

An approach for quantifying the Social Impact of Carbon Credit Projects and developing a GenAI Tool for UN SDG Claims

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under the supervision of Professor Dr.Farookh Khadeer Hussain and Co Supervision of Dr.Morteza Saberi

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CERTIFICATE OF ORIGINAL AUTHORSHIP

I, **Drishtant Leuva** declare that this thesis, is submitted in fulfilment of the requirements for the award of **Master of Analytics (Research)** in the **School of Computer Science, Faculty of Engineering and Information Technology** at the University of Technology Sydney.

This thesis is wholly my own work unless otherwise referenced or acknowledged. In addition, I certify that all information sources and literature used are indicated in the thesis.

This document has not been submitted for qualifications at any other academic institution.

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Abstract:

There's a critical need to address climate change issues, leading to the wide relinquishment of carbon credit mechanisms, which incentivise emission reduction efforts. Still, the carbon credit design must reduce carbon emissions, and it's also necessary for the assignment to have social counteraccusations for the original community. It is one of the most critical issues that the world is facing today, as well as one of the most essential issues that is calling for proper responses across all human activities. With the world turning into an unsafe place for humans and other living creatures, it is essential to utilise inventive technologies and approaches to decrease the emission of greenhouse gases. Of all such measures, carbon credit schemes have become a crucial instrument in transforming emission reduction into financially profitable activities. These projects enable entities to accrue carbon credits if they cut or store carbon in environments. Then, the credits can be sold to other entities that want to decrease carbon emissions. It is now one of the most convenient strategies for adapting to the climate because it does not impact the economy adversely.

However, looking at carbon credits, we always realize that these instruments are predominantly assessed by their ability to combat carbon emissions, but we also look at the other dimensions of this tool. These projects have significant inclusive socio-economic impacts within local communities, ranging from employment, economic growth and development, social well-being, and even health. Unfortunately, these broader impacts often remain unnoticed in the conventional evaluation frameworks, which, by their very nature, tend to be carbon-centred and try to measure their volume. Such a narrow conception might result in projects that may not harness development opportunities for the host community's sustainable welfare beyond the level of efficient carbon reduction or, at worst, reproduce social injustices.

As such, to fill this gap, this thesis seeks to bring about a paradigm shift by incorporating the United Nations Sustainable Development Goals (UN SDGs) into the assessment framework of Carbon credit projects. Accordingly, the UN SDGs can successfully present all the goals necessary for addressing poverty, inequality, climate change, environmental degradation, peace, and justice on an international level. Thus, this study intends to introduce these goals into assessments of carbon credits with the view of not only creating an informed approach to the analysis of the project's effects but also ensuring that they give back to their environment and the entire socio-economic fabric in a positive way.

The inclusion of the UN SDGs into the evaluation of carbon credits marks a new turn towards enhanced fairness and equity in environmental valuation policies. It is approved as it hastens the public realisation that sustainable development involves conserving ecological resources and establishing social and economic justice. It holds the potential to recast the standards of accomplishment for carbon credit projects and put them in context with the primary goals of undertaking carbon credit projects, that is, sustainable development and achieving a better quality of life for people around the world.

The first objective of this research is to develop an integrated framework that not only assesses the environmental impact of carbon credit projects but also systematically incorporates the UN SDGs to evaluate their social implications. This initiative seeks to transcend traditional environmental considerations by establishing evaluative criteria and metrics derived directly from the SDGs. Such metrics include indicators related to poverty alleviation, educational enhancements, gender equality, and economic growth, alongside environmental sustainability.

The framework aims to provide stakeholders with a multifaceted assessment tool that reflects the true breadth of a project's impact. To validate this framework, a series of pilot studies on existing carbon credit projects will be conducted. These studies will help refine the assessment tools to ensure accuracy and effectiveness in capturing the intended

impacts. By facilitating a holistic evaluation, the framework will encourage the implementation of projects that meet carbon reduction targets and contribute positively to global sustainability goals.

The second objective focuses on the design and empirical validation of robust statistical models capable of quantifying and predicting the social impacts of carbon credit initiatives. This research leverages traditional statistical analysis and machine learning techniques to create predictive models considering various socio-economic and environmental variables collected from diverse carbon credit projects.

These models assume broad goals with extensive data sets to determine the potential benefits and drawbacks in the community and environments where such projects reside. The acquired knowledge contributes to improvements in the accuracy of impact predictions, thus helping to advance strategic planning of carbon credit projects and optimising initiatives designed to maximise carbon credits' commercial, societal, and environmental value. Enhancing these models' reliability and generalizability through sound training and independent testing on diversified projects and geographical regions will facilitate decision-makers' accurate estimation towards carbon credit-related projects. The last goal mini-achievements include the development of the Gen AI Auditor, a new AI-based system designed to audit the SDG contributions that carbon credit projects report thoroughly. This system will incorporate complex heuristic algorithms that will scan the project reports and stream data to ensure that the contributions to SDGs are accurate and backed up.

The Gen AI Auditor has been developed to increase the solidity of impacts concerning carbon credit projects and improve general accountability by offering a means of audit. This development is to increase credibility in the carbon credit market and to promote projects that will be identified with the realisation of financial, social, and ecological gains among the developers, investors and communities.

This research is believed to generate new techniques with remarkable advancements in evaluating carbon credits. This will affect policy in providing a more sound and comprehensive evaluation; it will ensure the formation of better and fairer carbon management policies. Moreover, by connecting the assessments of carbon credits more directly to the persistent global objectives of sustainable development and climatic policy, this thesis will significantly assist in improving the field. It calls for a multilayered solution that solves all the problems associated with climate change and pumps funds towards programs that cut down CO₂ emissions around the world and improve the quality of life of communities in various parts of the planet.

Chapter 1: Introduction

1.1.Introduction

Climate change is an issue that concerns humanity more than ever before since it threatens the very existence of almost all living organisms and has adverse effects on human well-being and economic systems. This has led to the extension of an international social response that has brought in various advancements in technology, changes in policies, as well as formulations and mechanisms of a financial nature to reach out for a sustainable world and, at the same time, bringing about an end to the greenhouse gases. Among these, carbon credit projects have become one of the most crucial solutions, namely a market-based method to stimulate the cuts in emissions with the help of investing in renewable energy, forest, and other similar activities (Wissner & Schneider, 2022; Richard, 2023).

For this reason, carbon credit projects may provide one of the potential ways of lowering global carbon emissions; however, the existing techniques used to measure the efficiency of the implemented attempts are based almost solely on evaluating numerical carbon results. Such accentuation of carbon offset projects generalised only in terms of carbon achievements needs to pay more attention to these more giant socio-economic and global environmental footprints. Therefore, it is observed that in the scientific and regulatory world, carbon credit evaluations must be more based and inclusive of broader impacts associated with the range of carbon projects (Olhoff et al., 2004; Gabbi et al., 2015).

This thesis, responding to this significant gap, aims to develop a new approach to combining the UN SDGs into the evaluation framework of carbon credit projects. The UN SDGs have been designed to meet the significant global goals in the current world: environmental stewardship, social development, and economic growth. Incorporating these goals into carbon credit assessments will help make these projects more public and

clarify that the construction and implementation of carbon credit projects must support several other sustainable development objectives (Sachs et al., 2019; Schneider, 2007).

This research is based on the proposal that more out of the traditional, effective appraisal of carbon credit projects, Canadians make these valuable tools and assets for effective carbon management into natural and sustainable development enablers. Enhanced decision-making can embrace climate change objectives and upper-level goals with a framework that encapsulates both the environmental and socio-economic factors for such projects (Welfle & Röder, 2022; Rawhouser & Cummings, 2019).

Subsequently, one of the significant research findings explored in this thesis is the guidelines for measuring the relative social implications of carbon credit projects based on the UN SDG. This includes identifying and defining sets of goals and objectives developed from the UN Sustainable Development Goals to quantify projects' social, economic, and environmental impacts beyond the ability to absorb carbon dioxide. For instance, there is still a vital relevancy of the carbon credit evaluation of SDG 13: Climate Action. However, in this study, the indicators from various SDGs will also be evaluated, namely SDG 1, No Poverty; SDG 5, Gender Equality; SDG 8, Decent Work and Economic Growth, and all others.

It is a methodical approach and process of data collection that integrates both qualitative and quantitative data, hence providing a broad understanding of the impact of carbon credit projects on the targeted societies and ecosystems. According to this general framework, the actors involved are the project developers, the policymakers, etc. They may have a vision of the projects and policies they are implementing regarding this innocuous conception of sustainable development. Besides, it encourages the emergence

of projects that meet global carbon targets and goals in the spirit of society's welfare and enhanced communal support.

The second main research contribution relates to the design of the Gen AI Auditor. This robust intelligent control system intends to verify a project's carbon credit based on the claimed UN SDGs. It is, therefore, a revolutionary system in the advancement of environmental auditing. The employment of AI and machine learning systems will be helpful when it comes to assessing the shares and reports of the projects' performances, particulars on real-time performances, and compliance documents to decide whether the projects have been as altruistic and supportive of the SDG goals as claimed.

This method enables the system to analyse the data and display correctness and or inconsistencies in reporting, thus eradicating any human bias. Thus, the ability to substantiate the CO₂ emission reductions effectively assists in addressing the transparency challenges that characterise the carbon market due to the influence that project reporting has on the market's integrity. Therefore, by ensuring that projects can offer credible information as to the success in achieving the aims toward the seven sustainable development goals, the Gen AI Auditor builds confidence in sustainable projects, hence increasing funding for such projects among investors and the public.

However, many advantages are still associated with the ability to utilise the information provided by the applied AI system to rectify mistakes in project design and execution. According to the results of this study, the developers can identify areas in a project that fail to reach the SDG standards and focus on the areas that need to be changed for the betterment of social and environment. The above feedback mechanism is

advantageous to the individual undertakings and the performance and success of the carbon market.

While carbon credit mechanisms have proven successful in encouraging emission reductions, their sole focus on carbon offsetting often results in the neglect of broader socio-economic impacts. For instance, projects aimed at large-scale reforestation have, at times, displaced local communities without providing adequate social benefits, such as employment or improved local infrastructure. Therefore, there is a pressing need to integrate the evaluation of social and economic factors alongside environmental ones, to ensure that these projects contribute holistically to sustainable development.

Significance of the Study

The insights could assist policymakers in targeting and nurturing carbon credit projects with significant social co-benefits like big-scale RE, and re/afforestation.” These projects could get more funds and support for the optimisation of contributions towards the achievement of sustainable development goals and at the same time ensuring social-economic development because of emission reductions strategies.

The study developed an understanding of how carbon credit schemes can be designed and delivered to achieve nearer goals of SDG by the project developers. When project plans are aligned for better job creation, improved health, and economic uplift of the local communities, developers stand to benefit from their projects in delivering the best to the societies.

The study provides the investors with relevant data in funding decision making to support their investment. In this manner, it is possible that investors shall be able to realize a higher return on investment in terms of ‘the social worth’. This approach increases the sustainability of the assets in addition to increasing public support for carbon credit programs.

