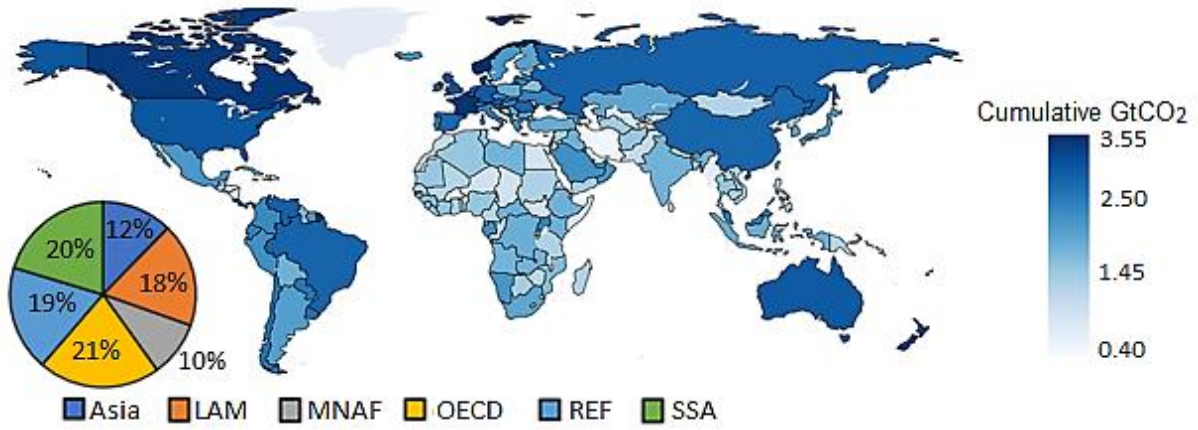
a) Forestation



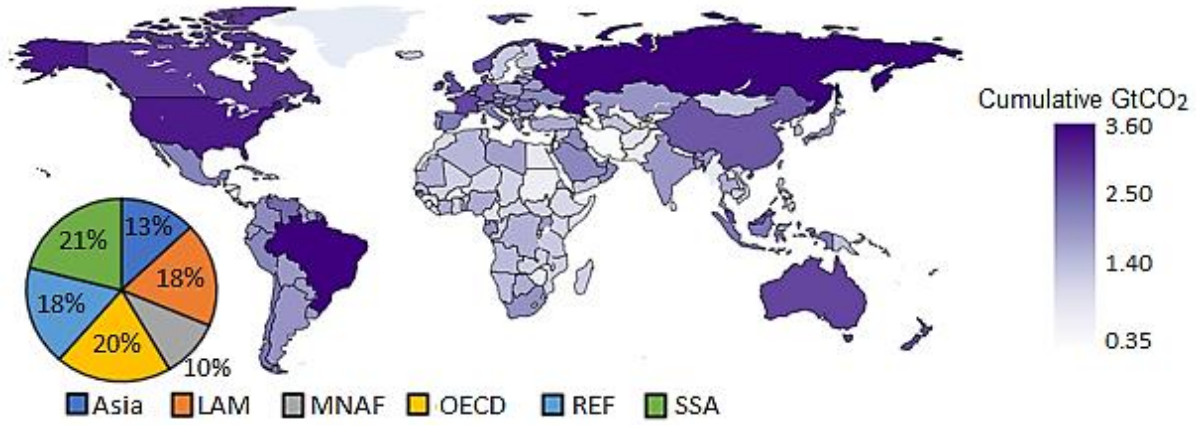
b) Enhanced weathering



c) DACCS



d) BECCS



e) Biochar

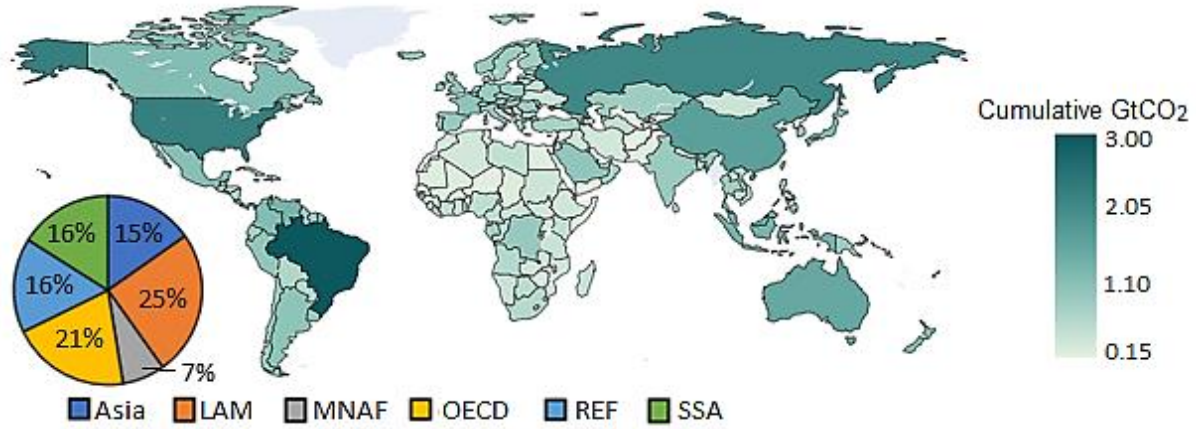


Figure 6-3 Maximum cumulative carbon dioxide removal (CDR) potential of countries by 2100 from five GGR methods: Forestation (a), Enhanced weathering (b), DACCS (c), BECCS (d) and Biochar (e).

(Countries are coloured according to their potential so that the darker the shade, the larger the CDR potential. Pie charts show the results aggregated into six regions (OECD, includes the countries in the OECD as of 1990; REF, reforming economies of Central and Eastern Europe and the Former Soviet Union; ASIA, Asian countries with the exception of the Middle East, Japan and Former Soviet states; MNAF, countries of the Middle East and North Africa; LAM, Latin America and the Caribbean; SSA includes Sub-Saharan countries; see the full list of countries in each region in **Appendix A**).

According to Figure 6-3a, countries in LAM, SSA as well as South East Asia were found to have the highest CDR potential via forestation accounting for about 60% of the global potential. This is mainly because of their favourable tropical climatic

conditions and vegetation characteristics. These countries, including Brazil, Brunei, Malaysia, Colombia, Costa Rica, Venezuela, Panama and the Democratic Republic of Congo, are largely in agreement with the priority regions identified by Roe et al., (2021). Countries in MNAF had the lowest CDR potential (5%) because of their arid climatic conditions. The OECD and REF countries accounted for about 27% on account of low land availability and less favourable climatic characteristics.

The assessment for EW was based on the assumed scenario of available rock resources for all countries, due to lack of available data. From Figure 6-3b, OECD and LAM countries had the highest potential for this technology (21% each) with major countries including Australia, New Zealand, Brazil, USA, Canada, Costa Rica and EU countries among others. This is as a result of their high GNI per capita (high financial capability) and available agricultural land for spreading the weathered rocks. Asian countries such as Singapore, China, Japan and Malaysia, as well as Middle Eastern countries like Saudi Arabia and Qatar were also identified as areas with high EW deployment potential. Parts of Central and Southern Africa were also identified as priority areas largely on account of the availability of low carbon energy. Given the high capital and energy requirement for this technology, most countries within MNAF, and parts of Asia and SSA were found to have a low potential for deploying this technology largely due to their low financial capability and development.

As shown in Figure 6-3c, OECD and REF countries with appropriate geological storage sites jointly accounted for 40% of the global DACCS potential. This is majorly because of their high financial capability given the high-cost requirement of deploying DACCS. This was closely followed by SSA and LAM which jointly accounted for 38% of the global potential. This is because of the availability of low carbon energy in these regions. Major countries identified include USA, Canada, Australia, Norway, Brunei, Saudi Arabia, the Netherlands, New Zealand, Russia and the UK. Developing countries (especially in SSA) and those without appropriate geological storage sites such as Azerbaijan, Haiti, Burkina Faso, Moldova, and Malawi had the lowest DACCS deployment potential.

With the CDR potential of BECCS dependent on the availability of biomass and appropriate geological storage sites, the same countries that had the low potential to deploy DACCS deployment were also found to have low BECCS CDR potential on account of the latter factor. Given that some of these countries are characterised by available biomass, they might still play a key role in BECCS deployment through collaboration with neighbouring countries with geological storage sites. From the BECCS CDR potential map shown in Figure 6-3d, major countries for this GGR technology include Brazil, Russia, USA, Canada, Australia, and the other tropical countries in LAM (18%), SSA (21%) and South-East Asia. These identified countries are in agreement with the priority regions identified by Roe et al. (2019). Though the BECCS potential of the EU is limited by the availability of biomass, its relatively high financial capacity is expected to play a major role in enhancing its potential through options such as biomass importation.

For biochar (Figure 6-3e), countries in LAM (25%) and OECD (21%) were found to have higher CDR potential with the major ones, including Brazil and the USA. Other countries with relatively high potential include Russia, Costa Rica, Malaysia, Brunei, Indonesia and Venezuela. However, it is important to note that the impact of soil characteristics was not considered in this assessment because of the complexity of interacting factors (Lorenz and Lal, 2014; Nair et al., 2017) and inadequate country-level data availability. Hence, this assessment was based on the generally accepted fact that biochar effects on soil are biochar-, soil-, and plant-specific, thus all countries were assumed to meet the soil characteristics requirement. MNAF countries, however had low CDR potential (7%) on account to their arid climate and low biomass availability.

This study builds on previous studies which have been largely limited to natural climate solutions (NCS) including Forestation, BECCS and Biochar. Our identified areas of high potential to deploy these technologies are broadly in line with previous studies with Griscom et al., (2020); Roe et al., (2021, 2019) reporting tropical countries of LAM, SSA and Asia to have the highest NCS mitigation potential estimated at 6.51 $GtCO_2e\ yr^{-1}$. Beyond these NCS-based

technologies, novel country-level assessment of two other mitigation pathways (EW and DACCS) have also been presented. Given the maturity of forestation, lots of progress has been made with regards to large-scale deployment. While most countries have included forestation and other land-use related measures in their NDCs (Roe et al., 2021), other international programmes such as the Bonn Challenge, New York Declaration on Forests (NYDF) have also been set up to drive the deployment of this method. While encouraging more actions in the restoration of forests, it is also important to ensure that efforts are made by governments to address the challenges of degradation and deforestation. This is very key because the 1.5 °C roadmap requires deforestation to decline 70% by 2030 and 95% by 2050 (Roe et al., 2019). While all five technologies at varying technological readiness levels (TRLs) (Haszeldine et al., 2018; The Royal Society, 2018) with their projected timeline of deployment captured in Figure 6-2, the need for increased investment in R&D cannot be over-emphasised if the mitigation target is to be met.

This study has explored the domestic potential of nations to deploy these technologies based on their respective available in-country resources. While this is aimed at enabling countries identify the suite of GGR technologies they can sustainably and efficiently deploy, it will also provide insight on areas they will require collaborations to boost their potentials. The actual decision making will require a consideration of resource sharing opportunities such as geological storage sites, as well as importation of resources such as biomass and low carbon energy. A consideration of how the deployment of potential GGR options will impact on existing resources will also influence the decision-making process. This is to ensure that adopted GGR options do not create a competition for resources such as land, water, and renewable energy, and compromise other societal objectives such as the Sustainable Development Goals which includes food security and biodiversity conservation (Batalini de Macedo et al., 2022; Fajardy et al., 2019; Förster et al., 2022).

6.3.2 Assessing the CDR quotas

Having obtained the cumulative CDR potential for 5 GGR technologies for the 182 countries considered, a comparative assessment was carried out on the basis of the work of Pozo et al. (2020), who allocated the global CDR quota of 687 $GtCO_2$ (IPCC SR1.5 'middle-of-the-road' P3 scenario (IPCC, 2018)) to 176 countries. This allocation of the CDR burden was carried out under 3 equity sharing principles of Responsibility (based on historical emission liability of countries); Capability (based on the financial ability of countries) and Equality (based on the population size of countries). Using their findings, we compared the obtained domestic CDR potential for each country with the quotas allocated under the 3 equity sharing principles. This was done to identify countries that will be able to meet up with their allocated quotas domestically using these five GGR methods as well as areas that will require regional partnerships and collaborations. Figure 6-4 presents the country-level cumulative CDR quotas and potential by 2100.

For Asia (Figure 6-4a), most member countries can domestically meet their respective CDR quotas under the three principles. The exceptions are China (CHN), India (IND), Indonesia (IDN), and Pakistan (PAK), who cannot meet their Equality-based quota brought about by their relatively high population. For Singapore (SGP) and South Korea (KOR), their respective CDR potential did not meet up with their Capability-based quota brought about by their high GDP per capita. CDR quota data for Kiribati (KIR), Marshall Islands (MHL) and Taiwan (TWN) were unavailable.