Therefore, the goal of this research is to improve this mechanism with an eye towards properly influencing carbon credits toward the achievement of sustainable development goals. Incorporating environmental, social, and economic cost assessments in the legislation, this study presents a clearer and more accurate perspective of carbon credit projects' worth and assists future policy formulation, project development and investment.

To underscore the overarching analysis of these issues, which is the focus of this paper, this section establishes the need for and likely consequences of adopting a mixed-methodology approach to evaluating carbon-credit projects. The following chapters will provide a more detailed analysis regarding the theoretical foundations for the stated framework, the methods used for the framework, and the Gen AI Auditor creation and testing, along with the potential recommendations regarding policy and practice in environmental sustainability.

The proposed framework not only has the potential to transform how carbon credit projects are evaluated within specific regions but could also serve as a model for other countries and sectors. By integrating socio-economic factors into sustainability reporting, this research will contribute to the global discourse on how to make carbon markets more equitable and effective in achieving long-term development goals.

1.2. Background

Carbon credits originated from global activities to address climate change challenges, especially after the Kyoto Protocol of 1997 that set mandatory emission-cutting objectives for developed nations. This framework also brought in the concept of trading where credits can be earned through projects that decrease

emissions and sold to nations that directly violate their limits. The Paris Agreement 2015 also emphasised carbon credits which encouraged voluntary commitments from all countries on a pledge and review system to keep the global temperature rise below 2 degrees Celsius.

Over time, the carbon credit market has evolved from the rigid frameworks established under the Kyoto Protocol's CDM to more flexible, voluntary mechanisms. This shift has heightened the need for transparent and comprehensive evaluation methods to ensure that the socio-economic impacts of these projects are not overshadowed by their carbon offset goals.

At the same time, the UN SDGs were established in 2015 as a comprehensive Charter to mobilize the efforts of the whole world to end poverty and invest in sustainable development to enhance well-being of people and life on the planet in the following perspective up to 2030. The SDGs are all-encompassing framework of development goals that consider the three facets of development, that is economic, social, and environmental. Linking of carbon credit projects with SDGs seeks to ensure that the objectives of reduction of carbon emission include even positive effects on other aspects of sustainable development.

Consequently, grounding an analysis on the historical development of carbon credits and on the formulation of the SDGs as used in this research, it has become possible to examine the multifaceted relationship between mitigating the climate crisis and advancing sustainable development and to call for a more integrated approach in the comprehensive evaluation of carbon credits that not only considers ecological gains but also the socio-economic outputs of climate mitigation activities.

The fight against climate change is necessary because of the devastating effects it has on the environment, world economies and societies. New studies come out as a sharp indication that severe cuts in CO₂ emissions are required to prevent drastic global warming. The Intergovernmental Panel on Climate Change (IPCC) also states that there is the need to act now to avoid the negative impacts on the society such as changing climate patterns, loss of species, and negative health impacts on individuals and communities across the globe. (IPCC, 2021).

Climate change alters processes that underpin ecosystem structure and overall ecosystem processes in terms of biodiversity. Global warming also results in changes of climate and climate conditions inhabitant affect wastes changing them to unfit small animals and other creatures. This results in changes of species ranges, changes in migratory patterns and phenological changes including, flowering, and breeding (Parmesan & Yohe, 2003). For example, heat sensitive corals bleach which results to loss of their structure and colour and is detrimental to the reef ecosystems (Hoegh-Guldberg, et al. , 2007). Forests, which are recognized to store large amounts of carbon and act as carbon reservoirs, are also vulnerable due to shift in climate conditions that leads to frequent and severe fires, pest / diseases infection (Allen et al. , 2010).

The consequences of climate change are enormous and diverse, and they cover economic aspects of industries, constructions, and people's living. These include hurricanes, floods and droughts which have a negative impact on the economy through property and infrastructure losses and reduced crop yields (Stern, 2006). Low laying areas of the world are at high risks especially the coastal areas, sea level rise which puts population at risk of being displaced and loss of agriculturally productive land (Nicholls & Cazenave, 2010). Also, the agriculture sector has challenges associated with climate change such as change in planting and harvesting seasons and high disease and pest

pressure, which poses risks to food production and insecurity, and the ability of farmers to earn a decent income (Lobell et al. 2008). The cost to adapt and reduce the effect of these impacts adds pressure on the economy especially for the developing countries with scarce resources (Tol, 2018).

Climate change has a very far-reaching and complex effect on health, both the physical and psychological. These heatwaves are on the rise and are prolonged with increased intensity; they cause heat disorders which lead to deaths especially among the most susceptible including the aged, children and those with chronic ailments (Haines et al. , 2006). Weather is also another factor which has an impact on the spread of infectious diseases. For instance, higher temperatures and rainfall variations may help vectors such as mosquitoes to inhabit new areas thus leading to the development of vector borne diseases such as malaria and dengue fever (Patz et al. , 2005). Furthermore, climate change intensifies air pollution which is known to be the cause of respiratory and cardiovascular diseases (Jacob & Winner, 2009). The social factors, which are rarely considered, are stress and anxiety resulting from disasters and consequent displacement, loss of jobs (Berry et al. , 2010).

Climate change also has political ramifications as it affects the social order in different ways. Some of the examples of the negative impacts of natural resources include; many societies face water and food shortage and this can result to conflicts and enmity among the societies (Gleditsch, 2012). Increased sea level and natural disasters as a consequence of climate change results into climate refugees, a burden to the affected individuals and the host communities (Myers, 2002). Also, the process of climate change adaptation and mitigation requires major policy shifts and international cooperation and this entails the intervention of political systems that have to work together for the common good while at the same time safeguarding the interests of their citizens (Ostrom, 2010).

The case provided here and the one availed by the IPCC as well as other analytical institutions, disclose that the world requires immediate and concerted intervention if the effects of climate change are to be minimized. This entails deep decarbonization of societies, utilizing no-s call climate change mitigation option, switch from fossil fuels to cleaner clean energy, sustainable management of land use, and strengthening the resilience of societies as alternatives (IPCC, 2021). To achieve these goals, it is required for all segments of societies and governments and organizations as well as individual stakeholders. The kind of efforts that is required must therefore be one that is Science based and fair as well as one that seeks to ensure that the planet is left intact for the generations to come (Rockström et al. , 2009).

Carbon credits appeared to be an economic instrument to stimulate the decrease of emissions based on the international treaties, for example, the Kyoto Protocol signed in 1997 and the Paris Agreement in 2015. These mechanisms allow entities to realize financial gains from employment, which other wise are considered to be involved in activities that emits or releases carbon. The Kyoto Protocol was the first comprehensive plan of emissions reduction for developed countries; It began using new trading methods such as the clean development mechanism (CDM), and Joint Implementation (JI) in order to achieve emissions reductions most efficiently (United Nations, 1998). Paris added to this schedule and noted the international cooperation in controlling the increase in the planet's average temperature to below two degrees Celsius (UNFCCC, 2015).

The residual frameworks are dedicated for trading carbon credits that are designed to incorporate the environmental sustainability into business and the government's decision-making systems. This approach, over the years, has fostered various projects which include the massive renewable energy projects, reforestation programs, and community-based programs inclined on the protection of forests and sustainable farming (Wissner and Schneider, 2022). For example, carbon credits associated with renewable power

development like wind and solar facilities are earned through replacement of conventional thermal power plants, and thus decreasing the total carbon footprint (REN21, 2021). Conserving CO₂ through reforestation as well as afforestation involves planting trees that remove CO₂ from the ecosystem and as a result reducing the effects of climate change while maintaining and promoting the diverseness of our ecosystems (Pistorius, 2012).

The Role and Expansion of the United Nations Sustainable Development Goals (UN SDG)

The theoretical framework guiding this research draws from **sustainability accounting theory**, which emphasizes the need for businesses and projects to account for their environmental, social, and governance (ESG) impacts. Integrating SDG indicators into carbon credit evaluations ensures that these projects contribute holistically to global sustainability objectives, aligning with broader sustainability accounting principles.

The UN SDGs agreed to in 2015 are a good example of a comprehensive approach to global issues. These 17 goals are comprehensive, and they contain all aspects of sustainable development in terms of the environment, the society, and the economy. Implementations to achieve the goals do not only address climate change (SDG 13) but also do sustainable economic growth (SDG 8), inequalities (SDG 10) ecosystems support (SDG 15) among others (United Nations 2015).

The SDGs were intended to be integrated; it was a good understanding that reaching goals on one area cannot be possible without on the other. For instance, achieving goal 7 which is Affordable and Clean Energy also leads to the realization of goal 13 which is Climate Action since the use of fossil derived energy increases emission of greenhouse gases (Sachs et al. , 2019). However, this has become challenging when

the broad objectives of such initiatives are incorporated into project evaluations and there is need to have methodologies that will measure the various impacts of these projects (Griggs et al. , 2013). This makes evaluation very crucial since it will have to ensure that projects positively impact on as many of the goals as possible without also having negative impacts on other goals.

The UN SDGs offer a holistic framework that extends beyond environmental sustainability to include critical socio-economic objectives, such as poverty reduction (SDG 1), gender equality (SDG 5), and decent work (SDG 8). By aligning carbon credit projects with these SDGs, we can ensure that they contribute to a broad range of global development goals, thereby promoting more inclusive and equitable outcomes.

Challenges in Evaluating Carbon Credit Projects

The assessment of carbon credit projects is most commonly based on carbon reduction numbers and this is mostly because such numbers are easy to measure and are directly connected to climate change issues. The same means quantifying the carbon in the form of CO₂ equivalent (CO₂e) emissions reduced or carbon sequestered is relatively easy and therefore most carbon credit projects have them as core objectives (Olhoff et al. , 2004). But it neglects other effects may happen around a project, for example some citizens might lose their habitat or their land to the project implementers (Gabbi et al. , 2015).

For instance, the mega-scale renewable energy generation may result to social issues like the displacement of the local people and social cultures leading to change the livelihood (McDermott et al. , 2012). Likewise, there is a possibility of land tenure problems affecting reforestation where tree plantations are erected on communal land thus displacing local people and giving room to other people (Corbera & Brown, 2010). These issues have led to debates on the effectiveness and social responsibility of carbon credit projects hence leading to the calls for better assessment methods.

An importantly growing consideration is that the ongoing process of carbon credit project assessment needs to take into account not simply the environmental goals of the project but also the social and economic consequences of their actions (Boyd et al. , 2007). This entails identifying more effective methods of measuring more and diverse sustainability indicators, as well as the UN SDGs indicators, to maximise the usefulness, effectiveness and impact of projects and programs for catering for sustainable needs in the longer term and in a sustainable pattern (Rawhouser and Cummings, 2019).

Key features of change is the emergence and further growth of the mechanisms of carbon credits, as well as the inclusion of the principles of the UN SDGs. That said, it is not easy to assess these projects, a fact that speaks to the need to establish all-encompassing and participative methods in analyzing the impact of different sustainability aspects. In response to such concerns, the Gen AI Auditor was developed to employ the help of AI in supplementing the evaluations of carbon credit projects and to guarantee that such projects operate for more multifaceted sustainable development goals.