While all the LAM countries (except Trinidad and Tobago (TTO)) were able to meet their quotas under the three principles (Figure 6-4b), Bahrain (BHR), Saudi Arabia (SAU) and the United Arab Emirate (ARE) were the only exceptions for the MNAF region (Figure 6-4c) as their CDR potential did not meet their Responsibility based quotas. For the OECD group (Figure 6-4d), only four member-countries (Fiji (FJI), Samoa (WSM), Solomon Islands (SLB) and Turkey (TUR)) met their quotas under all principles.

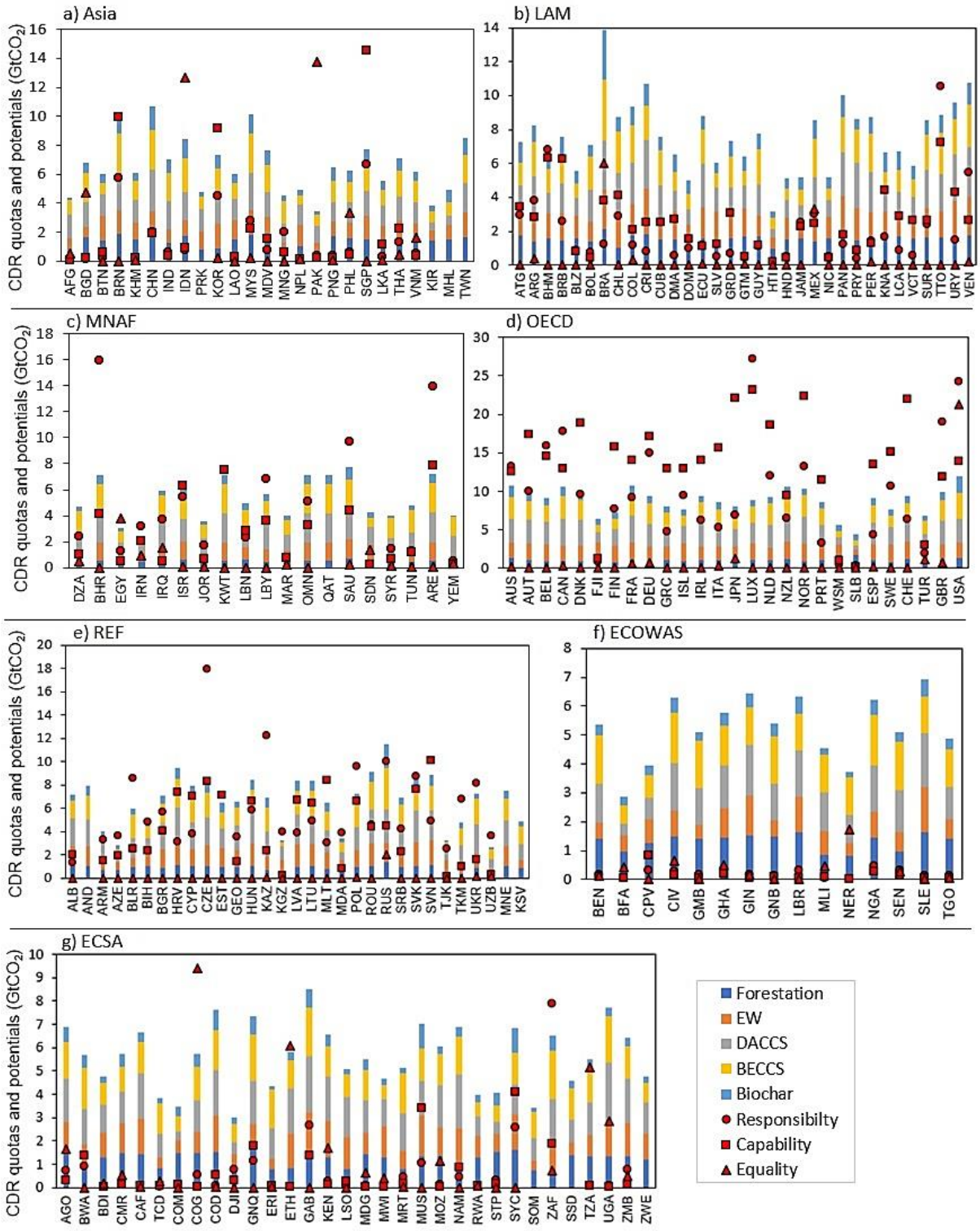


Figure 6-4 Comparison of Country-level cumulative CDR quotas (Pozo et al., 2020) and the obtained potential by 2100: a) Asia, b) LAM, c) MNAF, d) OECD, e) REF, f) ECOWAS, and g) ECSA.

(The CDR quota by equality for China (CHN), India (IND) and Nigeria (NGR) are not featured on the map on account of the relatively large value. SSA was split into ECOWAS (West African countries) and ECSA (East, Central and Southern Africa) for better visualisation).

This is largely because most of the other countries were allocated relatively higher CDR quotas under Responsibility and Capability principles as they constitute the bulk of the most industrialised (high historical emissions) and wealthiest nations of the world. They all, however, met their Equality-based quotas, with the only exception being the USA.

All the REF countries (Figure 6-4e) met their quotas under the three principles except for Belarus (BLR), Czech (CZE), Estonia (EST), Kazakhstan (KAZ), Turkmenistan (TKM), Poland (POL) and Ukraine (UKR), which did not meet their Responsibility-based quotas. Malta (MLT), Estonia and Slovenia (SVN) did not also meet their respective Capability-based quotas. CDR quota data for Kosovo (KSV) and Montenegro (MNE) were unavailable. For ECOWAS (Figure 6-4f), only Nigeria (NGA) did not meet its CDR quota for all three principles, with the Equality-based quota being the outstanding one on account of its high population. For East, Central and Southern Africa (ECSA), countries whose CDR potential did not meet their quota include the Republic of Congo (COG), Ethiopia (ETH) and South Africa (ZAF).

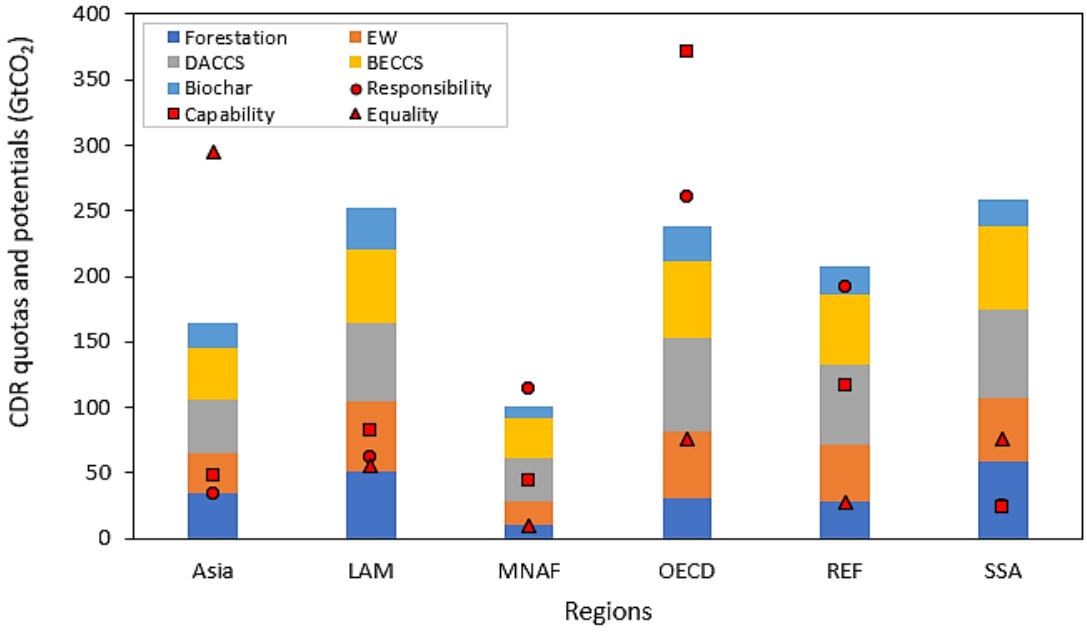


Figure 6-5 Comparing regional cumulative CDR quotas and potential by 2100.

Though this assessment has evaluated the maximum cumulative CDR potential by 2100, it is important to note that actual deployment is expected to be lower on account of factors such as deployment delay, the scale of deployment, and discount rate (Rueda et al., 2021) as well as socio-political considerations. While this may result in many countries not being able to meet up with one or more of their principle-assigned quotas (responsibility, capability, equality) domestically, a look at the regional comparison (Figure 6-5) presents very useful evidence on the need for regional co-operation in the attainment of the emission mitigation target. As shown, all the regions except Asia, MNAF and OECD can meet up with all their quotas under the 3 principles. For SSA and LAM, which are majorly developing countries, it can be observed that a combination of the cheaper GGR options (Forestation, biochar and BECCS) will be sufficient to meet up with their respective quotas. While the high population of China and India presents a high quota burden for Asia by the Equality principle, the high level of industrialisation and wealth of the OECD members presents a higher CDR burden beyond their CDR potential. Given the impact of bio-geophysical constraints and with the OECD expected to drive the development and deployment of these technologies, one major way to address their potential deficit will be to collaborate with regions having surplus CDR potentials such as LAM and SSA through the provision of the needed financial support and investments, especially in the deployment of the more expensive engineered solutions (DACCS, EW and BECCS).

6.3.3 Sensitivity Analysis of weight

To minimise the impact of probable subjectivity and account for uncertainties in the applied criteria weighting system (base wt), a sensitivity analysis was carried out to evaluate the robustness and stability of the obtained output (CDR potential and regional share) by assessing the impact of other weighting systems. For each GGR method, four criteria weight allocation scenarios (weighting systems) were considered: Equal weight scenario and three dominant variables scenarios (50%, 60%, 70%). While the same weights were assigned to all the variables under the Equal weight scenario, the dominant variables scenario involved assessing the

impact of assigned weights (50%, 60%, 70%) on key factors (criteria) that influence the performance of the respective GGR methods. For forestation, land availability & vegetation type (LV) was considered; for EW, cost and low carbon energy availability (CE); for DACCS, cost and geological storage potential (SC); for BECCS, geological storage potential and biomass availability (SB); and for biochar, biomass availability (B). Details of the various weighting systems for the five GGR methods are presented in Section 3.7.5 (Table 3-11 to Table 3-15).

Figure 6-6 presents the sensitivity analysis of the weights. It shows the CDR potential obtained for each region under the various criteria weighting scenario. The level of variation between the CDR potential for the applied weighting system (base wt) and those obtained for the other four weighting scenarios was evaluated to assess the uncertainty in results of the study. For forestation (Figure 6-6a), the variation in the CDR potential ranged from 0.28 – 25%, and this was obtained under the 70%-LV scenario (REF) and the Equal weighting scenario (MNAF), respectively. For EW (Figure 6-6b), the variation in the CDR potential ranged from 0.04% (70%-CE scenario for LAM) to 45% (Equal weighting scenario for SSA). For DACCS (Figure 6-6c), the variation in the CDR potential ranged from 0.15% (50%-SC scenario for Asia) to 19% (Equal weighting scenario for MNAF). For BECCS (Figure 6-6d), the variation in the CDR potential ranged from 0.26 – 17%, under 70%-SB and Equal weighting scenarios for MNAF, respectively. For Biochar (Figure 6-6e), the variation in the CDR potential ranged from 0.02% (60%-B scenario for Asia) to 40% (Equal weighting scenario for SSA).

Mean variation in the obtained CDR potential ranged from less than 3% - 15%, with overall changes in regional share less than 5% for forestation, EW, DACCS and BECCS. For biochar, the four modified weighting scenarios returned similar and consistent outputs (robust) for OECD, REF and SSA that varied with those obtained for the applied weighting system (base wt). Based on changes in regional share, the uncertainty in the applied weighting system for forestation, EW, DACCS and BECCS is set to 5%, while that of biochar is set to 20%.

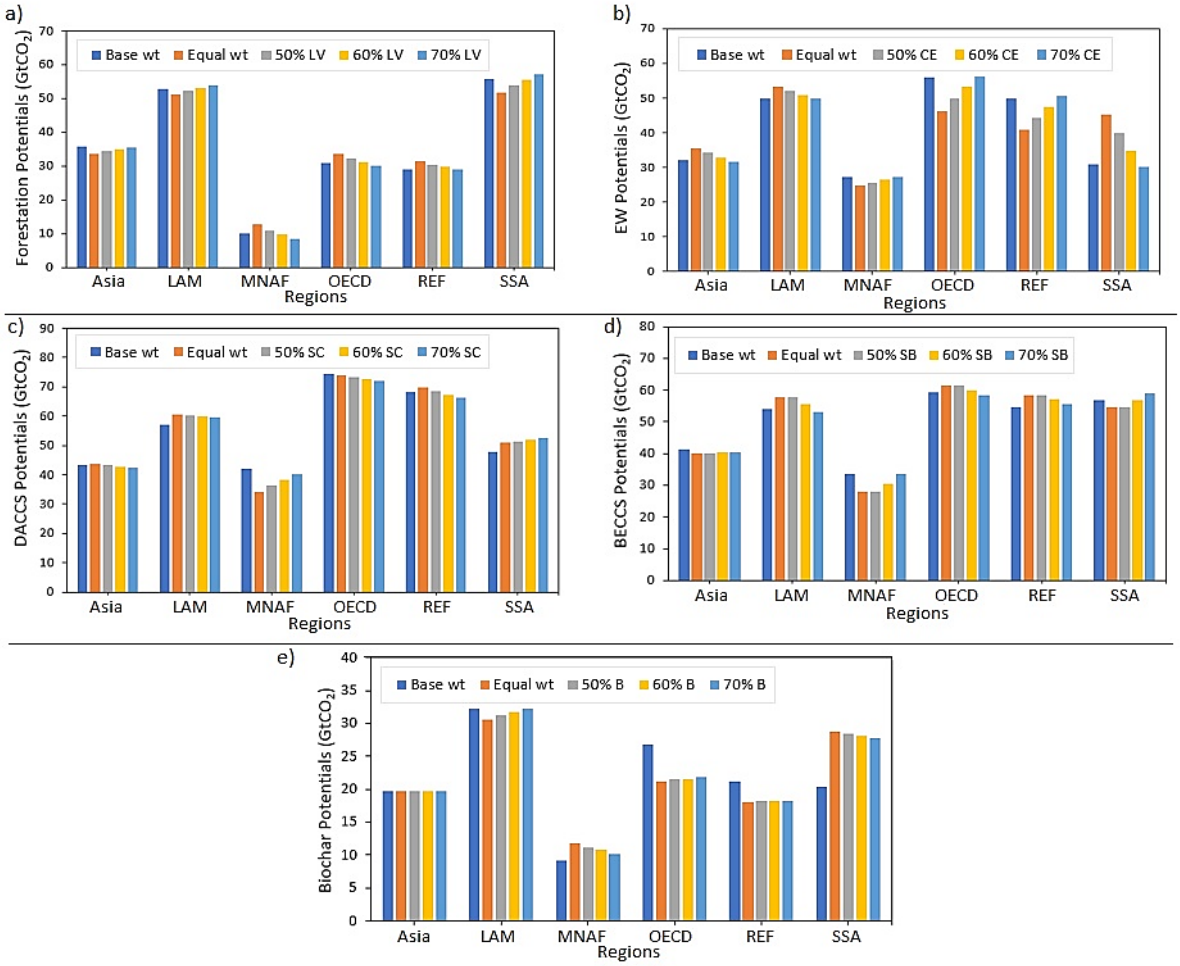


Figure 6-6 Sensitivity analysis of weighting system: Forestation (a), Enhanced weathering (b), DACCS (c), BECCS (d) and Biochar (e).

(Key: LV- Land availability & Vegetation type; CE- Cost & Energy availability; CS- Cost & Geological storage potential; SB- Geological storage potential & Biomass availability; B- Biomass availability).

6.3.4 Limitations and recommendations

The deployment potential of five GGR technologies has been obtained for 182 countries. In this section we highlight limitations and recommendations to guide and ensure best use of the obtained results. Given that the study is based on MCDA, it consequently inherits the strengths and limitations of this methodology. While the MCDA has proven to be a valuable approach in solving problems with multiple objectives, a key limitation lies in the subjective nature of some of its

crucial components such as the criteria weighting (Kujawski, 2003; Wang et al., 2009). To ascertain the robustness of the results and examine the impact of the criteria weights, sensitivity analysis was carried out using alternative weightings (Section **6.3.3**).

Another critical aspect is the availability of country-level data which was a key factor in the selection of criteria. All the major indicators of bio-geophysical and techno-economic factors required to assess the five GGR methods were selected as criteria and applied in the study. The only exception was in the case of EW in which availability of rock resources (basalt) was excluded because of unavailability of country-level data. An assumed scenario of available rock resources for all countries was however adopted for the EW assessment. This assumption is based on the widespread abundance of basalt which accounts for about 6.8 million km^2 of the earth's surface (about 4.56% of the world's land mass), with significantly more beneath the surface and under the oceans (Kantola et al., 2017).

While the study evaluated the cumulative GGR potential by 2100 based on bio-geophysical and techno-economic characteristics, it is important to note that the prevailing socio-political systems of the various countries will play a major role on the extent of deployment and choice of GGR options that will be eventually adopted from these outcomes. With this assessment largely based on estimates of currently available data, it is therefore recommended that the outcomes should be updated when new estimates are available.

6.4 Conclusion

A country-level assessment of the deployment potential of five GGR technologies, including forestation, enhanced weathering (EW), direct air carbon capture and storage (DACCS), bioenergy with carbon capture and storage (BECCS), and biochar, has been carried out. Using a multi criteria decision analysis (MCDA) approach consisting of bio-geophysical and techno-economic factors, priority regions for the deployment of these GGR technologies have been

identified. The extent of carbon dioxide removable by 2100 via these technologies has also been estimated for each of the 182 countries considered. An assessment of the CDR quotas identified LAM, SSA and REF as the only regions with sufficient potential to meet their allocated quotas domestically under the three equity sharing principles. For the OECD, addressing their potential deficit will involve collaborating with regions having surplus CDR potentials, especially LAM and SSA, through the needed financial support and investments. Sensitivity analysis of the criteria weighting system indicates the certainty of the obtained CDR potential to range from 80 – 95%. While the obtained results indicate the need for regional cooperation among countries, it also provides useful evidence on the need for countries to include and prioritise GGR technologies in their revised nationally determined contributions (NDCs).

Data availability statement

Data underlying this study can be accessed through the Cranfield University repository (CORD) at: https://doi.org/10.17862/cranfield.rd.20427804. It contains the normalised input data and the country-level GGR potential data. Data are available under the terms of the [Creative Commons Attribution 4.0 International (CC BY 4.0)].

6.5 References

Alcalde, J., Smith, P., Haszeldine, R.S., Bond, C.E., 2018. The potential for implementation of Negative Emission Technologies in Scotland. Int. J. Greenh. Gas Control 76, 85–91. https://doi.org/10.1016/j.ijggc.2018.06.021

Asibor, J.O., Clough, P.T., Nabavi, S.A., Manovic, V., 2021. Assessment of optimal conditions for the performance of greenhouse gas removal methods. J. Environ. Manage. 294, 113039. https://doi.org/10.1016/j.jenvman.2021.113039

Baik, E., Sanchez, D.L., Turner, P.A., Mach, K.J., Field, C.B., Benson, S.M., 2018. Geospatial analysis of near-term potential for carbon-negative bioenergy in the United States. Proc. Natl. Acad. Sci. U. S. A. 115, 3290–3295. https://doi.org/10.1073/pnas.1720338115

Batalini de Macedo, M., Nóbrega Gomes Júnior, M., Pereira de Oliveira, T.R., H. Giacomoni, M., Imani, M., Zhang, K., Ambrogi Ferreira do Lago, C., Mendiondo, E.M., 2022. Low Impact Development practices in the context of United Nations Sustainable Development Goals: A new concept, lessons learned and challenges. Crit. Rev. Environ. Sci. Technol. 52, 2538–2581. https://doi.org/10.1080/10643389.2021.1886889

Buylova, A., Fridahl, M., Nasiritousi, N., Reischl, G., 2021. Cancel (Out) Emissions? The Envisaged Role of Carbon Dioxide Removal Technologies in Long-Term National Climate Strategies. Front. Clim. 3. https://doi.org/10.3389/fclim.2021.675499

CIA, 2022. The World Factbook 2022 [WWW Document]. URL https://www.cia.gov/library/publications/resources/the-world-factbook/index.html (accessed 6.10.20).

Donnison, C., Holland, R.A., Hastings, A., Armstrong, L.M., Eigenbrod, F., Taylor, G., 2020. Bioenergy with Carbon Capture and Storage (BECCS): Finding the win–wins for energy, negative emissions and ecosystem services—size matters. GCB Bioenergy 12, 586–604. https://doi.org/10.1111/gcbb.12695

Element Energy, UKCEH, 2021. Greenhouse gas removal methods and their potential UK deployment.

Fajardy, M., Köberle, A., Dowell, N.M.A.C., Fantuzzi, A., 2019. BECCS deployment: A reality check, Grantham Institute Briefing paper No 28.

FAO, 2022a. FAO-AQUASTAT database [WWW Document]. URL http://www.fao.org/nr/water/aquastat/data/query/results.html (accessed 7.15.20).

FAO, 2022b. Global Ecological Zones (GEZ) mapping | Global Forest Resources Assessments [WWW Document]. URL https://www.fao.org/forest-resources-assessment/remote-sensing/global-ecological-zones-gez-mapping/en/ (accessed 3.1.22).

Förster, J., Beck, S., Borchers, M., Gawel, E., Korte, K., Markus, T., Mengis, N., Oschlies, A., Schaller, R., Stevenson, A., Thoni, T., Thrän, D., 2022. Framework for Assessing the Feasibility of Carbon Dioxide Removal Options Within the National Context of Germany. Front. Clim. 4. https://doi.org/10.3389/fclim.2022.758628

Fuss, S., Lamb, W.F., Callaghan, M.W., Hilaire, J., Creutzig, F., Amann, T., Beringer, T., De Oliveira Garcia, W., Hartmann, J., Khanna, T., Luderer, G., Nemet, G.F., Rogelj, J., Smith, P., Vicente, J.V., Wilcox, J., Del Mar Zamora Dominguez, M., Minx, J.C., 2018. Negative emissions - Part 2: Costs, potentials and side effects. Environ. Res. Lett. 13. https://doi.org/10.1088/1748-9326/aabf9f

Griscom, B.W., Busch, J., Cook-Patton, S.C., Ellis, P.W., Funk, J., Leavitt, S.M., Lomax, G., Turner, W.R., Chapman, M., Engelmann, J., Gurwick, N.P., Landis, E., Lawrence, D., Malhi, Y., Murray, L.S., Navarrete, D., Roe, S.,

Scull, S., Smith, P., Streck, C., Walker, W.S., Worthington, T., 2020. National mitigation potential from natural climate solutions in the tropics. Philos. Trans. R. Soc. B Biol. Sci. 375. https://doi.org/10.1098/rstb.2019.0126

Haszeldine, R.S., Flude, S., Johnson, G., Scott, V., 2018. Negative emissions technologies and carbon capture and storage to achieve the Paris Agreement commitments. Philos. Trans. R. Soc. A Math. Phys. Eng. Sci. 376. https://doi.org/10.1098/rsta.2016.0447

Haszeldine, S., Cavanagh, A., Scott, V., Sohi, S., Mašek, O., Renforth, P., 2019. Greenhouse Gas Removal Technologies-approaches and implementation pathways in Scotland Executive summary. ClimateXChange.

Hepburn, C., Adlen, E., Beddington, J., Carter, E.A., Fuss, S., Mac Dowell, N., Minx, J.C., Smith, P., Williams, C.K., 2019. The technological and economic prospects for CO2 utilization and removal. Nature 575, 87–97. https://doi.org/10.1038/s41586-019-1681-6

IEA, 2020. IEA Energy Atlas [WWW Document]. URL http://energyatlas.iea.org/#!/tellmap/-1118783123/1 (accessed 9.15.20).

IEAGHG, 2011. Global Storage Resources Gap Analysis for Policy Makers.

IPCC, 2022. Summary for Policymakers, in: Shukla, P.R., Skea, J., Slade, R., Al Khourdajie, A., van Diemen, R., McCollum, D., Pathak, M., Some, S., Vyas, P., Fradera, R., Belkacemi, M., Hasija, A., Lisboa, G., Luz, S., Malley, J. (Eds.), Climate Change 2022: Mitigation of Climate Change. Cambridge University Press, Cambridge, UK, pp. 1–30.

IPCC, 2018. Global warming of 1.5°C An IPCC Special Report on the impacts of global warming of 1.5°C above pre-industrial levels and related global greenhouse gas emission pathways, in the context of strengthening the global response to the threat of climate change,.

IRENA, 2021. Statistical Profiles [WWW Document]. URL https://www.irena.org/Statistics/Statistical-Profiles (accessed 12.10.20).

Jiang, K., He, C., Dai, H., Liu, J., Xu, X., 2018. Emission scenario analysis for China under the global 1.5 °C target. Carbon Manag. 9, 481–491. https://doi.org/10.1080/17583004.2018.1477835

Kantola, I.B., Masters, M.D., Beerling, D.J., Long, S.P., DeLucia, E.H., 2017. Potential of global croplands and bioenergy crops for climate change mitigation through deployment for enhanced weathering. Biol. Lett. 13. https://doi.org/10.1098/rsbl.2016.0714

Kearns, J., Teletzke, G., Palmer, J., Thomann, H., Kheshgi, H., Chen, H., Paltsev, S., Herzog, H., 2017. Developing a Consistent Database for Regional Geologic CO2 Storage Capacity Worldwide. Energy Procedia 114, 4697–4709. https://doi.org/10.1016/j.egypro.2017.03.1603

Kujawski, E., 2003. Multi-Criteria Decision Analysis: Limitations, Pitfalls, and

Practical Difficulties. Lawrence Berkeley Natl. Lab. 13, 1169–1176. https://doi.org/10.1002/j.2334-5837.2003.tb02692.x

Lorenz, K., Lal, R., 2014. Biochar application to soil for climate change mitigation by soil organic carbon sequestration. J. Plant Nutr. Soil Sci. 177, 651–670. https://doi.org/10.1002/jpln.201400058

Maher, B., Symons, J., 2022. The International Politics of Carbon Dioxide Removal: Pathways to Cooperative Global Governance. Glob. Environ. Polit. 22, 44–68. https://doi.org/10.1162/glep_a_00643

Mulligan, J., Rudee, A., Lebling, K., Levin, K., Anderson, J., Christensen, B., 2020. CarbonShot: Federal Policy Options for Carbon Removal in the United States, World Resources Institute.