As we will note, the typical methods of current analysis have been characterized with some key shortcomings hence the emerging demands for a more expanded set of sustainability metrics, of which the UN SDGs are an example. More conventional analyses of carbon credits have been known to consider only the purely environmental impacts, for example, the ‘tonnes of CO₂ avoided’. Though these are useful indicators by which the direct effects of contributions towards climate change mitigation can be measured, they do not incorporate many other aspects that such a project can present to the local and global society.

It has been seen that there is increased realization among the researchers, policy makers and practitioners regarding the developing global consensus on the need to have a more comprehensive carbon credit assessment. This entails not just the evaluation of the

costs and impacts of the environment, but also the benefits of the society and economy for example through employment, improved health, and innovation of survival mechanisms (Rawhouser & Cummings, 2019). For example, a renewable energy project might have a positive impact on both the environment by cutting down carbon emission and accessibility to clean energy for the less privileged as will address SDG 7 and SDG 10 respectively.

The integration of the SDG into these assessments could go a long way in providing an insight of how such projects will benefit the society bearing in mind the intended sustainable development goals in as much as to ascertain if the gains are real and sustainable. The swot analysis focuses on the integrated nature of the sustainability problems because the environmental, social and the economic problems cannot be solved separately (Griggs et al. , 2013).

As a response to these challenges, the Gen AI Auditor suggests creating a new approach for evaluating carbon credit projects with the use of artificial intelligence to improve the efficiency of fundamental assessments. This is done systematically in the Gen AI Auditor where the UN SDGs are integrated into the assessment and checking of the impacts of a project.

This tool is powered by artificial intelligence and the functions of natural language processing and machine learning to parse through descriptions of projects and project performance reports and other documents. In this way, it can confirm the alleged part in achieving the certain indicators of the SDGs, as well as (potential) weak points. Another feature that is incorporated within the design of the Gen AI Auditor is prompt engineering to focus in on the auditor's work and to ensure the AI model is providing precise and semantically appropriate results (Lou, 2020).

There are several benefits with the Gen AI Auditor tool and the first one is the real-time of the performance and the conformance. This capability provides improved accuracy and increased credibility in reporting which in turn helps project developers and stakeholders in making better decision. For instance if a project purports to address SDG 13: Climate Action and SDG 8: Decent Work and Economic Growth categories, the Gen AI Auditor is capable of mirroring these indicators with performance figures and determine whether the reported impact is valid (Welfle & Röder, 2022).

Also, the Gen AI Auditor promotes feedback-seeking by providing suggestions on how project-related information can be utilised to improve conformity with the goals of the SDGs. This feedback loop is important to consider in raising any dispute arising out of reporting and to ensure that project developers improve on the standards on sustainability (Schneider, 2007). Thus, the Gen AI Auditor contributes to filling the gap in the integration of social and environmental responsibilities for carbon credit projects as well as revealing socially important changes and challenges.

The commitment of the UN SDGs into carbon credit assessments is, therefore, a step up in sustainability measures. Through implementing this comprehensive approach, the view of the Gen AI Auditor bring the focus to the relation between environmental and social impacts of carbon credit projects with the aspiration to contribute to the full set of sustainable development goals. This methodology further increases the reliability of sustainability reporting which enables stakeholders to have increased trust in organizational environmental efforts and leads to better and effective environmental measures. The use of such AI tools is central to supporting the international processes in the sphere of sustainable development and climate change that strive to coordinate economic processes and policy goals that are to enhance earth's sustainable development.

1.3.Aims

This research aims to develop a comprehensive framework that integrates the United Nations Sustainable Development Goals (UN SDGs) into the evaluation of carbon credit projects. This framework will facilitate a holistic assessment of these projects, considering their environmental impacts and their social and economic benefits. The traditional focus on quantifying carbon reductions has proven inadequate, as it often overlooks the broader implications of these projects on local communities and ecosystems. By incorporating the UN SDGs, this research aims to provide a more balanced and inclusive approach to evaluating the efficacy and sustainability of carbon credit projects.

The lack of a comprehensive evaluation framework limits the ability of stakeholders to fully assess the broader impacts of carbon credit projects. For example, without tools to quantify social impacts, policymakers may overlook projects that, while effective in reducing emissions, fail to deliver meaningful socio-economic benefits to local communities.

The main aim of this study is to contribute to determining social cost calculation by building a proper system to facilitate statistical modelling. This systematic approach is a data-driven way to create a social framework, including modelling to calculate the social impact and cost.

1. Extensive Analysis of UN SDGs.
2. Generate quantitatively matrix from UN SDGs
3. Convert the social impact to a quotative number.
4. Apply statistical modelling to predict social costs.
5. Create a rule-based monitoring system to check the claimed UN SDG against the project description

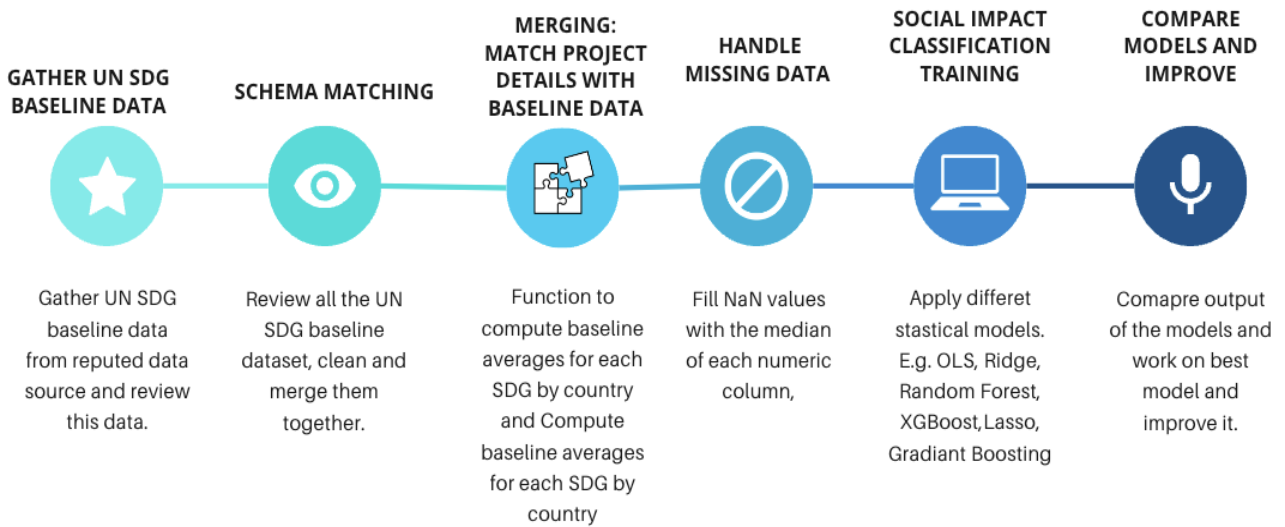


Figure 1.1 : Proposed Solution to Social Cost

Developing a Comprehensive Evaluation Framework

The first objective of this research is to create an evaluation framework that systematically incorporates the UN SDGs into the assessment process of carbon credit projects. The UN SDGs, adopted in 2015, encompass 17 goals that address global challenges across environmental, social, and economic dimensions. These goals include climate action (SDG 13), sustainable economic growth (SDG 8), reduced inequalities (SDG 10), and support for ecosystems (SDG 15), among others. By aligning the evaluation framework with these goals, the research seeks to move beyond traditional environmental considerations and provide a more balanced view of project impacts.

To achieve this, the framework will identify specific SDG indicators that reflect the social and economic impacts of carbon credit projects. These indicators will be used to measure the broader outcomes of these projects, such as improvements in community health, economic development, and social equity. This comprehensive approach aims to enhance the transparency and accountability of carbon credit projects, ensuring that they deliver genuine, long-lasting benefits aligned with global sustainability targets.

Designing and Validating Statistical Models

The second objective focuses on designing robust statistical models to quantify and predict the social impacts of carbon credit projects. Traditional evaluation methods often rely on simple metrics that fail to capture the complex interactions between environmental, social, and economic factors. To address this limitation, the research will utilize a combination of statistical analysis and machine learning techniques to develop more sophisticated models.

These models will be designed to analyze a wide range of data, including project descriptions, baseline data on UN SDGs, and other relevant indicators. By uncovering the nuanced effects of carbon credit projects on local communities and ecosystems, the models will enhance the precision of impact predictions. This will facilitate better strategic planning and optimization of carbon credit projects, enabling project developers to maximize their social benefits while meeting environmental targets.

The validation of these models is a critical aspect of this objective. The research will employ rigorous testing methods to ensure the accuracy and reliability of the models. This includes cross-validation techniques, performance metrics such as mean squared error (MSE) and R-squared (R^2), and comparison with baseline data. The goal is to develop models that can provide reliable predictions of social impacts, thereby supporting more effective decision-making in the planning and implementing carbon credit projects.

Establishing a Gen AI Auditor System

As the global carbon market evolves, the need for more comprehensive evaluation frameworks becomes increasingly apparent. This research addresses that need by incorporating AI technologies, such as the Gen AI Auditor, into the evaluation of carbon credit projects against a broader set of socio-economic and environmental goals."

The third objective introduces the development of a cutting-edge Generative AI (Gen AI) Auditor system. This system uses artificial intelligence to rigorously verify the UN SDG contributions claimed by carbon credit projects. The need for such a system arises from the challenges associated with ensuring the accuracy and transparency of project reporting. Traditional verification methods often involve manual audits that can be time-consuming, costly, and prone to human error.

The Gen AI Auditor system aims to address these challenges by leveraging advanced AI technologies to automate the verification process. The system will analyze project reports, performance metrics, and compliance documents to determine whether the reported contributions to the UN SDGs are accurate and substantiated. This involves using natural language processing (NLP) techniques to interpret and analyze textual data, as well as machine learning algorithms to identify patterns and anomalies in the data.

The Gen AI Auditor leverages natural language processing and machine learning to automate the verification of SDG claims. Unlike traditional manual verification methods, AI enables scalable and real-time assessments, significantly reducing the risk of human error and increasing the transparency and accuracy of sustainability reporting.

By leveraging AI, specifically through the development of the Gen AI Auditor, this research aims to automate the process of verifying the contributions of carbon credit projects to the UN SDGs. This AI-driven tool will analyze project data in real-time, offering a more efficient and accurate way to ensure that projects genuinely contribute to both environmental and socio-economic goals.

One of the key innovations of the Gen AI Auditor system is its ability to provide real-time feedback to project developers. By identifying discrepancies and inconsistencies in the reported data, the system can alert developers to potential issues

and recommend corrective actions. This feedback loop enhances the accuracy and reliability of project reporting, fostering greater transparency and accountability.

The implementation of the Gen AI Auditor system also aims to build trust among stakeholders, including project developers, local communities, and investors. By ensuring that projects can provide accurate information regarding their contributions to the UN SDGs, the system helps to maintain the credibility of the carbon market. This, in turn, encourages greater investment in carbon credit projects and supports the broader goals of sustainable development.