Nair, V.D., Nair, P.K.R., Dari, B., Freitas, A.M., Chatterjee, N., Pinheiro, F.M., 2017. Biochar in the agroecosystem-climate-change-sustainability Nexus. Front. Plant Sci. 8. https://doi.org/10.3389/fpls.2017.02051

Pour, N., Webley, P.A., Cook, P.J., 2018. Opportunities for application of BECCS in the Australian power sector. Appl. Energy 224, 615–635. https://doi.org/10.1016/j.apenergy.2018.04.117

Pozo, C., Galán-martín, Á., Reiner, D.M., Dowell, N. Mac, Guillén-gosálbez, G., 2020. Equity in allocating carbon dioxide removal quotas. Nat. Clim. Chang. https://doi.org/10.1038/s41558-020-0802-4

Ritchie, H., Roser, M., Rosado, P., 2020. Renewable Energy - Our World in Data [WWW Document]. URL https://ourworldindata.org/renewable-energy (accessed 6.14.22).

Roe, S., Streck, C., Beach, R., Busch, J., Chapman, M., Daioglou, V., Deppermann, A., Doelman, J., Emmet-Booth, J., Engelmann, J., Fricko, O., Frischmann, C., Funk, J., Grassi, G., Griscom, B., Havlik, P., Hanssen, S., Humpenöder, F., Landholm, D., Lomax, G., Lehmann, J., Mesnildrey, L., Nabuurs, G.J., Popp, A., Rivard, C., Sanderman, J., Sohngen, B., Smith, P., Stehfest, E., Woolf, D., Lawrence, D., 2021. Land-based measures to mitigate climate change: Potential and feasibility by country. Glob. Chang. Biol. 1–34. https://doi.org/10.1111/gcb.15873

Roe, S., Streck, C., Obersteiner, M., Frank, S., Griscom, B., Drouet, L., Fricko, O., Gusti, M., Harris, N., Hasegawa, T., Hausfather, Z., Havlík, P., House, J., Nabuurs, G.J., Popp, A., Sánchez, M.J.S., Sanderman, J., Smith, P., Stehfest, E., Lawrence, D., 2019. Contribution of the land sector to a 1.5 °C world. Nat. Clim. Chang. 9, 817–828. https://doi.org/10.1038/s41558-019-0591-9

Rogelj, J., Elzen, M. Den, Höhne, N., Fransen, T., Fekete, H., Winkler, H., Schaeffer, R., Sha, F., 2016. Paris Agreement climate proposals need a boost to keep warming well below 2 ° C. Nature 534. https://doi.org/10.1038/nature18307

Rueda, O., Mogollón, J.M., Tukker, A., Scherer, L., 2021. Negative-emissions technology portfolios to meet the 1.5 °C target. Glob. Environ. Chang. 67. https://doi.org/10.1016/j.gloenvcha.2021.102238

Schiermeier, Q., 2015. Combined climate pledges of 146 nations fall short of 2 ° C target. Nature 2–4. https://doi.org/10.1038/nature.2015.18693

The Royal Society, 2018. Greenhouse Gas Removal. PostNote 1–5.

Thoni, T., Beck, S., Borchers, M., Förster, J., Görl, K., Hahn, A., Mengis, N., Stevenson, A., Thrän, D., 2020. Deployment of NETs at the National Level: A Need for Holistic Feasibility Assessments. Front. Clim. 2, 12.

Wang, J.J., Jing, Y.Y., Zhang, C.F., Zhao, J.H., 2009. Review on multi-criteria decision analysis aid in sustainable energy decision-making. Renew. Sustain. Energy Rev. 13, 2263–2278. https://doi.org/10.1016/j.rser.2009.06.021

World Bank, 2022. World Bank Climate Change Knowledge Portal [WWW Document]. URL https://climateknowledgeportal.worldbank.org/ (accessed 7.21.20).

World Bank, 2021. GNI per capita, Atlas method (current US$) | Data [WWW Document]. URL https://data.worldbank.org/indicator/NY.GNP.PCAP.CD (accessed 10.9.21).

7 General Discussions

7.1 Introduction

This chapter presents a unifying discussion on the findings of this study and its impact on the state of the GGR research area. It reflects on the aims and objectives of the work, key outcomes and its probable impact on policy directions and choice of deployment pathways. The chapter is concluded by a discussion of recent trends and developments in GGR technologies.

The study was aimed at assessing the country-level deployment potential of GGR technologies based on their respective bio-geophysical and techno-economic characteristics using ML and MCDA approach. It aimed to provide useful insights for countries on GGR options that can be sustainably and effectively deployed in their respective territories, and also provide an evidence-base to drive the need for international collaboration and resource sharing. The objectives of the study that were undertaken to meet this aim, are outlined as follows:

1. Assess and identify the operational conditions required for optimum performance of GGR methods.
2. Categorise the global deployment suitability of GGR methods at the country-level using hierarchical clustering ML.
3. Apply supervised ML algorithms for resource mapping of GGR methods.
4. Evaluate the cumulative amount of CO_2 removable by 2100 via these GGR methods by each country using a MCDA approach, assessing sufficiency to meet quotas, and identify areas of regional competitive advantages and collaborations.

With focus on the five GGR technologies covered in this study (forestation, EW, DACCS, BECCS and Biochar), the key findings of the study and their impact on the state of the art are presented in the following sections.

7.2 Forestation

Forestation is generally regarded as one of the cheapest carbon sequestration pathways with a cost requirement of US$5–50/$tCO_2$ (Fuss et al., 2018). Based on the assessment of the literature, climatic condition and land availability were found to have the highest impact on the deployment and performance of this technology. The tropical climatic region with high average temperature of 25 °C and high precipitation was identified as the most suitable location for this GGR method. Given the high land requirement (0.03–0.16 ha/ tCO_2) and the need to ensure that the implementation of this technology has no negative effects on other competing land uses, agroforestry practice was, thus, recommended to maximise land use and minimise cost, while using deciduous, broadleaved, native, mixed tree species.

Using the hierarchical clustering ML model to assess the climatic condition (average quarterly temperature and precipitation), forestation land use (FLu) and water availability of 182 countries, the level of suitability of countries to deploy forestation was obtained. Countries within the tropical regions such as those of LAM, SSA, South East Asia as well as Australia were found to be most suitable for the deployment of forestation. Further investigation was carried out using MCDA to evaluate their respective cumulative maximum CDR potential. These same tropical countries were found to have the highest cumulative CDR potential accounting for about 60% of the global potential. These countries, include Brazil (2.46 $GtCO_2$), Brunei (2.33 $GtCO_2$), Malaysia (2.26 $GtCO_2$), Colombia (2.06 $GtCO_2$), Costa Rica (2.26 $GtCO_2$), Venezuela (2.0 $GtCO_2$), Panama (2.13 $GtCO_2$) and the Democratic Republic of Congo (1.67 $GtCO_2$). Countries in MNAF had the lowest CDR potential (5%) while the OECD and REF countries accounted for about 27%.

While trees can, no doubt, be planted in most countries, there is need to ensure that the deployment of this GGR method for the purpose of climate change mitigation is focused on the tropical region. This is because of its more favourable characteristics such as higher aboveground carbon density, higher tree productivity, increased evapotranspiration and increased surface reflectivity

(albedo) which offers the best carbon sequestration potential compared to the subtropical, temperate and boreal forests.(Bala, 2014; Fuss et al., 2018; Goodman and Herold, 2015). Though priority areas have been identified, there are some barriers that could still limit the large-scale deployment of this technology, even in these identified suitable areas. These include prevailing local land ownership and management systems, lack of incentives to land owners to implement tree planting especially, considering the long time between planting to maturity, competition with other land uses that could provide more immediate income (Smith et al., 2023; The Royal Society, 2018).

With most of the countries within the identified suitable areas largely in the low-to-medium income spectrum (developing countries), there will be need for financial support from the richer nations and organisations, to aid the deployment of this method. This is because, while the overall operating cost of forestation management is typically low, the initial cost of establishing plantations can be high (The Royal Society, 2018). Some international programmes and organisations that have been set up to support and currently driving the deployment of this method include the Bonn Challenge, the International “4 per 1000” Initiative and the Forest Declaration Platform.

While encouraging more actions in the restoration of forests, it is also important to ensure that efforts are made by governments to address the challenges of degradation and deforestation including wildfires, diseases and pests. This is a very important aspect because the 1.5 °C roadmap requires deforestation to decrease 70% by 2030 and 95% by 2050 (Roe et al., 2019).

7.3 Enhanced Weathering

With co-benefits of this GGR method ranging from soil productivity improvement to ocean acidity reduction, this technology is characterised by high energy (0.81 – 12.5 GJ/tCO_2) and cost requirement (52 – 480 US$/t$CO_2$). The major requirements identified for the deployment of this technology thus, included good financial capability and availability of low carbon energy sources. Another key requirement is the availability of basaltic and/or dunite rocks. Warm tropical and humid climatic regions as well as the availability of agricultural land for application

of the crushed rocks were also identified from the literature assessment as minor requirements for the deployment of EW.

Using the hierarchical clustering ML model to assess the availability of the identified factors in 182 countries, the level of suitability of countries to deploy EW was obtained. Some of the suitable countries identified include Canada, EU countries, New Zealand, Chile, USA, Japan and Argentina. The respective cumulative maximum CDR potential was also obtained using MCDA as follows; OECD and LAM countries had the highest CDR potential for this technology (21% each) with major countries including Australia (2.59 $GtCO_2$), New Zealand (2.3 $GtCO_2$), Brazil (1.89 $GtCO_2$), USA (2.49 $GtCO_2$), Canada (2.08 $GtCO_2$), Costa Rica (1.90 $GtCO_2$) and EU countries (totalling 60.23 $GtCO_2$) among others. Asian countries such as Singapore (2.51 $GtCO_2$), China (2.31 $GtCO_2$), Japan (2.29 $GtCO_2$) and Malaysia (2.41 $GtCO_2$), as well as Middle Eastern countries like Saudi Arabia (2.40 $GtCO_2$) and Qatar (2.29 $GtCO_2$) were also identified as areas with high EW deployment potential.

Though priority areas for the deployment of this technology have been identified, a lot of barriers still needs to be overcome to achieve full scale deployment. EW is still a developing technology with technological readiness still at the demonstration level. Before deployment at the identified suitable locations, there will still be need for further development, demonstration and field tests, robust life cycle analysis and cost-benefit analysis in order to fully assess its potential, co-benefits, feasibility and environmental impact. This is in addition to the need for standards for monitoring, reporting and verification of the removed CO_2. Though it can be argued that the technology for the mining and crushing of the rocks are fully matured, it is, however, important to note that only low carbon energy sources can be deployed in driving these heavy machineries. Feasible options include low carbon hydrogen and biofuels. The current relative high cost of these low carbon fuel will thus impact on the cost of EW deployment. It is however important to highlight that this cost is expected to decrease significantly in the future on account of advancement in technology (Fuss et al., 2018). Its co-benefit

of soil improvement is also expected to play a big role in the deployment of this technology, especially in regions where price of fertilisers increase.

On the policy side, there will be need for local and national regulations, standards and permits to cater for probable environmental impacts such as air quality brought about by the spreading of the crushed rocks on land, noise and disruptions associated with the mining, transportation and spreading activities as well as heavy metal contamination such as chromium and nickel which are associated with dunite rocks (Smith et al., 2023; The Royal Society, 2018).

7.4 DACCS

Based on the review of the literature, DACCS was found to enjoy advantages of minimal competition for land and nutrients as well as absence of climatic constraints. It is however characterised by high energy requirement (9 -12.3 GJ/tCO_2) owing to the low concentration of CO_2 in atmospheric air, and a high-cost requirement (US$600-1000/t$CO_2$). This cost requirement is expected to decrease to US$100–300/t$CO_2$ by 2050 (Fuss et al., 2018; Psarras et al., 2017). The availability of appropriate storage site for the captured CO_2 was also identified as a major requirement for the deployment of this technology. Water requirement was found to be dependent on the DAC technology adopted (4.7 to 30 m^3/tCO_2).

By assessing the availability of appropriate geological storage sites, financial capability (GNI) and availability of LCE, using the hierarchical clustering ML model, major countries that were identified for the deployment of DACCS include The USA, Canada, Russia, EU, Kazakhstan, Australia, Argentina and Norway. The cumulative maximum CDR potential for each country was also obtained using MCDA. The OECD and REF countries with appropriate geological storage sites jointly accounted for 40% of the global CDR potential. This was closely followed by SSA and LAM which jointly accounted for 38% of the global potential. Major countries identified include USA (3.78 GtCO_2), Canada (3.56 GtCO_2), Australia (3.56 GtCO_2), Norway (3.54 GtCO_2), Brunei (3.54 GtCO_2), Saudi Arabia (3.29 GtCO_2), the Netherlands (3.42 GtCO_2), New Zealand (3.54 GtCO_2), Russia (3.51 GtCO_2) and the UK (3.34 GtCO_2).

The deployment of DACCS is currently at a small scale estimated at 0.01 $MtCO_2$ (IEA, 2022a). This indicates that there is need for a rapid scale-up if the DACCS CDR target of 85 $MtCO_2$ in 2030 and 980 $MtCO_2$ by 2050, under the IEA Net Zero Emissions Scenario is to be met (IEA, 2022a). There are a total of 18 small-scale DACCS facilities currently operational in Canada, Europe and the USA, with the first large-scale DAC plant with capacity 1 $MtCO_2$/year is currently being developed in the USA and expected to be operational by the mid-2020s. While these currently operational locations are in full agreement with the priority locations identified in this study, the obtained CDR potential for the various countries provides additional information on the extent of possibilities. This will provide the needed drive for capacity expansion in these countries and contribute to the growing momentum for DACCS globally.

Government and industry support for the development and deployment of DACCS is on the increase, with governments commitments estimated at about US$4 billion since 2010. Additional funding efforts to drive R&D are also ongoing in countries such as the US, Australia, Canada, Japan and the UK among others (IEA 2022). On the private front, there has been an increase in interest and investments since 2020, with major companies including Microsoft, United Airlines, Breakthrough Energy Catalyst and Stripe, among others, all making millions of dollar worth of investments in DACCS projects. There is also the US$100 million XPRIZE carbon removal competition funded by Elon Musk and the Musk Foundation to provide support for eligible CDR technologies. While these efforts are commendable, there is need for more investments from other governments and organisations. Such sustained and enhanced contributions will drive innovation, which will lead to improvement in the technology, a decrease in the capture cost to under US$100/$tCO_2$ and increased deployment of DACCS.

Beyond financial incentives and investments, there will also be need to develop policies and operational standards at the national and global levels. This will include agreed methodologies for conducting LCA, international certifications, cost-benefit analysis, programmes to drive demonstration, carbon utilisation, the development of business models and inclusion in carbon markets.

7.5 BECCS

BECCS has been part of many Integrated Assessment Models (IAMs) scenarios, and thus, expected to play a major role as part of the mitigation efforts. Based on the assessment of the literature, the major requirements for the deployment of this technology are availability of CO_2 storage site and biomass. Land requirement was found to be dependent on the choice of biomass feedstock ranging from 0.01 – 0.5 ha/tCO_2. The water requirement is typically high (60 – 218 m^3/tCO_2) covering the biomass production and the CCS use. Cost was found to be dependent on choice of biomass source and adopted technology ranging from US $100–200/t$CO_2$.

Priority regions identified for the deployment of BECCS, from the hierarchical clustering ML model include the USA, Canada, EU, China, Russia, Australia as well as the tropical countries in South America. The cumulative maximum CDR potential for each country was also obtained using MCDA. SSA accounted for 21% of the global CDR potential. This was followed by OECD (20%), LAM (18%) and REF (18%). Major countries identified for this GGR technology include Brazil (3.98 GtCO_2), Russia (3.89 GtCO_2), USA (3.73 GtCO_2), Canada (3.28 GtCO_2), Australia (3.14 GtCO_2) and South-East Asia (18.29 GtCO_2).

The current amount of CO_2 captured and stored from biogenic sources is estimated at 2 MtCO_2 and 1MtCO_2, respectively (IEA, 2022b). The largest BECCS projects is the Illinois Industrial CCS Project, USA which captures 1 MtCO_2 per year. Other major projects include the Red Trail Energy bioethanol project in North Dakota, USA; the Mikawa BECCS power plant in Japan and the Drax power plant in the United Kingdom. There are other small-scale BECCS facilities currently operational in Europe and the United States. While over 90% of the current BECCS deployment is from ethanol facilities, there are numerous projects at varying levels of development covering this route and other bioenergy applications. They include the Midwest Carbon Project consisting of over 30 bioethanol facilities in the USA, which is expected to be operational by 2030, with an aggregate capture capacity of over 15 MtCO_2. Another 15 MtCO_2 is expected from heat and power projects including Drax power plant (40%). Other

applications include integration of BECCS in the cement industry (the Brevik Norcem plant in Norway, the Cementa Slite plant in Sweden and the K6 Lumbres project in France), the pulp and paper mills (Norway and Indonesia) as well hydrogen production facilities.

While these efforts are encouraging, a lot more still needs to be done if the 2030 BECCS deployment Net Zero Scenario target is to be met. Under this scenario, annual CO_2 capture by 2030 is expected to be 60 Mt (power sector), 170 Mt (fuel transformation sector) and 20 Mt for industrial sector (IEA, 2022b). Some challenges that will need to be addressed in order to drive full scale deployment, even in the most suitable locations that have been identified in this study include the low-to-medium TRLs of some BECCS route such as large-scale biomass combustion (commercial demonstration stage), gasification for synthetic applications (prototype stage) and CO_2 capture from kilns and blast furnace (prototype stage). There are also issues around retrofitting of existing bioenergy facilities with CCS. This include the possibility of low compatibility of local biomass feedstock with retrofitted plants, thus, leading to low performance efficiency and the need for importation of compatible biomass feedstock.

There will be need for increased financial investment to drive the development of BECCS technologies. Adequate policies, regulations and standards will also be needed at national and international levels. This will address issues regarding business models for BECCS, contracts-for-difference, uncertainty in carbon pricing and credits with focus on biomass imports, additionality, permanence and leakage risks, standards for MRV, and the socio-environmental sustainability of biomass sourcing and CCS infrastructure.

7.6 Biochar

Based on the review of the literature, the major requirements for the deployment of this method include availability of biomass and agricultural land for biochar application. Other factors include climatic condition (temperate and humid regions) and soil characteristics. The cost requirement estimated between US$30 and 120/$tCO_2$ was found to be dependent on factors such as the biomass

feedstock, the biochar production technique, and the adopted application strategy.

Using the hierarchical clustering ML model to assess the climatic condition (average quarterly temperature and precipitation), agricultural land use, financial capability (GNI) and water availability of 182 countries, the level of suitability of countries to deploy biochar was obtained. Priority regions identified include the USA, Canada, EU, China, Russia, Australia as well as the tropical countries in South America. The cumulative maximum CDR potential for each country was also obtained using MCDA. Countries in LAM and OECD were found to have higher CDR potential, accounting for 25% and 21% of the global potential respectively. Major countries included Brazil (2.75 $GtCO_2$), the USA (2.41 $GtCO_2$), Russia (2.05 $GtCO_2$), Costa Rica (1.34 $GtCO_2$), Malaysia (1.34 $GtCO_2$), Brunei (1.39 $GtCO_2$), Indonesia (1.29 $GtCO_2$) and Venezuela (1.3 $GtCO_2$).

Having identified the priority regions for the deployment of this technology and evaluated their respective biochar CDR potential, there are still a couple of challenges that will need to be resolved to ensure full scale-up of this technology. With biochar currently at mid TRL, characterised by the absence of large-scale field trials and lack of practice experience, there is relatively high uncertainty regarding its feasibility and long-term environmental impacts. There will, thus, be need for investments by both the public and private sectors in R&D to enhance the development of this method, especially with respect to large-scale field trials and demonstration projects. On the policy side, given the complex site-dependent interactions of soil, biomass feedstock and climatic factors, there will be need for policy support at national and local levels. Similar areas of policy focus highlighted for BECCS will also largely apply for biochar.

7.7 Recent Trends, Development and Outlook

This section presents an overview of the current status, recent progress and future outlook of GGR technologies. It is based on a review of the recently published report, “The State of Carbon Dioxide Removal - 1st Edition”, by Smith et al. (2023).

7.7.1 Current status of GGR deployment and the warming target

The current globally deployed GGR is estimated at 2 $GtCO_2$/yr. The bulk of this amount is contributed by the conventional land based GGR methods (afforestation, reforestation and land management), with the novel methods (DACCS, BECCS, EW, biochar, and other GGRs of low-to-mid TRLs) accounting for a tiny 0.002 $GtCO_2$/yr. This current rate of deployment clearly indicates a big gap, that needs to be urgently addressed if the warming target is to be met. Closing this gap will require a simultaneous increased deployment of the conventional GGR methods and an accelerated scale-up of the novel GGR technologies.

Despite the urgent need for deployment, the NDCs of over 120 countries indicates a low intent to deploy these technologies. While only a handful explicitly integrate conventional GGR as part of their climate mitigation strategies, no pledge has yet been made by any of the countries to scale the novel GGR technologies by 2030. A few countries such as the EU, UK, the US and Brazil have, however, published proposals indicating a 2050 target for the upscaling of the novel technologies. This current situation makes the attainment of the warming target difficult to attain. There is thus, a need for urgent response and policies by respective governments to drive the development and deployment of these technologies in the next decade.

7.7.2 Growth in GGR research

Despite the lapse in deployment, there has been astronomical growth in the GGR research area, with the current peer-reviewed scientific literature estimated at over 28,000 English-language studies. Accounting for about 4% of studies in the climate change area, GGR scientific works have grown by about 19% per year between 1990 and 2021, with annual publications projected to double every three to four years. The literature is currently dominated by studies in biochar, soil carbon sequestration and forestation. Studies related to the novel GGR technologies such as DACCS and BECCS are expected to also increase in the coming years. Regarding the geographical distribution of authorship (considering the affiliation of first authors), China accounts for the highest share (32%) of all

the published scientific works on GGR technologies. This was followed by the US (9%) and Australia (4%).

7.7.3 Growth in GGR innovation

From 2010 to 2022, global public investments in R&D for GGR technologies have grown substantially to an estimate of US$4.1 billion. Over 80% of these investments were made by the USA. There has also been a rise in patents with China emerging as the leading nation. In addition to public investments, major companies within the private sector have also been actively involved driving research and innovation in GGR technologies. Notable ones include Microsoft, United Airlines, Breakthrough Energy Catalyst, Shopify, Audi and Stripe. Other efforts include the US$100 million XPRIZE carbon removal competition funded by Elon Musk and the Musk Foundation to support the development of CDR solutions.

7.7.4 GGR technologies and the society

On the social side, there has been increase in public support for research in GGR technologies, with more concerns for environmental impacts that will be associated with deployment at scale. There is overwhelming support for the more familiar GGR methods such as forestation, with ocean-based options largely discouraged (Bui and Mac Dowell, 2022). Public awareness of GGR technologies and their role in climate change mitigation is still low, in comparison to other decarbonisation options. Regarding impact on social media, GGR discussions on platforms such as LinkedIn and Twitter has grown rapidly in the past ten years, with daily average tweets reported to have increased from 15 in 2010 to 350 in 2021 (Smith et al., 2023). A lot more still needs to be done by government and other stakeholders to educate and inform the public on GGR technologies.

Overall, there is an urgent need to expand and scale-up the deployment of GGR technologies. While this study has identified priority locations for sustainable deployment of these technologies, and also evaluated their respective CDR potentials, adequate policy support that are tailored to national contexts will be required to drive the development and deployment of these technologies.

7.8 References

Bala, G., 2014. Can planting trees help to reduce global warming? Curr. Sci. 106, 1551–1552. https://doi.org/10.1111/ner.12135

Bui, M., Mac Dowell, N., 2022. Greenhouse Gas Removal Technologies. Royal Society of Chemistry.

Fuss, S., Lamb, W.F., Callaghan, M.W., Hilaire, J., Creutzig, F., Amann, T., Beringer, T., De Oliveira Garcia, W., Hartmann, J., Khanna, T., Luderer, G., Nemet, G.F., Rogelj, J., Smith, P., Vicente, J.V., Wilcox, J., Del Mar Zamora Dominguez, M., Minx, J.C., 2018. Negative emissions - Part 2: Costs, potentials and side effects. Environ. Res. Lett. 13. https://doi.org/10.1088/1748-9326/aabf9f

Goodman, R., Herold, M., 2015. Why Maintaining Tropical Forests is Essential and Urgent for a Stable Climate. SSRN Electron. J. https://doi.org/10.2139/ssrn.2622758

IEA, 2022a. Direct Air Capture: A key technology for net zero, International Energy Agency.

IEA, 2022b. Bioenergy with Carbon Capture and Storage. Paris.