Anticipated Outcomes

By achieving these objectives, the research anticipates several significant outcomes. First, the development of a comprehensive evaluation framework will enable more accurate and inclusive assessments of carbon credit projects. This framework will provide a clearer picture of the broader social and economic impacts of these projects, helping to ensure that they contribute to sustainable development in meaningful ways.

Second, the design and validation of robust statistical models will enhance the precision of impact predictions. These models will support more effective strategic planning and optimization of carbon credit projects, enabling project developers to maximize their social benefits while meeting environmental targets. The use of advanced statistical and machine learning techniques will also contribute to the broader field of environmental modeling and prediction.

Third, the implementation of the Gen AI Auditor system will improve the accuracy and transparency of project reporting. By automating the verification process, the system will reduce the costs and time associated with manual audits, while also

minimizing the risk of human error. This will foster greater trust among stakeholders and encourage greater investment in carbon credit projects.

Finally, the research aims to support policy-making that fosters more equitable and effective carbon credit initiatives. By providing a comprehensive evaluation framework and robust statistical models, the research will inform the development of policies that promote both environmental sustainability and social equity. This, in turn, will contribute to the broader goals of sustainable development and climate policy.

1.4. Research Problems

Problem 1: Quantifying Social Costs of Carbon Credit Projects

While the primary objective of carbon credit projects is to reduce greenhouse gas emissions, there is a significant gap in systematically quantifying their social impacts. Current methodologies predominantly focus on carbon reduction metrics, which often overlook the broader social implications of these projects. This research aims to bridge this gap by developing a comprehensive framework that integrates UN Sustainable Development Goals (SDGs) into the evaluation of carbon credit projects, ensuring a holistic assessment that includes social, economic, and environmental impacts.

Problem 2: Verifying UN SDG Contributions

The integrity of carbon credit projects is frequently questioned due to the lack of a standardized system for verifying claimed contributions to the UN SDGs. Many projects report their alignment with SDGs without a robust mechanism to validate these claims, leading to potential misinformation and reduced trust among stakeholders. This research proposes the development of an LLM-powered Gen AI Auditor that leverages prompt engineering to assess and verify the UN SDG claims of carbon credit projects, ensuring transparency and accountability.

Problem 3: Integrating Social and Environmental Impact Assessments

Existing models for evaluating carbon credit projects tend to focus either on environmental benefits or social impacts but rarely integrate both dimensions. This lack of integrated assessment tools makes it difficult to capture the full spectrum of a project's contributions to sustainable development. The research seeks to create an interdisciplinary framework that simultaneously evaluates the social and environmental benefits of carbon credit projects, providing a more comprehensive understanding of their overall impact.

Problem 4: Lack of Standardized Monitoring Systems

There is an absence of standardized, rule-based monitoring systems to continuously verify and validate the claims made by carbon credit projects regarding their contributions to the UN SDGs. The existing ad-hoc approaches to monitoring are insufficient for ensuring consistent and reliable evaluation. This study aims to establish a rule-based monitoring system powered by generative AI to provide consistent, objective, and scalable assessment of carbon credit projects.

Problem 5: Enhancing Decision-Making through Data-Driven Insights

Decision-making in carbon credit markets is often hampered by the lack of reliable data and robust analytical tools that can predict the social and environmental impacts of projects. By employing statistical models and machine learning techniques, this research aims to provide data-driven insights that enhance the decision-making processes for policymakers, investors, and other stakeholders, ensuring that projects contribute effectively to the UN SDGs.

1.5. Research Question

The pressing global challenge of climate change has spurred numerous initiatives aimed at reducing greenhouse gas emissions. Carbon credit projects have emerged as a vital tool in this Endeavor, providing market-based incentives for reducing carbon footprints. However, these projects must be evaluated not only for their environmental

benefits but also for their broader social and economic impacts. The integration of the United Nations Sustainable Development Goals (UN SDGs) into the assessment of carbon credit projects presents a promising approach to achieving this comprehensive evaluation. This chapter delineates the central research question and sub-questions that guide this study, aiming to develop advanced AI-driven frameworks for evaluating and verifying the contributions of carbon credit projects to the UN SDGs.

Main Research Question

“How can artificial intelligence be leveraged to integrate the United Nations Sustainable Development Goals (UN SDGs) into the evaluation and verification of carbon credit projects, enhancing the accuracy, transparency, and accountability of sustainability reporting?”

This primary question captures the essence of the research objectives, focusing on the comprehensive integration of UN SDGs into the assessment of carbon credit projects. The aim is to develop methodologies that utilize these global goals as quantifiable metrics, thereby providing a thorough evaluation framework that includes environmental, social, and economic impacts.

Sub-Questions:

To address the main research question, several sub-questions have been formulated:

1. What are the key indicators from the UN SDGs that can be used to evaluate the social impacts of carbon credit projects?

- Objective: Identify and define specific indicators from the UN SDGs that are relevant to the evaluation of carbon credit projects.
- Rationale: This question seeks to establish relevant SDG indicators that can be integrated into the evaluation framework, ensuring a holistic assessment of carbon credit projects.

2. How can statistical models be developed and validated to quantify and predict the social impacts of these projects?

- Objective: Create and validate statistical models that quantify and predict the social impacts of carbon credit projects using statistical analysis and machine learning techniques.
- Rationale: By developing robust statistical models, this research aims to provide tools for stakeholders to better understand and predict the social outcomes of these projects, thereby enhancing planning and implementation strategies.

3. What AI technologies and methodologies are most effective in automating the verification of UN SDG contributions in carbon credit projects?

- Objective: Investigate and implement AI technologies, particularly natural language processing (NLP) and machine learning algorithms, to automate the verification process.
- Rationale: This question addresses the need for reliable and efficient systems to verify the claims made by carbon credit projects regarding their contributions to the UN SDGs, enhancing transparency and accountability.

4. How can the Gen AI Auditor system be designed and implemented to provide real-time performance metrics and compliance evaluations?

- Objective: Design and implement the Gen AI Auditor, a chatbot-based system that automates the verification of UN SDG contributions, utilizing prompt engineering with ChatGPT-4.
- Rationale: The Gen AI Auditor aims to provide real-time analysis and feedback, ensuring that carbon credit projects genuinely contribute to sustainable development goals.

1.6. Research Objective

This research aims to develop a comprehensive and robust framework for evaluating the social impacts of carbon credit projects, integrating the United Nations

Sustainable Development Goals (UN SDGs) into this evaluation. This framework will leverage advanced artificial intelligence (AI) technologies, particularly ChatGPT-4 with prompt engineering, to enhance the accuracy, transparency, and accountability of sustainability reporting. The specific research objectives are as follows:

- 1) Develop an Integrated Evaluation Framework:
 - a) Objective: To design a structured and holistic framework that incorporates UN SDG indicators into assessing carbon credit projects.
 - b) Rationale: Current evaluation methodologies focus primarily on environmental metrics, neglecting broader social impacts. By integrating SDG indicators, the framework will provide a more balanced view of project contributions to sustainable development.
- 2) Identify Key Indicators from the UN SDGs:
 - a) Objective: To identify and define specific UN SDG indicators relevant to evaluating carbon credit projects.
 - b) Rationale: Establishing relevant indicators is crucial for ensuring that the evaluation framework captures these projects' social, economic, and environmental impacts.
- 3) Design and Validate Statistical Models:
 - a) Objective: To create and validate statistical models that quantify and predict the social impacts of carbon credit projects using statistical analysis and machine learning techniques.
 - b) Rationale: Developing robust statistical models will provide stakeholders with tools to understand better and predict social outcomes, enhancing planning and implementation strategies.
- 4) Develop the Gen AI Auditor System:

- a) Objective: To introduce and implement the Gen AI Auditor, a chatbot-based system that automates the verification of UN SDG contributions in carbon credit projects, utilising prompt engineering with ChatGPT-4.
 - b) Rationale: The Gen AI Auditor will provide real-time analysis and feedback, ensuring that carbon credit projects contribute to sustainable development goals and enhance transparency and accountability.
- 5) Enhance Verification Processes:
- a) Objective: To establish a rule-based monitoring system to verify the alignment of carbon credit projects' claimed UN SDG contributions with actual project outcomes.
 - b) Rationale: This system will address the need for reliable verification processes, reducing misinformation and increasing stakeholder trust.

The formulated research questions and their corresponding objectives are designed to address the significant gaps identified in the literature. By focusing on integrating UN SDGs into the assessment of carbon credit projects' social impacts, the research aims to develop methodologies and tools that enhance the transparency, accountability, and effectiveness of these projects. This comprehensive approach is expected to contribute to the broader goals of sustainable development and climate action.

1.7.Methodology Overview

The methodology for this research is designed to create a comprehensive framework for evaluating the social impacts of carbon credit projects, incorporating the United Nations Sustainable Development Goals (UN SDGs). This involves leveraging advanced artificial intelligence (AI) technologies, particularly ChatGPT-4 with prompt engineering, to improve the accuracy, transparency, and accountability of sustainability reporting. The research methodology consists of several key phases, each involving

specific activities and processes to achieve the research objectives. These phases are outlined below.

The methodology for this research is designed to create a comprehensive framework for evaluating the social impacts of carbon credit projects, incorporating the United Nations Sustainable Development Goals (UN SDGs). This involves leveraging advanced artificial intelligence (AI) technologies, particularly ChatGPT-4 with prompt engineering, to improve the accuracy, transparency, and accountability of sustainability reporting. The research methodology consists of several key phases, each involving specific activities and processes to achieve the research objectives. These phases are outlined below.

Phase 1: Literature Review and Theoretical Framework

Objective: Establish a solid theoretical foundation for the research by gathering and synthesizing existing knowledge on carbon credit projects, UN SDGs, social impact assessment, and AI technologies.

- **Literature Review:** Conduct an extensive review of academic papers, industry reports, policy documents, and case studies. This review will cover topics such as carbon credit mechanisms, the role of UN SDGs in sustainability, social impact assessment methodologies, and the application of AI in sustainability reporting.
- **Theoretical Framework:** Develop a theoretical framework that integrates insights from the literature review to guide the subsequent phases of the research.

Phase 2: Data Collection and Pre-processing

Objective: Gather and pre-process data required for developing and validating the evaluation and verification models.

- **Data Sources:** Collect data from various sources, including Core Markets, project developers, third-party evaluators, and publicly available datasets. Data will include

project descriptions, performance reports, social impact assessments, and relevant UN SDG indicators.

- **Data Cleaning:** Perform data cleaning to handle missing values, outliers, and inconsistencies, ensuring the data is accurate and suitable for analysis.
- **Data Integration:** Integrate data from different sources to create a unified dataset that aligns project details with SDG indicators. This involves merging datasets, normalizing values, and engineering features.

Phase 3: Development of Statistical and AI Models

Objective: Create and validate statistical and AI models that quantify and predict the social impacts of carbon credit projects and verify their contributions to the UN SDGs.

- **Statistical Model Development:** Develop statistical models, such as linear regression, logistic regression, random forests, and gradient boosting, to integrate identified variables and compute social impacts.
- **AI Model Development:** Utilize AI technologies, particularly natural language processing (NLP) and machine learning algorithms, to automate the verification of UN SDG contributions. Develop the Gen AI Auditor, a chatbot-based system using ChatGPT-4, to analyze project data and provide real-time verification.
- **Model Validation:** Conduct cross-validation and sensitivity analysis to ensure the accuracy and reliability of the developed models, testing them on different datasets.

Phase 4: Development of the Gen AI Auditor System

Objective: Design and implement the Gen AI Auditor system to automate the verification of UN SDG contributions in carbon credit projects.

- **System Design:** Design the architecture of the Gen AI Auditor, including its components and interactions. Develop a user-friendly interface for project developers and evaluators to input data and receive real-time analysis and feedback.

- **Prompt Engineering:** Utilize prompt engineering with ChatGPT-4 to develop effective prompts and templates for the Gen AI Auditor. Design prompts to guide the AI in assessing project data and verifying UN SDG contributions.
- **Implementation and Testing:** Implement the Gen AI Auditor system and conduct extensive testing to ensure its accuracy and reliability. Evaluate the system's performance on different datasets and assess its ability to provide accurate verification of UN SDG claims.

Phase 5: Data-Driven Insights for Policy and Decision-Making

Objective: Provide policymakers and project developers with reliable and comprehensive tools for evaluating the impacts of carbon credit projects.

- **Data-Driven Insights:** Offer data-driven insights to enhance decision-making processes for policymakers, investors, and other stakeholders. These insights will be derived from the developed statistical and AI models, providing practical recommendations for policy decisions and the development of more equitable and effective carbon credit projects.
- **Policy Recommendations:** Provide practical recommendations for policy decisions based on the findings from the data-driven insights and validated models.

The methodology above provides a comprehensive approach to developing, implementing, and validating a robust framework for evaluating the social impacts of carbon credit projects, integrating the UN SDGs. By leveraging advanced AI technologies and incorporating rigorous data analysis and validation processes, this research aims to enhance the accuracy, transparency, and accountability of sustainability reporting in the carbon credit market. The results of this research are expected to contribute significantly to the broader goals of sustainable development and climate action.

While both the statistical modelling framework and the Gen AI Auditor address aspects of evaluating project performance, they operate as separate analytical pathways. The statistical model is designed to estimate the social impact score based on verified SDG-related project details. The Gen AI Auditor, by contrast, functions as a standalone verification tool for SDG claims, using generative AI and rule-based prompt engineering to assess the plausibility and alignment of claims with the UN SDG framework. Importantly, the social impact score from the statistical model is **not** used as an input, threshold, or decision criterion within the Gen AI Auditor. This separation ensures that SDG claim verification remains an independent exercise, reducing the risk of circular reasoning. The direction of dependency is one-way: verified SDG claims inform the calculation of social impact, but the statistical outputs do not influence the claim verification process.

Although the Gen AI Auditor provides avenues for scaled automation of SDG claim verification, there are very important ethical issues when implementing this tool that need to be taken into consideration at the outset. These include the potential for biased training data - there is a risk where bias may occur in his training data if descriptions of projects are not equally distributed across geographies, sectors, and claim types. If this is true, it could yield skewed results in audits. Relatedly, to achieve fairness in audits, we need to provide a clear design around the rules and prompts behind the audit, and we need to ensure the model is consistent across similar inputs. To diminish risk in using the Gen AI Auditor we put forth a human-in-the-loop review process to allow domain experts to validate decisions raised as red flags, fine-tune prompt designs, and monitor edge cases. This facilitates accountability and avoids the risk of interpreting the outputs of the model through a lens where the model is inferred as being a replacement for human judgement. In addition, we will also periodically assess model

performance on fairness, accuracy, and transparency metrics in order to track, discover, and mitigate emerging biases over time.

1.8. Justification of Thesis

Addressing climate change is critical due to its significant impacts on ecosystems, economies, and communities globally. Carbon credit mechanisms are crucial in mitigating these effects by incentivizing emission reductions. However, existing evaluation methods focus primarily on environmental metrics, often overlooking social and economic impacts. This thesis seeks to fill this gap by integrating United Nations Sustainable Development Goals (UN SDGs) into the evaluation framework of carbon credit projects. The justification for this research includes:

- **Comprehensive Evaluation:** By integrating UN SDGs, the research aims to provide a balanced evaluation framework that captures environmental, social, and economic impacts.
- **Enhanced Transparency and Accountability:** The Gen AI Auditor, developed using ChatGPT-4 with prompt engineering, ensures accurate and substantiated SDG claims, fostering greater trust among stakeholders.
- **Support for Policy and Decision-Making:** The data-driven insights and tools developed through this research will support policymakers, project developers, and stakeholders in making informed decisions, leading to more equitable and effective carbon credit projects.
- **Contribution to Sustainable Development:** Aligning carbon credit evaluations with global sustainability goals promotes better decision-making and ensures that carbon credit projects deliver genuine, long-lasting benefits to communities and the environment.

1.9. Organisation of The Thesis

This thesis is organized into several chapters, each building on the previous one to provide a comprehensive understanding of the research objectives, methods, and findings. The organization ensures a logical flow of information, guiding the reader through the research process from introduction to conclusion. Below is an overview of what each chapter will cover:

Chapter 1: Introduction

The introduction sets the context for the research by discussing the urgent need to address climate change and the role of carbon credit mechanisms in mitigating greenhouse gas emissions. It emphasizes the importance of evaluating the social impacts of these projects and introduces the concept of integrating UN SDGs into the assessment framework. This chapter outlines the key issues, research problems, questions, and objectives, providing a foundation for the subsequent chapters.

Chapter 2: Literature Review

The literature review provides a comprehensive overview of existing research relevant to the study. It covers the historical development of carbon credit mechanisms, the role of UN SDGs in sustainability reporting, and the current methodologies for evaluating carbon credit projects. This chapter identifies gaps in existing research and highlights the need for integrated evaluation frameworks that encompass environmental, social, and economic dimensions.

Chapter 3: Quantification of Social Impact in Carbon Credit Project

This chapter is divided into several sub-chapters, each focusing on specific aspects of the research methodology:

Chapter 3.1: Research Methodology and Significance

Our research focuses on carbon credit projects' qualitative and quantitative impacts on communities. The chosen methodology leverages qualitative and quantitative methods, aligning well with our objectives to capture comprehensive, real-world consequences. This dual approach allows us to gather detailed insights

into community experiences and project outcomes, providing a rich dataset for analysis.

Chapter 3.2: Data Collection and Preprocessing

This section details the process of collecting and preprocessing data for the research. It describes the datasets used, including Core Market data and project details. The section discusses steps to clean, merge, and prepare the data for analysis, including handling missing values, normalisation, and feature engineering.

Chapter 4: Rule-Based Monitoring System

This chapter is divided into several sub-chapters, each focusing on specific aspects of the research objectives:

Chapter 4.1: Statistical Modelling and Machine Learning Approaches

This sub-chapter focuses on developing and validating statistical models and machine learning algorithms for quantifying and predicting the social impacts of carbon credit projects. It includes the selection of variables, model training, and performance metrics. This section also discusses applying models to predict future social impacts and carbon credit prices, comparing model performance, and selecting the best model.

Chapter 4.2: Rule-Based Monitoring System and AI Gen Tool

This chapter details the development and implementation of a rule-based monitoring system. It discusses how the system verifies the claimed UN SDG contributions of carbon credit projects, integrates project data, and uses machine learning for cross-verification. The chapter covers the system's implementation and testing with real project data, evaluating its accuracy and reliability. The integration with language models to enhance the auditing process is also

elaborated on, emphasizing the innovative approach to ensuring transparency and accountability in sustainability reporting.

Chapter 5: Summary, Findings, and Conclusion

This chapter presents the key findings from the research, discussing the main results from the three research objectives. It interprets social impact scores, model performance, and validation outcomes. The chapter also discusses the implications of the findings for policymakers, market participants, and stakeholders, examining how the findings align with or diverge from existing literature. Additionally, it addresses any limitations encountered during the research and suggests potential areas for improvement in future studies. The chapter concludes by summarizing the overall findings and contributions of the research, providing recommendations for future research directions, and reflecting on the significance of the study.

Chapter 2 : Literature Review

2.1 Introduction

The previous chapter sought to introduce the topic of carbon credits, its life cycle, and what kind of improvement is necessary in this structure. The literature reviewed in this chapter discusses the problems associated with the Carbon Credit life cycle. The literature review is the starting point for understanding what we already know and where we need more research in evaluating carbon credit projects, especially regarding the UN Sustainable Development Goals (SDGs). It looks at current methods, our challenges, and new advancements, paving the way for a new AI-driven approach to evaluate these projects. This review combines environmental science, artificial intelligence, and socioeconomic impacts, emphasising the need for a comprehensive way to evaluate carbon credit efforts.

Tackling climate change is now a major global priority, and carbon credit projects are crucial for encouraging the reduction of greenhouse gas emissions. Traditionally, these projects were judged mainly by their environmental benefits, but it's increasingly recognized that we also need to look at their social and economic impacts. By integrating the UN Sustainable Development Goals into these evaluations, we're moving towards a more holistic way of assessing the overall effectiveness of these projects.

In this thesis, *social impact* refers to the overall effect of a carbon credit project on society, encompassing both qualitative outcomes (e.g., community well-being, education, health) and quantitative outcomes (e.g., economic benefits or losses). When these impacts are expressed in monetary terms, they are referred to as *social cost* — representing the net economic valuation of the project's externalities, whether positive or negative. In other words, social cost is the quantified, economic expression of the broader social impact. This approach allows the research to assess social impact qualitatively

where appropriate, while also enabling integration of a quantified, monetary metric into statistical models and pricing frameworks.

AI has undeniably opened up opportunities to improve the assessment of sustainability metrics. However, the deployment of AI has many challenges. Poor data quality, low explainability of model outputs (model interpretability), and the lack of robust human governance processes are risks that can all prevent AI assessing credibly. For example, bias in the input data would provide biased outputs, while using a black-box model using hybrid AI might be detrimental to trust and acceptance by regulators. It is therefore, prudent to adopt explainable AI approaches and build governance structures to validate human oversight, ethical safeguards, and accountability. Identifying weaknesses from the outset can help create more balanced and reliable AI resources for sustainability.

This literature review will encapsulate the current state of research and critically analyse where further innovation and investigation are necessary. By aligning the evaluation of carbon credit projects with broader sustainability goals through advanced AI technologies, this review sets a precedent for future research in environmental policy and project assessment.

While the environmental impacts of carbon credit projects have been the primary focus of many studies, the integration of broader socio-economic dimensions—particularly through the United Nations Sustainable Development Goals (SDGs)—remains underexplored. This gap highlights a critical need for frameworks that assess not only carbon reduction but also the socio-economic outcomes of these projects. The next section will delve into the limitations of current evaluation methodologies, demonstrating the necessity for a more comprehensive and data-driven approach to carbon credit assessments.

Using the systematic review methodology that Kitchenham and Charters suggested (Kitchenham & Charters,2007), The purpose of this review is to

improve the research's reproducibility. The goal of this evaluation is to locate and assess every piece of literature that addresses the social impact and cost of carbon credit initiatives.