Psarras, P., Krutka, H., Fajardy, M., Zhang, Z., Liguori, S., Dowell, N. Mac, Wilcox, J., 2017. Slicing the pie: how big could carbon dioxide removal be? Wiley Interdiscip. Rev. Energy Environ. 6, 1–21. https://doi.org/10.1002/wene.253

Roe, S., Streck, C., Obersteiner, M., Frank, S., Griscom, B., Drouet, L., Fricko, O., Gusti, M., Harris, N., Hasegawa, T., Hausfather, Z., Havlík, P., House, J., Nabuurs, G.J., Popp, A., Sánchez, M.J.S., Sanderman, J., Smith, P., Stehfest, E., Lawrence, D., 2019. Contribution of the land sector to a 1.5 °C world. Nat. Clim. Chang. 9, 817–828. https://doi.org/10.1038/s41558-019-0591-9

Smith, S.M., Geden, O., Nemet, G., Gidden, M., Lamb, W.F., Powis, C., Bellamy, R., Callaghan, M., Cowie, A., Cox, E., Fuss, S., Gasser, T., Grassi, G., Greene, J., Lück, S., A., M., Müller-Hansen, F., Peters, G., Pratama, Y., Repke, T., Riahi, K., Schenuit, F., Steinhauser, J., Strefler, J., Valenzuela, J.M., Minx, J.C., 2023. The State of Carbon Dioxide Removal, 1st ed. https://doi.org/10.17605/OSF.IO/W3B4Z

The Royal Society, 2018. Greenhouse Gas Removal.

8 Conclusions and Recommendations

This chapter provides a summary of the findings of the thesis and their implications, and highlights recommendations for future research.

8.1 Conclusions and contributions made

The deployment of GGR technologies has been identified as an indispensable option in meeting the warming target of 1.5 °C by the end of the century. With the Nationally Determined Contributions (NDCs) of countries indicating a low intent to deploy these technologies, this thesis therefore aimed to assess the potential of countries to deploy them. The assessment covered five of the most promising GGR technologies, including forestation, EW, DACCS, BECCS, and biochar. In doing this, the study has achieved the following: 1) it has identified the major factors required for optimum performance of GGR methods and ranked their impact, 2) it has identified the range of GGR technologies that respective countries can suitably and effectively deploy, 3) it has also explored Machine Learning in assessing GGR deployment suitability, and 4) it has evaluated the national potential, assessed domestic sufficiency, and provided an evidence-base for international collaboration in GGR deployment.

8.1.1 Major factors required for optimum performance of GGR methods

In Chapter 2, a comparative literature-based assessment of the impact of operational factors on the performance of GGR methods was carried out. These factors which include climatic condition, vegetation type, availability of land, water, energy and biomass, cost and soil characteristics, were accessed with the aim of identifying the conditions and requirements necessary for their optimum performance. While these factors formed the input variables for the study, the identified conditions for optimum performance serve as a standard for assessing the suitability of locations to deploy the technologies.

For forestation, the tropical climatic region has been identified for deployment, with agroforestry practice also recommended to maximise land use and minimise cost, while using deciduous, broadleaved, native, mixed species. In the case of

EW, warm tropical and humid regions have been identified for optimum deployment using the more common basaltic rocks on preferably arable land with acidic soil. Low carbon renewable energy sources have also been prescribed as means of reducing the high energy (0.81 – 12.5 GJ/tCO_2) and cost requirement (52 – 480 US$/$tCO_2$). For biochar, temperate and humid regions have been highlighted for optimum deployment in arable land that are characterised by well drained sandy soil. Plant-based biomass (preferably crop residue and herbaceous feedstock) have also been recommended as feedstock. Finally, the CCS-based technologies (BECCS and DACCS) have been found to have more locational flexibility. However, the need for cost optimal siting of the CCS plant is very much necessary and dependent on the presence of appropriate geological storage facility.

Given that locations might not meet all the requirements for deployment of a particular GGR technology, there was need to also assess and rank these requirements in order of importance. This ensures that availability of major requirements is given priority of consideration in assessing the GGR deployment suitability of location. Major factors (high importance ranking) identified for the GGR methods are as follows: for forestation, land availability and climatic factor; for EW, availability of rock, LCEA and cost considerations; for DACCS, GSP, LCEA and cost consideration; for BECCS, GSP and biomass availability; and for biochar, biomass availability. This ranking of the extent of influence of these factors on the performance of the various GGR methods was quantified on a scale of 0 – 5 (low to high). This obtained impact ranking was also applied in the MCDA assessment (Chapter 6).

This assessment is important as it provides a guide (point of reference) to enhance the decision-making of stakeholders at various levels (policy makers, investors) on the type of GGR technology that can be deployed in a particular area based on the locational characteristics and available resources. Though specific climatic regions and requirements have been identified for optimum performance of these GGR methods on account of favourable resource

availability, the need for international co-operation and collaboration remains a major factor if the mitigation target is to be met.

8.1.2 What GGR technologies can nations suitably deploy?

A country-level assessment of the range of GGR technologies that nations can suitably deploy has been carried out and presented in Chapter 4. This suitability-categorisation assessment which covered 182 countries was done using hierarchical clustering ML. The novel application of this unsupervised ML model was adopted to minimise the likelihood of human bias in the assessment and ensure that outputs were wholly based on the applied data. By assessing the bio-geophysical and techno-economic characteristics of 182 countries (inputs) and comparing them to the requirements identified in Chapter 2, each country was categorised into one of four suitability categories for each GGR method. The four categories being: Highly Suitable, Suitable, Possible and Unsuitable.

Priority regions and countries suitable for the deployment of these technologies have been identified as follows: countries within the tropical regions such as those of South America, Sub-Saharan Africa as well as Australia were found to be most suitable for the deployment of forestation. This is mainly because of their favourable climatic conditions, vegetation characteristics and land availability. For EW deployment, characterised by high cost and energy requirement, some of the suitable countries identified include Canada, EU countries, New Zealand, Chile, USA, Japan and Argentina. By assessing the availability of appropriate geological storage sites, financial capability and availability of LCE, major countries that were identified for the deployment of DACCS include: The USA, Canada, Russia, EU, Kazakhstan, Australia, Argentina and Norway. For BECCS and biochar, identified deployment priority regions include: the USA, Canada, EU, China, Russia, Australia as well as the tropical countries in South America.

From these findings, countries are able to identify the range of technologies that they have comparative advantage to deploy sustainably and effectively, as well as areas they can collaborate and share resources. This will thus enhance their decision making and planning with regards to the development and inclusion of these technologies in their NDCs. These findings also indicate that the richer

countries have a significant role to play in driving the development and deployment of the more expensive and energy-intensive technologies such as EW, DACCS and BECCS. While these categorisation outcomes are based on the most current data, sensitivity analysis was also carried out to assess the impact of changes in dynamic variables such as GNI, LCEA, FLu and BA, under optimistic (+50%) and pessimistic (-50%) scenarios of resource availability. The level of certainty of the obtained deployment suitability categorisation was found to range from 65-98%. It is therefore recommended that the categorisation results be updated when new data estimates are available.

8.1.3 Role for Machine Learning in GGR assessment

This study has also explored the power of Machine Learning (ML) in assessing GGR deployment suitability. Firstly, in Chapter 4, where it was applied for suitability categorisation of countries using the Hierarchical Clustering ML algorithm, thus, providing category labels for the input dataset. In Chapter 5, using the now labelled dataset, supervised ML algorithms were applied to predict the suitability of a location to deploy five GGR methods based on a location's bio-geophysical and techno-economic characteristics. This is particularly important as it offers a tool for assessing locational suitability to deploy GGR technologies at the national, regional and sub-national levels. It will also cater for future assessments brought about by availability of new data estimates.

To ensure best performance of the model, seven ML classification algorithm were applied in training and testing the labelled dataset. These algorithms include Logistic Regression, Decision Trees, k-Nearest neighbour (k-NN), Naïve Bayes, Random Forest, Gradient Boost and Artificial Neural Network (ANN). While the performance accuracy of the ML models was typically high (76 – 100%), ANN, k-NN and Random Forest algorithms were found to have the highest performance accuracies of 96%, 98% and 100%, respectively. A case study of Scotland's suitability to deploy these GGR methods was carried out to validate the model, with obtained results indicating a high correlation between the ML model results and information in the available literature.

Given the black-box nature of ML models, an assessment of its decision-making logic (model interpretation) was also carried out and it revealed some limitations regarding the impact of the various input variables on the outputs. This was linked to some of the applied input data characteristics and the lack of actual labelled data to enhance the model's training, especially given the fact that most of these technologies are yet to be deployed at scale. It is however expected that the development and large-scale deployment of these GGR technologies in the near future will positively impact on the quantity and quality of data, thus enhancing the performance and role of ML in achieving the 1.5 °C warming target.

8.1.4 National Potential and Evidence for International Collaboration

In Chapter 6, a country-level assessment of the deployment potential of five GGR technologies has been carried out. A multi criteria decision analysis (MCDA) approach was applied. It assessed the bio-geophysical and techno-economic characteristics of countries using a weighting system that was adapted from the impact ranking obtained in Chapter 2 (Table 2.4). Identified priority regions for the deployment of these GGR technologies were very much similar to those obtained in the ML study (Chapter 4). However, while the ML assessment was limited to categorisation – identifying the range of suitable technologies that nations can deploy, this MCDA assessment went further and explored the extent of carbon dioxide removable by 2100 via these technologies. Thus, providing novel detail and mapping on the national maximum cumulative CDR potential via each GGR technology, for each of the 182 countries considered. This is important as it allows nations, including those with similar deployment suitability categories, to better assess their prospects, areas of comparative advantages and collaborative opportunities.

For forestation, countries in LAM, SSA as well as South East Asia were found to have the highest cumulative CDR potential accounting for about 60% of the global potential. These countries, include Brazil (2.46 $GtCO_2$), Brunei (2.33 $GtCO_2$), Malaysia (2.26 $GtCO_2$), Colombia (2.06 $GtCO_2$), Costa Rica (2.26 $GtCO_2$), Venezuela (2.0 $GtCO_2$), Panama (2.13 $GtCO_2$) and the Democratic Republic of

Congo (1.67 $GtCO_2$). Countries in MNAF had the lowest CDR potential (5%) while the OECD and REF countries accounted for about 27%.

In the case of EW, OECD and LAM countries had the highest CDR potential for this technology (21% each) with major countries including Australia (2.59 $GtCO_2$), New Zealand (2.3 $GtCO_2$), Brazil (1.89 $GtCO_2$), USA (2.49 $GtCO_2$), Canada (2.08 $GtCO_2$), Costa Rica (1.90 $GtCO_2$) and EU countries (totalling 60.23 $GtCO_2$) among others. Asian countries such as Singapore (2.51 $GtCO_2$), China (2.31 $GtCO_2$), Japan (2.29 $GtCO_2$) and Malaysia (2.41 $GtCO_2$), as well as Middle Eastern countries like Saudi Arabia (2.40 $GtCO_2$) and Qatar (2.29 $GtCO_2$) were also identified as areas with high EW deployment potential.

For DACCS, OECD and REF countries with appropriate geological storage sites jointly accounted for 40% of the global CDR potential. This was closely followed by SSA and LAM which jointly accounted for 38% of the global potential. Major countries identified include USA (3.78 $GtCO_2$), Canada (3.56 $GtCO_2$), Australia (3.56 $GtCO_2$), Norway (3.54 $GtCO_2$), Brunei (3.54 $GtCO_2$), Saudi Arabia (3.29 $GtCO_2$), the Netherlands (3.42 $GtCO_2$), New Zealand (3.54 $GtCO_2$), Russia (3.51 $GtCO_2$) and the UK (3.34 $GtCO_2$).

For BECCS, SSA accounted for 21% of the global CDR potential. This was followed by OECD (20%), LAM (18%) and REF (18%). Major countries identified for this GGR technology include Brazil (3.98 $GtCO_2$), Russia (3.89 $GtCO_2$), USA (3.73 $GtCO_2$), Canada (3.28 $GtCO_2$), Australia (3.14 $GtCO_2$) and South-East Asia (18.29 $GtCO_2$).

For biochar, countries in LAM and OECD were found to have higher CDR potential, accounting for 25% and 21% of the global potential respectively. Major countries included Brazil (2.75 $GtCO_2$), the USA (2.41 $GtCO_2$), Russia (2.05 $GtCO_2$), Costa Rica (1.34 $GtCO_2$), Malaysia (1.34 $GtCO_2$), Brunei (1.39 $GtCO_2$), Indonesia (1.29 $GtCO_2$) and Venezuela (1.3 $GtCO_2$).

Having obtained the national cumulative CDR potential, a comparative assessment has also been carried out to evaluate the sufficiency of this potential against nationally allocated CDR quotas derived from the IPCC SR1.5 ‘middle-

of-the-road' P3 scenario. This was done to determine which nations and regions will be able to use these five GGR methods to domestically fulfil their quotas, and thus provide evidence for regional collaborations. This allocated CDR quotas were based on three equity sharing principles of Responsibility, Capability and Equality.