The following subsections contain a list of the steps in this systematic review protocol:

- Step 1: Search protocol
 - In this step, key word concepts are defined and the types of sources to collect research data are determined.
- Step 2: Inclusion and Exclusion criteria
 - The population, sample, and setting criteria serve as the guidelines which surround the search and help to identify the valuable research.
- Step 3: Study Selection Process
 - In this step, studies that meet the requirements in step 2 are chosen to be included in the review.
- Step 4: Data Extraction
 - Following review, data is taken from the included research.

2.2 Search Protocol:

This study attempts to cover and review every pertinent paper in the literature, as is the goal of any systematic literature review (SLR). We looked online for any further relevant publications in the four scientific databases listed below. These databases were chosen because they offer good coverage for the pertinent literature and are well-known in the field of engineering study.

- I. Scopus (<https://www.scopus.com/search/form.uri?display=basic>)
- II. IEEE Xplore (<https://ieeexplore.ieee.org/>)
- III. SpringerLink (<https://link-springer-com.ezproxy.lib.uts.edu.au/>)

IV. ACM Digital Library (<https://dl-acm-org.ezproxy.lib.uts.edu.au/>)

Table 1 provides a list of all the keywords employed to conduct this search for related literature. The following search terms were derived from the research questions. The hypothesis underpinning the organisation of the Three categories were used in the search process: the first dealt with the social impact of carbon credits, and the second dealt with how to compute social cost.

To maximise the search results, we employed brackets, the Boolean operators "AND," and "OR." In order to achieve maximum coverage, Most search terms are composed of two components. The union of equivalent phrases (joined by "OR") is the first component. The union of words mainly associated with the three categories given in Table 1 is included in the second section.

Table 2. 1: Search categories and keywords used in this review

Search Category	Keywords
Social Impact of carbon credit or social impact caused by carbon reduction or carbon credit projects	((social impact) OR (social development)) AND ((carbon credit project) OR (carbon emission project) OR (carbon reduction project))
Calculate social cost	(Calculate social cost) and (carbon credit project)

2.3 Inclusion and Exclusion Criteria:

The selection of papers for the review has been based on the inclusion and exclusion criteria. The inclusion and exclusion processes were made according to the following listed factors.

Inclusion Criteria

1. Does the article offer a way to choose a robot for a certain job, like “how to calculate social impact or social cost of carbon credit project or carbon reduction projects”?
 - This criterion ensures that the selected articles directly address the research question of calculating the social impact or social cost of carbon credit projects and provide a systematic approach or solution.
2. Does the article propose a solution to quantify the social cost of carbon credit?
 - Articles that offer solutions for quantifying the social cost of carbon credits are relevant to your research and should be included.
3. Is the full text available and written in English?
 - Including articles with full-text availability in English ensures accessibility and language consistency in your review.
4. Is the article academic and subject to peer review?
 - Peer-reviewed articles are a hallmark of academic rigour. Including only scholarly, peer-reviewed articles ensures the quality and reliability of the sources.
5. Does the article provide information regarding social impact or carbon credit platform?
 - Articles that discuss the social impact or platforms related to carbon credit projects are valuable for gaining insights into the topic and should be included.

Exclusion Criteria

1. Non-English papers.

- The exclusion of non-English papers is essential to maintain language consistency within the systematic literature review. Conducting the review exclusively in English ensures that the research team can effectively understand, analyse, and synthesise the findings from the selected studies. While valuable research may be published in other languages, focusing on English-language papers helps ensure accessibility for a broader audience and facilitates seamless communication of the review's results.
2. Articles with no published or accessible full text.
- Excluding papers for which the full text is unavailable or published is a practical necessity for conducting a comprehensive review. Access to the complete content of selected documents is crucial for in-depth analysis, verification of data and methods, and the synthesis of findings. Research-based on abstracts or incomplete information may need more details to contribute effectively to the systematic review.
3. Duplicate papers of the same study.
- Eliminating duplicate papers representing the same study is fundamental to maintaining the review's integrity and avoiding redundancy. Duplicate publications can distort the perceived quantity of evidence on a particular topic, potentially leading to biased conclusions. By excluding duplicates, the review ensures that each unique study is considered only once, preventing over-representation, and providing a more accurate representation of the available literature.

2.4 Study Selection Process

268 papers were obtained from the databases under investigation using the search parameters specified in section 2.1; one of these was eliminated because it

was duplicated. The remaining 267 publications have undergone a second filtering procedure based on the article titles. Excluded were studies with unrelated tags. The abstracts of all 112 research were examined at the third filtration step in order to determine the publications' eligibility. This filtration stage produced just 30 studies. Examining the study introduction served as the foundation for the final filtering procedure. Ultimately, as Figure 3 illustrates, 14 research were approved for this evaluation. Figure 4 visualises the exact numbers of accepted and rejected papers. Compared to other databases, Scopus and Springer have been the most resourceful, while ACM has delivered the least relevant paper, as illustrated in Figures 5(a) and (b).