At the country-level, most countries in LAM, SSA, MNAF, Asia and REF were able to meet their quotas under the three principles. The exceptions were China, India, Indonesia, Nigeria and Pakistan, who did not meet their Equality-based quota brought about by their relatively high population; Trinidad and Tobago, Bahrain, Saudi Arabia, the United Arab Emirate, Belarus, Czech, Estonia, Kazakhstan, Turkmenistan, Poland and Ukraine, which did not meet their Responsibility-based quotas; and Singapore, Malta, Estonia and Slovenia and South Korea, which did not meet their respective Capability-based quotas. For the OECD group, only four member-countries: Fiji, Samoa, Solomon Islands and Turkey met their quotas under all principles. The others did not as they are characterised by higher CDR quotas under Responsibility and Capability principles.

At the regional level, only LAM, SSA and REF were found to have sufficient potential to meet their allocated quotas under the three equity sharing principles. This thus implies that identified member countries with deficit within these regions can benefit and cover their lapses through appropriate regional collaborations. For LAM and SSA, it is important to note that they had surplus potentials, with findings indicating that the deployment of a combination of the cheaper natural climatic solutions such as forestation, biochar and BECCS will be adequate to fulfil respective quotas. With these two regions majorly characterised by countries with relatively low financial capability, this thus implies that these developing countries can conveniently deploy the cheaper options and also serve as a major hub to support the other regions such as the OECD. This could take the form of resource trading, provision of financial support for GGR development and deployment as well as investments in these regions. Sensitivity analysis of the

criteria weighting system was also carried out, with results indicating the certainty of the obtained CDR potential to range from 80 – 95%.

Overall, this thesis has explored and evaluated the potential of nations to include and deploy GGR technologies as part of their revised NDCs, and provided an evidence base for international collaboration in GGR deployment. It has also explored Machine Learning in assessing GGR deployment suitability.

8.2 Future works

This section highlights some suggestions on potential areas of future research that will advance the development and deployment of GGR technologies.

8.2.1 Inclusion of other factors

Though the major required indicators of bio-geophysical and techno-economic factors were applied in the study, it is recommended that were adequate data is available, further assessment that includes other input variables such as soil characteristics, vegetation characteristics, availability of rocks (mafic and ultramafic), prevailing local land management practices, resource trading and logistics among others, should be carried out.

The impacts of socio-political factors were also not considered in this work. Though this study was focussed on bio-geophysical and techno-economic characteristics, it is important to note that the prevailing socio-political systems of the different countries will significantly impact on the extent and choice of GGR options that will be eventually adopted. Hence, it is therefore recommended that the impact of these factors should be investigated in the future.

8.2.2 Co-deployment of GGR methods

For each country, the deployment potential of each GGR method was assessed independently from the others. While this is well suited for this study which is aimed at assessing the maximum deployment possibility, there is need to also assess the scenario of co-deployment of these GGR methods for each nation.

This is important given the fact that these technologies are not going to be deployed singly, but in different combinations by nations. Though there is lack of data regarding the mix of GGR technologies to be deployed by nations, assessment of the co-deployment of these GGR methods will provide information on areas of synergies of technologies and enhance resource management.

8.2.3 Compatibility with other priorities

This study has determined deployment potential by assessing the availability of bio-geophysical and techno-economic resources. Given that the deployment of these technologies will require significant resources, it is recommended that further research is carried out to assess its impact on existing resources and societal objectives. This is to enhance resource management and prevent competition for resources such as land, water, and renewable energy. It will also ensure that other societal priorities such as food security, water, flood management and biodiversity conservation, are not compromised.

8.2.4 Assessing other GGR methods

Further research to assess the deployment potential of other promising GGR technologies which are not covered in this study, especially at local and sub-national levels should be carried out. These include methods such as soil carbon sequestration, habitat restoration (peatlands and coastal wetlands), and building with biomass.

8.2.5 Other roles for Machine Learning

Though dependent on the availability of data, Machine Learning is expected to play a key role in the development and deployment of GGR technologies. Probable areas of application and research include resource mapping, technical assessments with focus on the CCS technologies, technology development and optimisation studies, as well as Monitoring, Reporting and Verification (MRV).

APPENDICES

Appendix A : List of countries

Table A-1 List of countries

Regions	Countries
Asia	Includes the following Asian countries: Afghanistan, Bangladesh, Bhutan, Brunei, Cambodia, China, India, Indonesia, North Korea, South Korea, Laos, Malaysia, Maldives, Mongolia, Nepal, Pakistan, Papua New Guinea, Philippines, Singapore, Sri Lanka, Thailand, Vietnam, Kiribati, Marshall Islands, and Taiwan.
LAM	Includes the following Latin American and Caribbean countries: Antigua and Barbuda, Argentina, The Bahamas, Barbados, Belize, Bolivia, Brazil, Chile, Colombia, Costa Rica, Cuba, Dominica, Dominican Republic, Ecuador, El Salvador, Grenada, Guatemala, Guyana, Haiti, Honduras, Jamaica, Mexico, Nicaragua, Panama, Paraguay, Peru, Saint Kitts and Nevis, Saint Lucia, Saint Vincent and the Grenadines, Suriname, Trinidad and Tobago, Uruguay and Venezuela.
MNAF	Includes the following countries of the Middle East and North Africa: Algeria, Bahrain, Egypt, Iran, Iraq, Israel, Jordan, Kuwait, Lebanon, Libya, Morocco, Oman, Qatar, Saudi Arabia, Sudan, Syria, Tunisia, United Arab Emirates and Yemen.
OECD	Includes the countries in the OECD as of 1990: Australia, Austria, Belgium, Canada, Denmark, Fiji, Finland, France, Germany, Greece, Iceland, Ireland, Italy, Japan, Luxembourg, Netherlands, New Zealand, Norway, Portugal, Samoa, Solomon Islands, Spain, Sweden, Switzerland, Turkey, United Kingdom and the United States of America.

REF	Includes the reforming economies of Central and Eastern Europe and the Former Soviet Union: Albania, Andorra, Armenia, Azerbaijan, Belarus, Bosnia and Herzegovina, Bulgaria, Croatia, Cyprus, Czech Republic, Estonia, Georgia, Hungary, Kazakhstan, Kyrgyzstan, Latvia, Lithuania, Malta, Moldova, Poland, Romania, Russia, Serbia, Slovakia, Slovenia, Tajikistan, Turkmenistan, Ukraine, Uzbekistan, Montenegro and Kosovo.
SSA	Includes Sub-Saharan countries: Angola, Benin, Botswana, Burkina Faso, Burundi, Cameroon, Cape Verde, Central African Republic, Chad, Comoros, Republic of the Congo, Democratic Republic of the Congo, Cote d'Ivoire, Djibouti, Equatorial Guinea, Eritrea, Ethiopia, Gabon, The Gambia, Ghana, Guinea, Guinea-Bissau, Kenya, Lesotho, Liberia, Madagascar, Malawi, Mali, Mauritania, Mauritius, Mozambique, Namibia, Niger, Nigeria, Rwanda, Sao Tome and Principe, Senegal, Seychelles, Sierra Leone, Somalia, South Africa, South Sudan, Tanzania, Togo, Uganda, Zambia and Zimbabwe.

Appendix B : A Machine Learning Approach for Country-level Deployment of Greenhouse Gas Removal Technologies

B.1 Sensitivity analysis data

Table B-1 presents the result of the sensitivity analysis. It shows the number of countries that moved from their obtained suitability category (in bold) to a new category due to changes in resource availability under optimistic and pessimistic scenarios. It is important to note that the results are written in coordinate format

(e.g., x,y,z) to indicate the corresponding new suitability category (e.g., P,S,HS) where applicable.

Table B-1 Sensitivity Analysis Results

GGR Method	Variable	Scenario	Change in Suitability Category (No. of countries)							
			Positive			Negative			Total	Change (%)
			U→ (P, S,HS)	P→ (S, HS)	S→ HS	HS→ (S,P, U)	S→ (P,U)	P→ U		
Forestation	FLu	Optimistic	0,0,0	0,0	37	-	-	-	37	20
		Pessimistic	-	-	-	31,0,0	0,0	0	31	17
EW	GNI	Optimistic	15,0,0	32,3	13	-	-	-	63	35
		Pessimistic	-	-	-	0,0,0	21,4	5	30	17
	LCEA	Optimistic	0,2,0	13,0	1	-	-	-	16	9
		Pessimistic	-	-	-	0,0,0	34,0	1	35	19
DACCS	GNI	Optimistic	1,5,3	2,7	11	-	-	-	29	16
		Pessimistic	-	-	-	1,28,0	0,5	2	36	20
	LCEA	Optimistic	0,0,0	25,0	0	-	-	-	25	14
		Pessimistic	-	-	-	0,0,1	0,7	2	10	6
BECCS	BA	Optimistic	0,0,0	0,0	0	-	-	-	0	0
		Pessimistic	-	-	-	0,0,0	4,0	0	4	2
Biochar	BA	Optimistic	0,0,14	0,0	2	-	-	-	16	9
		Pessimistic	-	-	-	0,0,0	21,17	0	38	20

Figures B-1 – B-7 presents the corresponding optimistic and pessimistic global country-level maps.