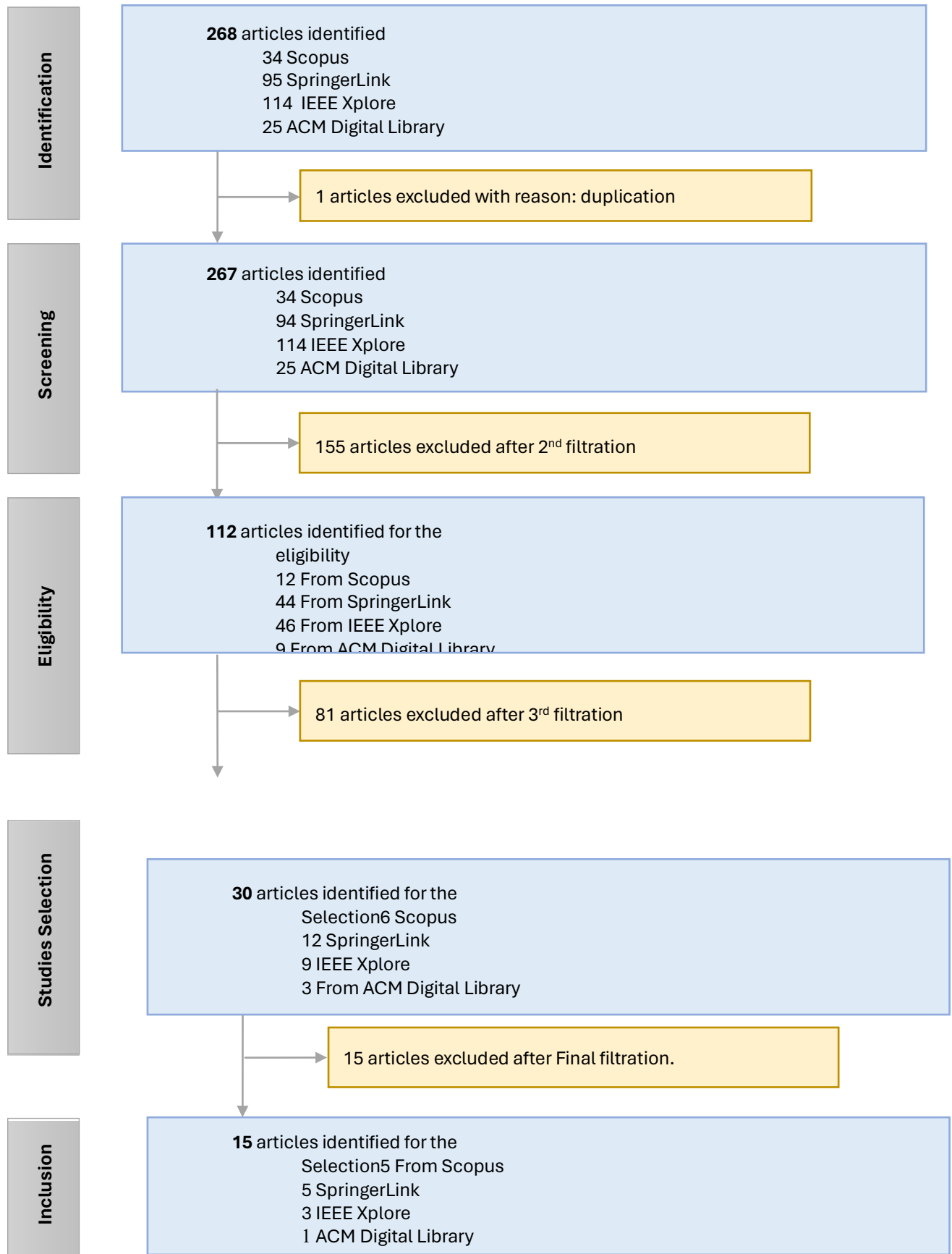


Figure 2. 1.: Process of study selection

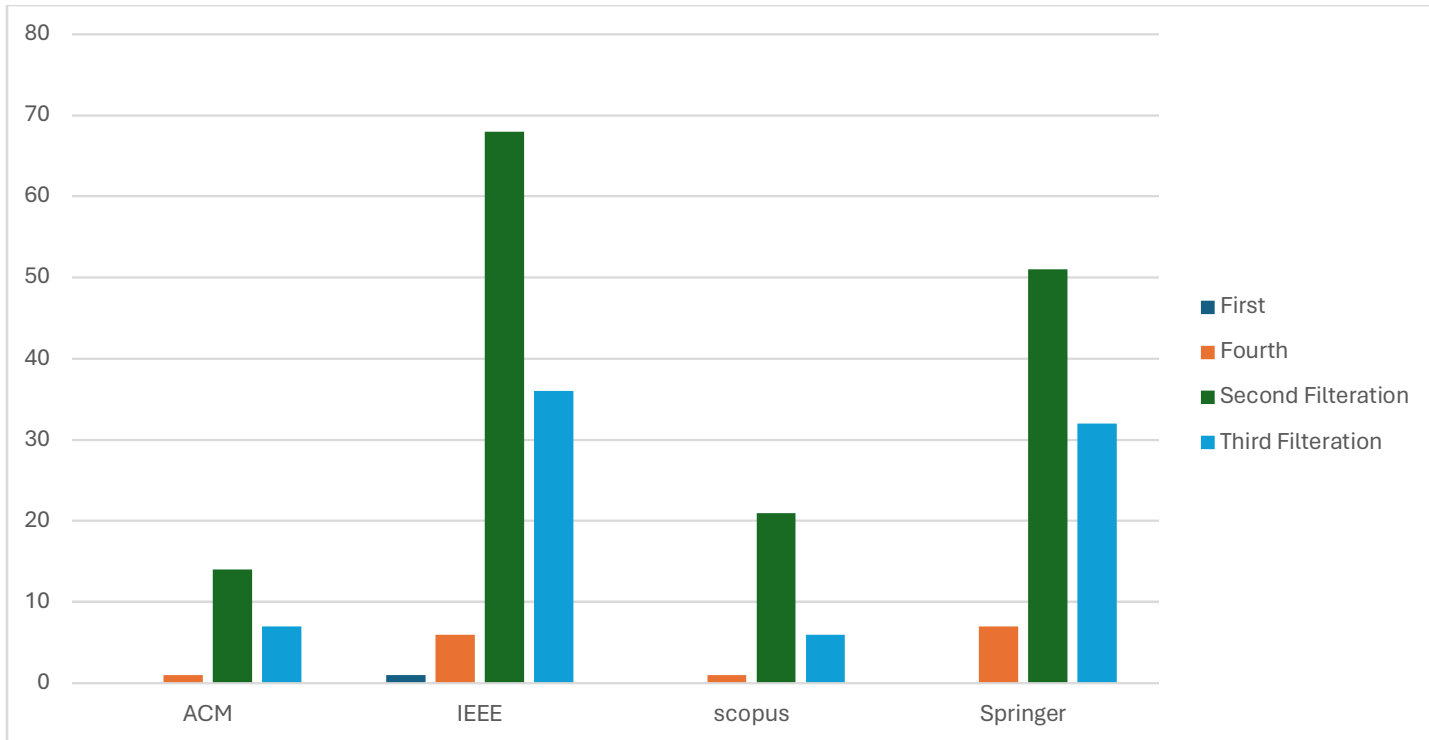


Figure 2. 2.:Studies Filtration processes per search engine

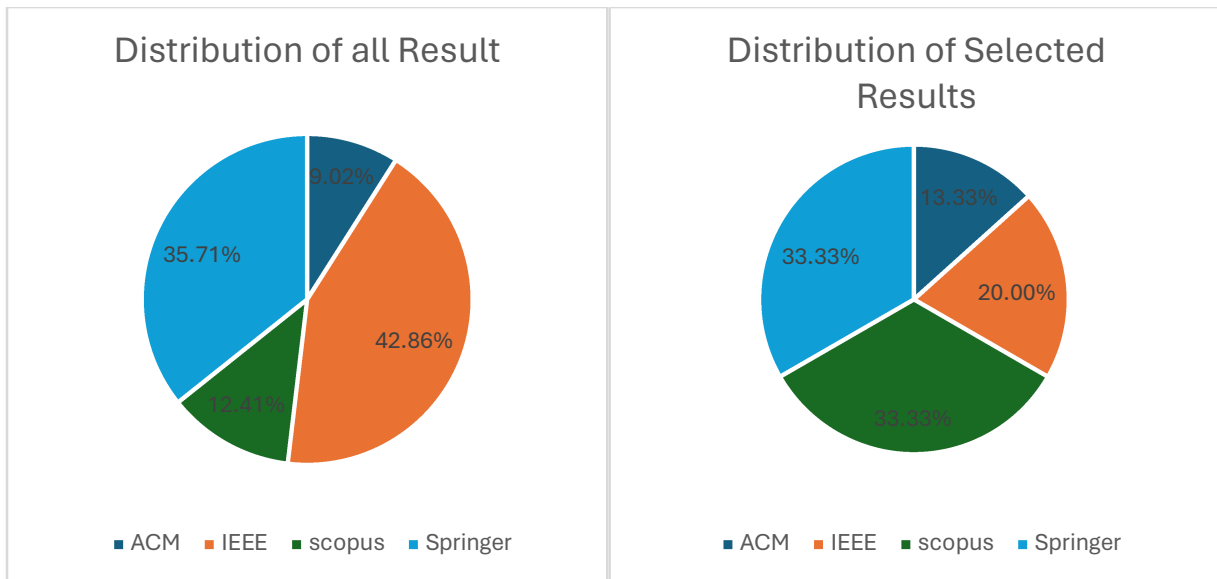


Figure 2. 3.:Distribution of results across search engines

2.5 Data Extraction:

The final group of 15 papers has been examined to determine how they tackled the issue of determining societal cost and impact. The included studies, their contributions to the problem, and the instruments employed in each investigation are shown in Table 2.

The included studies can be classified into two main groups: The first group is concerned with carbon credit, or the social impact of carbon emissions. The second group, on the other hand, attempts to respond to the query about the cost of carbon credits.

Examining the body of research on social effect and carbon credits, it is observed that a relatively large number of articles tried to tackle social impact or social development issues. In contrast, only 1 or 2 articles provide any solution to address the social cost issue. Most of the literature uses the supply chain to solve social impact issues.

(Dong-Ho Lee., Dong-hwan Kim & Seong-il Kim.,2018) The co-benefit enhancement effect of forest carbon projects influences carbon credit transactions. Large-scale IFM and REDD projects show higher RTR ratios than AR projects, indicating they have strengthened market competitiveness through additional CCB standards labelling.

According to (Carvalho, M., de Santana Freire, R., & de Brito, A. M. V. G.

(2016)), the The development of the ISO 14040 standards and a rise in ecological discourse in the 1990s reignited society's interest in environmental analysis, which had been ignited by the oil crisis of the 1970s. One effective strategy for raising awareness is the quantification of environmental effects. Some studies go one step farther and look for equilibrium or balance between various viewpoints (economic and environmental). Sustainable growth is the cornerstone of effective resource management, and modern businesses strive to strike a balance between growing their operations and protecting the environment. Accurate understanding of production processes helps businesses minimise risks and maximise profits, preventing future penalties for environmental harm.

Similarly, Das, D., & Sengupta, P. P. (2010, November) – review the CDM methodology in the context of developed countries and the carbon market. A certified emissions reduction (CER) is a payment for the project developer to reduce GHG emissions. Fast-developing countries may be considered potential markets for CDM, and industrialised By buying credits, nations can meet their emission reduction goals relatively more affordably. This provides how CDM and Carbon Market works.

Galatowitsch, S. M. (2009, September), explains how to create a green supply chain in a carbon trading scenario using a stochastic programming approach. The model is used to a real-world case study and takes into account the uncertainty of product demand and carbon prices. Two well-liked environmental regulatory policy systems that try to reduce emissions through taxation are carbon pricing and trading mechanisms. The primary challenge with carbon pricing is establishing the tax to encourage the reduction of emissions and lessen its

economic impact. For an organisation operating in Australia, where the government has been implementing carbon reduction regulatory schemes, they create a two-stage stochastic SCND model. Decisions on supply chain design and planning are made using the model, which accounts for uncertainty in carbon/allowance price.

$$\begin{aligned} \min \quad & c^T x + \sum_{k=1}^K p_k q_k^T y_k \\ \text{Subject to:} \quad & Ax = b, \\ & T_k x + W y_k = h_k, \quad k = 1, \dots, K, \\ & x \geq 0, \quad y_k \geq 0, \quad k = 1, \dots, K. \end{aligned}$$

Figure 2. 4.:Supply Chain Under Consideration in Article

If x represents the stage 1 choice variables, c is the row vector of x 's coefficient in the stage 1 objective function, b is the problem's right-hand side column vector, and A is the matrix of variable coefficients in the constraints set. A two-stage stochastic model for a supply chain in a carbon trading environment that takes product demand and carbon price uncertainty into account was given in this work. The findings demonstrate that pricing carbon emissions lowers emissions and transportation costs, and that supply chains that have higher carbon prices are more environmentally friendly.

According to Mneimneh, F., Al Kods, M., Chamoun, M., Basharoush, M., & Ramakrishna, S. (2023, April 18), ESG ratings aim to improve workers' socio-economic standards, companies' government and environmental footprint, and the relationship between green innovation and ESG ratings. ESG ratings are threatened by a number of obstacles, including "greenwashing" and the absence of

rules and openness in underdeveloped nations. Investors are now paying more attention to ESG factors as a result of climate change and the global government focus on moving towards greener economies. This study examined “How ESG ratings are implemented in developed and developing countries?” This study showed the advantages and drawbacks of ESG ratings. Due to the absence of a global or even national ESG rating, it highlighted the various forms of green innovation greenwashing. Creating a uniform dimension for the environmental component of the ESG rating should be the main goal of future study.

As per (Limmeechokchai, B., Winyuchakrit, P., & Pita, P. (2022, October 26)), The Paris Agreement is a legally binding international treaty on climate change that aims to limit global warming to well below 2 degrees Celsius and pursue efforts to limit it to 1.5 degrees Celsius before the end of the century. Generally, private, and external costs are used to evaluate project investment. The social cost of carbon (SCC) estimates the advantages of lowering emissions and the financial consequences of releasing one more tonne of carbon dioxide into the environment. The cost per unit of CO₂ or CO₂ equivalent emissions is how SCC is displayed, and it is the most critical factor that can set the carbon price in setting climate rules/regulations/policies in many countries. At the moment, industrialised nations' climate change initiatives take into account both the social and private costs of greenhouse gas emissions and the effects of climate change. A carbon price is applied in different mechanisms, depending on the policies. The evaluation of SCC is based on two fundamental principles, and details of each principle are presented below. The SCC is estimated in concept 1 using the "Future worldwide damage cost" as the monetary unit for the future worldwide

damage function. The "Cost-benefit" analysis (CBA) idea serves as the foundation for this assessment. In concept 2, cost-effectiveness analysis (CEA) is used to assess the carbon price, and the monetary unit per unit of GHG reduction is frequently expressed using the Marginal Abatement Cost (MAC). Constant discount rates combined with SCC can be used to encourage the production of electricity from renewable energy sources for short-term projects or low-challenge targets. For long-term projects with a high challenge target of CO₂ emissions reduction, declining discount rates can be applied together with SCC.

This paper (Eales, A., Walley, L., Buckland, H., Frame, D., & Strachan, S. (2018, June)) aims to quantify the holistic impact of mini-grids within the context of the Sustainable Development Goals. Fieldwork was conducted in three case study sites in Peru and Nepal using various evaluative methods, including semi-structured interviews with users and managers, transect walks, photographic evidence, and observations. A series of 43 sustainability indicators were developed for evaluating the mini-grids. A detailed case study analysis of a microgrid in rural Kenya found that access to electricity improved social and business services, improved academic performance, and increased teacher retention, with additional benefits identified through ICT use and vocational courses. Profitability and social effect are not inherently mutually exclusive. Mini-grids' social impact can be measured and improved to boost customer value and business models' financial sustainability. Although mini-grid evaluation methodologies have been studied, there is currently no standard methodology for calculating the direct social impact of a mini-grid effort. A technique will be created to evaluate the social effects of Africa's current mini-grids.

As per (Simao, M. S., Dagnese, L. L., Ribeiro, E., Martins, M. A. I., Green, V., & Tomaz, K. D. (2022, December 4)), Large investments are required in grid infrastructures in the electricity sector to meet future demands, even in countries with full-grown and well-developed network flows. The "2030 Agenda for Sustainable Development" was introduced by the UN in 2015, and it outlines 169 objectives and 17 SDGs that must be accomplished globally by 2030. The 2030 Agenda strongly emphasises how governments, corporations, individuals, non-governmental organisations, and other stakeholders may work together to address global concerns. The ESG approach has to do with business practices that are essential to an organization's long-term growth as a social entity. The purpose of this research is to determine how the electric power burial project might improve sustainability development. After completing the SDGs-IAE Framework, 80 synergies and ten trade-offs were obtained. Synergies score highly on these relationships and are shown in green. The three main sections of the questionnaire—Economy, Society, and Environment—present the findings based on the ESG methodology. SDG 12: "Responsible Consumption and Production" quantified the negative effects of the Urban Factorability initiative. The project involved a lot of material removal and produced a lot of garbage from building development, which can affect the environment, human health, and food production.