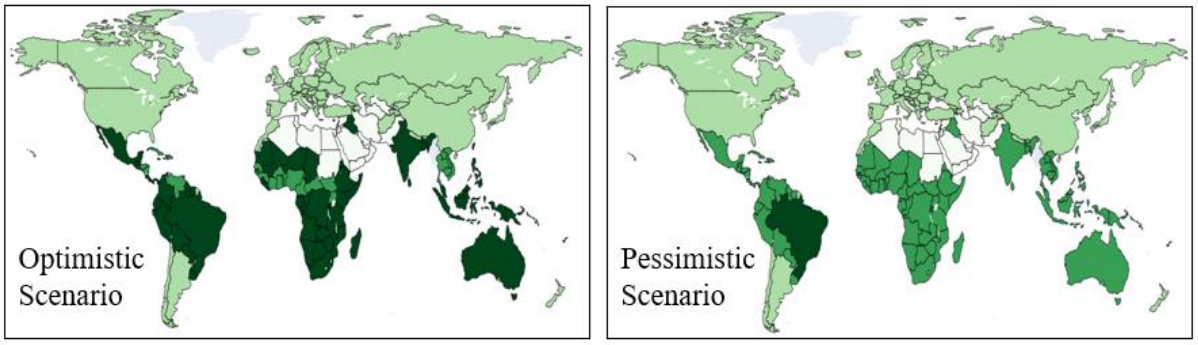


Figure B-1 Impact of land availability on Forestation

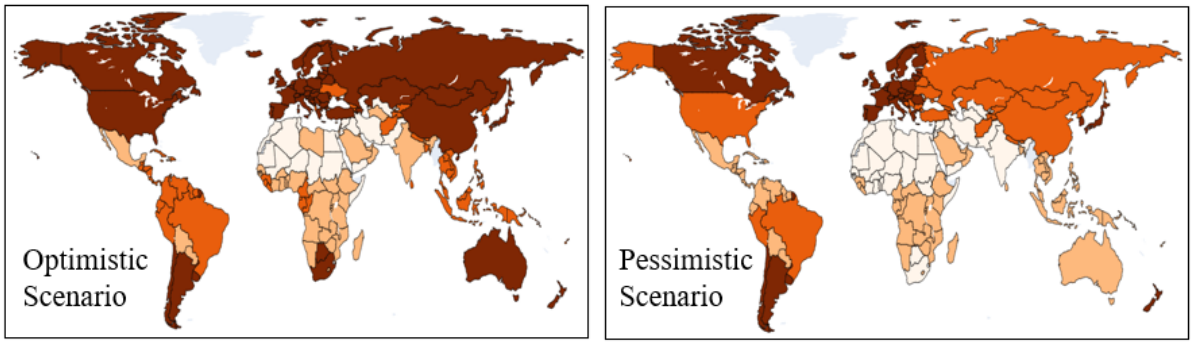


Figure B-2 Impact of GNI on Enhanced Weathering

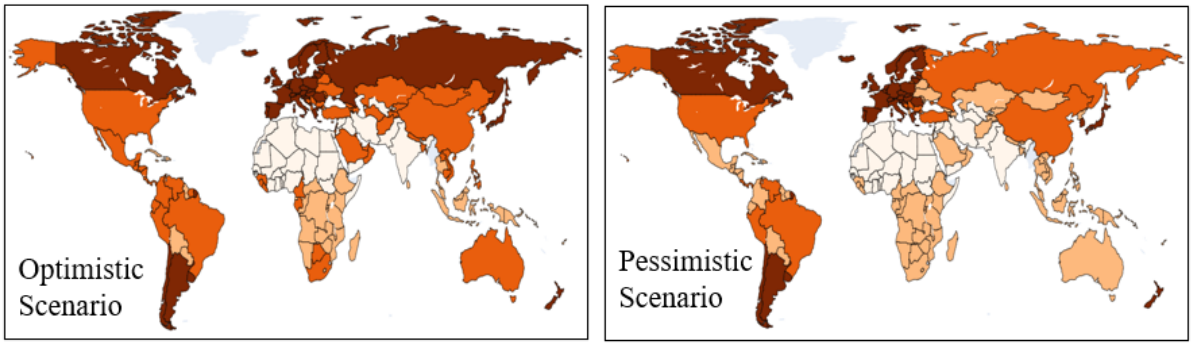


Figure B-3 Impact of LCEA on Enhanced Weathering

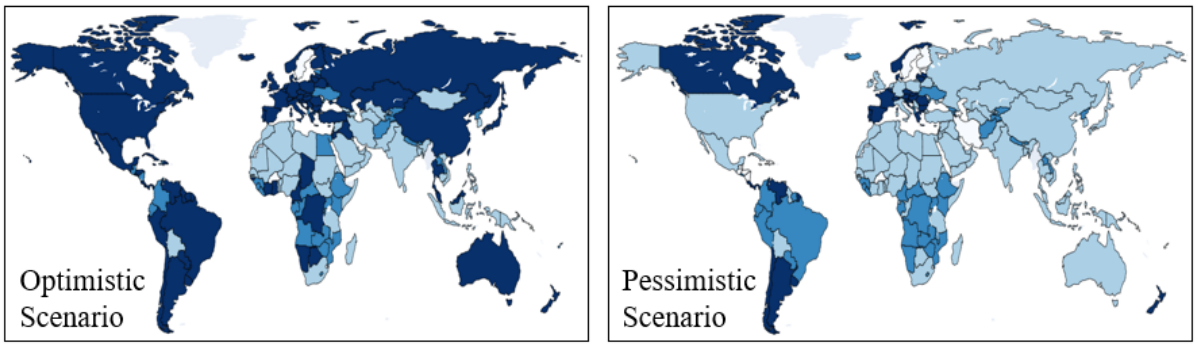


Figure B-4 Impact of GNI on DACCS

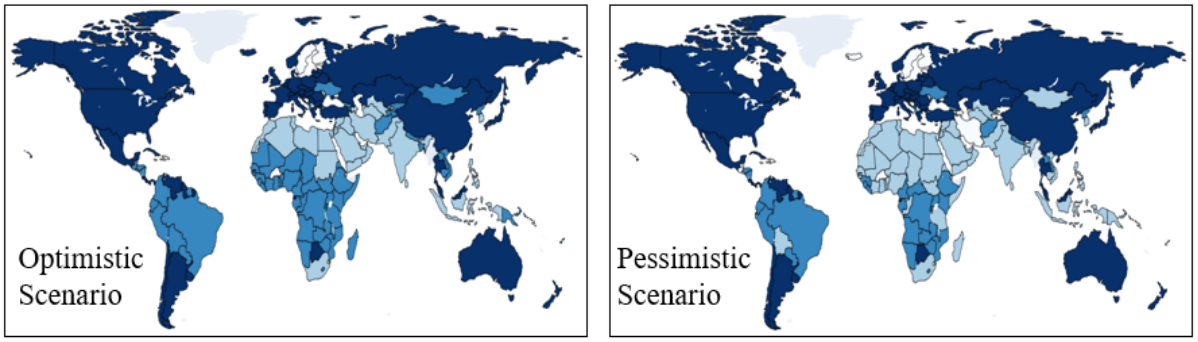


Figure B-5 Impact of LCEA on DACCS

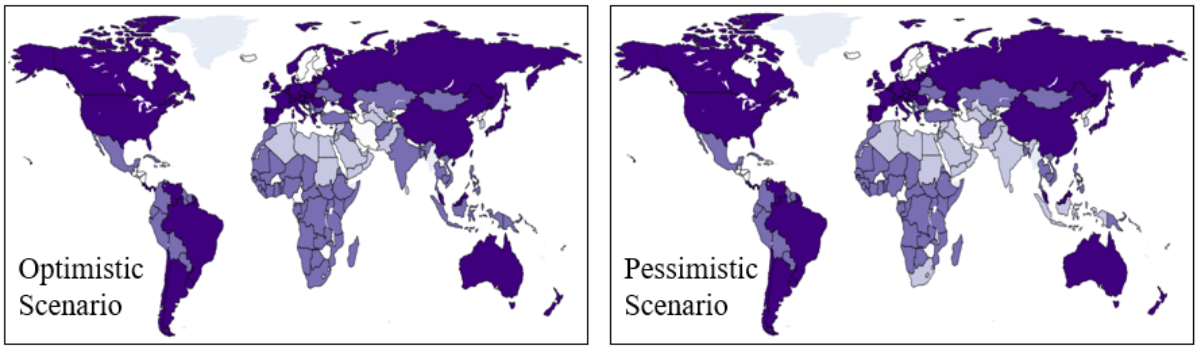


Figure B-6 Impact of Biomass availability on BECCS

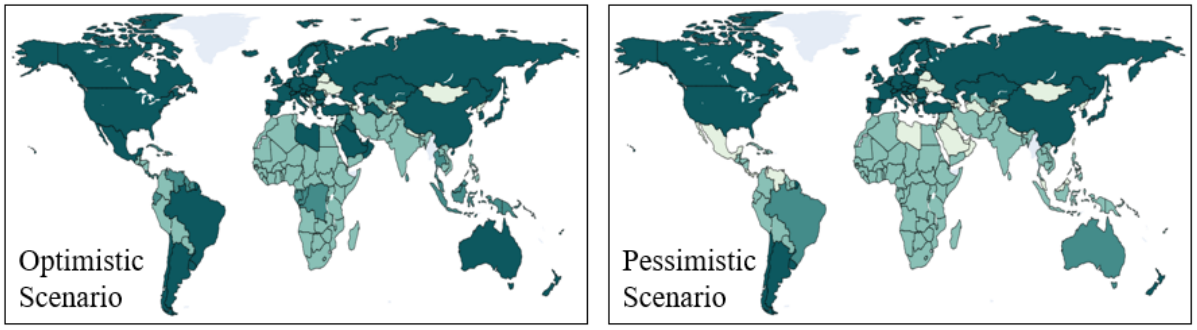


Figure B-7 Impact of Biomass availability on Biochar

Appendix C : Application of Supervised ML for Resource Mapping of GGR Methods

C.1 Codes for the various supervised ML algorithms

Figures C-1 – C-7 present the code written in Python for the various supervised ML algorithms which was applied for the forestation dataset. Similar code was applied for the other GGR methods using their respective dataset (line 10 of code), with changes made to line 13 of code (specify the respective input variables).

```
1  # Logistic Regression to classify GGR deployment suitability
2
3  import pandas as pd
4  import matplotlib.pyplot as plt
5  plt.rcParams['figure.figsize'] = (9, 6)
6  from sklearn.linear_model import LogisticRegression
7  from sklearn.model_selection import train_test_split
8
9  # Reading data
10 df = pd.read_csv("Updated labelled Forestation data2.csv")
11
12 # creating input identity
13 sub_df = df[['Q1T','Q2T','Q3T','Q4T','Q1P','Q2P','Q3P','Q4P','WA','FLu']]
14
15 X = sub_df
16 y = df.Category
17 X_train, X_test, y_train, y_test = train_test_split(X, y, train_size=0.7, random_state=1)
18
19 # creating Model
20 logmodel = LogisticRegression()
21 # Fitting training data
22 logmodel.fit(X_train, y_train)
23
24 # y prediction for set of data
25 predictions = logmodel.predict(X_test)
26
27 print(predictions)
```

Figure C-1 Python code for Logistic Regression.

```python
# Decision Tree to classify GGR deployment suitability

import pandas as pd
import matplotlib.pyplot as plt
plt.rcParams['figure.figsize'] = (9, 6)
from sklearn.tree import DecisionTreeClassifier
from sklearn.model_selection import train_test_split

# Reading data
df = pd.read_csv("Updated labelled Forestation data2.csv")

# creating input identity
sub_df = df[['Q1T','Q2T','Q3T','Q4T','Q1P','Q2P','Q3P','Q4P','WA','FLu']]

X = sub_df
y = df.Category
X_train, X_test, y_train, y_test = train_test_split(X, y, train_size=0.7, random_state=0)

# creating Model
dt = DecisionTreeClassifier(random_state=1)

# Fitting training data
dt.fit(X_train, y_train)

# y prediction
y_pred = dt.predict(X_test)

print(y_pred)
```

Figure C-2 Python code for Decision Tree

```python
# k-NN to classify GGR deployment suitability

import pandas as pd
import matplotlib.pyplot as plt
plt.rcParams['figure.figsize'] = (9, 6)
from sklearn.neighbors import KNeighborsClassifier
from sklearn.model_selection import train_test_split

# Reading data
df = pd.read_csv("Updated labelled Forestation data2.csv")

# creating input identity
sub_df = df[['Q1T','Q2T','Q3T','Q4T','Q1P','Q2P','Q3P','Q4P','WA','FLu']]

X = sub_df
y = df.Category
X_train, X_test, y_train, y_test = train_test_split(X, y, train_size=0.7, random_state=1)

# creating Model
knn = KNeighborsClassifier(n_neighbors=5, metric='euclidean')
# Fitting training data
knn.fit(X_train, y_train)

# y prediction
y_pred = knn.predict(X_test)

print(y_pred)
```

Figure C-3 Python code for k-Nearest Neighbour.

```python
# Naive Bayes to classify GGR deployment suitability

import pandas as pd
import matplotlib.pyplot as plt
plt.rcParams['figure.figsize'] = (9, 6)
from sklearn.naive_bayes import GaussianNB
from sklearn.model_selection import train_test_split

df = pd.read_csv("Updated labelled Forestation data2.csv")

# creating input identity
sub_df = df[['Q1T','Q2T','Q3T','Q4T','Q1P','Q2P','Q3P','Q4P','WA','FLu']]

X = sub_df
y = df.Category
X_train, X_test, y_train, y_test = train_test_split(X, y, train_size=0.7, random_state=1)

# creating Model
gnb = GaussianNB()

# Fitting training data
gnb.fit(X_train, y_train)

# y prediction
y_pred = gnb.predict(X_test)

print(y_pred)
```

Figure C-4 Python code for Naïve Bayes.

```python
# Random Forest to classify GGR deployment suitability

import pandas as pd
import matplotlib.pyplot as plt
plt.rcParams['figure.figsize'] = (9, 6)
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import train_test_split

# Reading data
df = pd.read_csv("Updated labelled Forestation data2.csv")

# creating input identity
sub_df = df[['Q1T','Q2T','Q3T','Q4T','Q1P','Q2P','Q3P','Q4P','WA','FLu']]

X = sub_df
y = df.Category
X_train, X_test, y_train, y_test = train_test_split(X, y, train_size=0.7, random_state=0)

# creating Model (with 100 trees)
rf = RandomForestClassifier(n_estimators=100)

# Fitting training data
rf.fit(X_train, y_train)

# y prediction
# for set of data
y_pred = rf.predict(X_test)

# for specific case
#y_pred = rf.predict([[0.4947,0.2858,0.2458,0.4721,0.314,0.1839,0.1547,0.3098,1,0.007]])

print(y_pred)
```

Figure C-5 Python code for Random Forest

```python
# Gradient Boost to classify GGR deployment suitability

import pandas as pd
import matplotlib.pyplot as plt
plt.rcParams['figure.figsize'] = (9, 6)
from sklearn.ensemble import GradientBoostingClassifier
from sklearn.model_selection import train_test_split

# Reading data
df = pd.read_csv("Updated labelled Forestation data2.csv")

# creating input identity
sub_df = df[['Q1T','Q2T','Q3T','Q4T','Q1P','Q2P','Q3P','Q4P','WA','FLu']]

X = sub_df
y = df.Category
X_train, X_test, y_train, y_test = train_test_split(X, y, train_size=0.7, random_state=0)

# creating Model
gb = GradientBoostingClassifier(random_state=0)

# Fitting training data
gb.fit(X_train, y_train)

# y prediction
y_pred = gb.predict(X_test)

print(y_pred)
```

Figure C-6 Python code for Gradient Boost.

```python
# ANN to classify GGR deployment suitability

import pandas as pd
import matplotlib.pyplot as plt
plt.rcParams['figure.figsize'] = (9, 6)
from sklearn.neural_network import MLPClassifier
from sklearn.model_selection import train_test_split

df = pd.read_csv("Updated labelled Forestation data2.csv")

# creating input identity
sub_df = df[['Q1T','Q2T','Q3T','Q4T','Q1P','Q2P','Q3P','Q4P','WA','FLu']]

X = sub_df
y = df.Category
X_train, X_test, y_train, y_test = train_test_split(X, y, train_size=0.7, random_state=1)

# creating Model
# solver='lbfgs' was used instead of 'adam' on account of small data size.
clf = MLPClassifier(solver='lbfgs')

# Fitting training data
clf.fit(X_train, y_train)

# y prediction
y_pred = clf.predict(X_test)

print(y_pred)
```

Figure C-7 Python code for Artificial Neural Network.