This position paper (Xu, R., Lin, X., Dong, Q., & Chen, Y. (2018).), Proposes BLESS, a blockchain-enabled social credit system that offers tamper-proof transaction data in the trustless network environment and enables

encapsulated rating algorithms. The BLESS system is expected to improve transparency in public events, encourage people to participate in the construction of the social credit system, and make the entire community more trustworthy and safer. The integrated system design and implementation of a decentralised social trust infrastructure is not easy based on existing technologies. It requires extensive efforts by experts from multiple disciplines, including social science, political science, public policy, finance and businesses.

Real-world examples highlight the critical need for integrating SDGs into carbon credit evaluations. For instance, a reforestation project in Kenya under the **Clean Development Mechanism (CDM)** led to significant carbon sequestration. However, it failed to consider the displacement of local communities, leading to social unrest and economic hardship (Corbera & Brown, 2010). In contrast, the **Grameen Shakti Solar Program** in Bangladesh not only reduced carbon emissions by promoting renewable energy but also contributed to local job creation and improved gender equality by training women as solar technicians (REN21, 2021).

These examples underscore the importance of evaluating carbon credit projects not only for their carbon-offset potential but also for their broader socio-economic contributions. By integrating SDG indicators into the evaluation framework, as proposed in this study, it becomes possible to identify both the positive and negative externalities of such projects and ensure that they contribute meaningfully to sustainable development.

Table 2. 2.:Relevant Papers Including Publication Information

Index paper	Title	Authors	Journal / Conference Name	Document Type	Contributions
1	Characteristics of forest carbon credit transactions in the voluntary carbon market	Lee, D.-H., Kim, D.-H., Kim, S.-I.	Climate Policy	Article	co-benefit enhancement effect of forest carbon projects
2	Promotion of sustainability by quantifying and reducing the carbon footprint: New practices for organizations	Carvalho, M., de Santana Freire, R., de Brito, A.M.V.G.	Green Energy and Technology	Article	Quantification of environmental impacts
3	Sustainable Land Management and Carbon Finance: The experience of the BioCarbon Fund	Baroudy, E., Hooda, N.	Climate Change Mitigation and Agriculture	Book Chapter	Carbon project financing and climate change solution based on local community awareness

4	Social cost of environmental pollution & application of counter measures through clean development mechanism with the effect of Additionality & Baseline - In the context of developing countries	Das, D., Sengupta, P.P.	ICEMT 2010 - 2010 International Conference on Education and Management Technology, Proceedings	Conference Paper	how CDM and carbon market works
5	Carbon offsets as ecological restorations	Galatowitsch, S.M.	Restoration Ecology	Article	Information about Carbon estimation, verification and accounting
6	Green supply chain network design with stochastic demand and carbon price	Ahmad RezaeeFarzad DehghanianBehnam FahimniaBenita Beamon	Annals of Operations Research	Article	a stochastic programming model to design a green supply chain in a carbon trading environment

7	Sustainable business models for social enterprises in developing countries: a conceptual framework	Ridge McGibbon Armstrong Sara S. Saartjie Grobbelaar	Management Review Quarterly	Article	
8	Evaluating cost impacts on reverse logistics using an Economic Order Quantity (EOQ) model with environmental and social considerations	Lucas Dias Condeixa Pierry Silva Diego Moah Brenda Farias Adriana Leiras	Central European Journal of Operations Research	Article	Mathematical model for evaluating social impact
9	How Can Green Energy Technology Innovations Improve the Carbon-Related Environmental Dimension of ESG Rating?	Farah Mneimneh Michel Al Kods Marc Chamoun Mohammad Bashar Oush Seeram Ramakrishna	Circular Economy and Sustainability	Article	Advantages and drawbacks of ESG ratings

10	Social participation and climate change	Ricardo Braun	Environment, Development and Sustainability	Article	
11	The Role of Discount Rate and Social Cost of Carbon in Long Term Climate Policy on Renewable Electricity in Thailand	B. Limmeechokchai; P. Winyuchakrit; P. Pita	2022 International Conference and Utility Exhibition on Energy, Environment and Climate Change (ICUE)	IEEE Conferences	The evaluation of SCC & long-term projects with a high challenge target of CO2 emissions reduction, declining discount rates can be applied together with SCC
12	Social Impacts of Mini-Grids: Towards an Evaluation Methodology	A. Eales; L. Walley; H. Buckland; D. Frame; S. Strachan	2018 IEEE PES/IAS PowerAfrica	IEEE Conferences	the holistic impact of mini-grids within the context of the Sustainable Development Goals
13	Multisectoral Sustainable Development Impacts Survey From the Application of the SDGs-IAE Framework: A Case Study	M. S. Simões; L. L. Dagnese; E. Ribeiro; M. A. I. Martins; V. Green; K. D. Tomaz	2022 IEEE Sustainable Power and Energy Conference (iSPEC)	IEEE Conferences	identify the potential contribution that the electric power burial project can offer to enhance sustainability development

14	Constructing Trustworthy and Safe Communities on a Blockchain-Enabled Social Credits System	Ronghua Xu, Xuheng Lin, Qi Dong, Yu Chen	MobiQuitous '18: Proceedings of the 15th EAI International Conference on Mobile and Ubiquitous Systems: Computing, Networking and Services	EAI Conference	Blockchain Network as integrated system design and implementation of a decentralised social trust infrastructure
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2.5.1 Data Analysis and Data Synthesis

To precisely identify gaps in the literature, we examined every reviewed study using a number of criteria. Table 3 lists the analysis criteria that were applied in this review.

There were operational definitions for every criterion analyzed in order to ensure that the evaluation was rigorous and consistent between selected papers. The term "social cost" indicated that externalities, either monetary or non-monetary, associated with societal costs were included. "Social impact" captures how, more generally, projects would have qualitative or quantitative impacts on communities due to the project implementation. A "carbon pricing algorithm" reflected a specified approach or model designed to price carbon emissions, either via a market based approach or social cost approach. The ability to "quantify socioeconomic impact" indicated that measurable indicators would be used (e.g., employment change, reduction in poverty index, health indicators etc.) to demonstrate social and economic impacts.

Table 2. 3.: Analysis criteria used to evaluate the included 15 papers

Analysis Criteria
1. Did the study provide information on social cost or social impact from these kinds of projects?
2. Does the paper offer a carbon pricing or social cost algorithm?
3. Does the paper offer a way to quantify social economic impact?
4. Does the study provide a solution for calculating the social cost of carbon credit based on the UN SDG?

The chosen studies were examined using the evaluation standards listed in Table 3. A score of 1 or 0 was assigned to each of these criteria. 1 shows that the study meets the necessary requirements, while a value of 0 means that it doesn't.

Table 2. 4: Assesment of Selected Papers against analysis criterial

<i>Study</i>	<i>Social cost or social impact information</i>	<i>Algorithms for social cost or carbon pricing</i>	<i>Way to quantify social impact</i>	<i>Solution for carbon pricing based on UN SDG</i>	<i>Total</i>
<i>S1</i>	<i>1</i>	<i>0</i>	<i>0</i>	<i>0</i>	<i>1</i>
<i>S2</i>	<i>1</i>	<i>0</i>	<i>1</i>	<i>0</i>	<i>2</i>
<i>S3</i>	<i>0</i>	<i>0</i>	<i>0</i>	<i>0</i>	<i>0</i>
<i>S4</i>	<i>1</i>	<i>0</i>	<i>0</i>	<i>0</i>	<i>1</i>

<i>S5</i>	<i>1</i>	<i>0</i>	<i>0</i>	<i>0</i>	<i>1</i>
<i>S6</i>	<i>0</i>	<i>1</i>	<i>1</i>	<i>0</i>	<i>2</i>
<i>S7</i>	<i>1</i>	<i>0</i>	<i>1</i>	<i>0</i>	<i>2</i>
<i>S8</i>	<i>1</i>	<i>1</i>	<i>1</i>	<i>0</i>	<i>2</i>
<i>S9</i>	<i>1</i>	<i>0</i>	<i>0</i>	<i>0</i>	<i>1</i>
<i>S10</i>	<i>1</i>	<i>0</i>	<i>1</i>	<i>0</i>	<i>2</i>
<i>S11</i>	<i>1</i>	<i>0</i>	<i>0</i>	<i>1</i>	<i>2</i>
<i>S12</i>	<i>1</i>	<i>0</i>	<i>0</i>	<i>0</i>	<i>1</i>
<i>S13</i>	<i>1</i>	<i>0</i>	<i>0</i>	<i>0</i>	<i>1</i>
<i>S14</i>	<i>0</i>	<i>1</i>	<i>0</i>	<i>0</i>	<i>1</i>
<i>S15</i>	<i>0</i>	<i>0</i>	<i>1</i>	<i>0</i>	<i>1</i>

2.6. Research Gaps

As evident in the previous section, 15 studies (Table 2) have been selected from well-known databases. Most were taken from top-ranked journals, while others were from conference proceedings. These studies have been carefully studied and reviewed to identify research gaps and determine the limitations in the existing literature. The following sub-section summarises the SLR results, including the typical limitations of the 15 selected studies.

2.6.1. RG1: Integration of UN SDGs in Carbon Credit Pricing:

Current methodologies for carbon credit pricing largely overlook the explicit integration of the United Nations Sustainable Development Goals (SDGs). This significant gap in research highlights the need for innovative frameworks that aim to

reduce emissions and contribute directly towards SDGs' achievements. Such frameworks should ideally assess the environmental impact of carbon credit projects through the lens of SDG targets, ensuring that the pricing mechanism incentivizes projects that offer tangible benefits towards these global goals. Developing these methodologies requires a multidisciplinary approach, combining environmental science, economics, and social policy insights to create a cohesive and impactful pricing strategy.

As the study in Paper 11 directly tackles the integration of social cost pricing linked to UN SDGs in carbon credit projects, the AIM model could serve as an argument for the necessity of such research. The model provides the means to quantify and assess the broader societal and economic impacts of carbon credit projects beyond mere emissions reduction.

2.6.2. RG2: Quantification of Social Impact of Carbon Credit Projects

Despite the increasing awareness of the significance of social impacts in carbon credit projects, there remains a notable shortfall in research specifically aimed at their systematic quantification in alignment with the United Nations Sustainable Development Goals (UN SDGs). The deficiency is particularly acute in methodologies that can effectively measure both direct and indirect impacts of these projects on local communities. Addressing this gap is crucial for advancing the effectiveness and credibility of carbon credit initiatives.

Direct impacts, such as job creation, improved air quality, and access to cleaner technologies, are often more visible and immediately quantifiable. These impacts can lead to immediate benefits for local populations, improving their quality of life and health conditions. However, the methodologies to quantify these impacts need to be refined to ensure they capture the full extent of the benefits provided by carbon credit projects. This

involves not only measuring the number of jobs created or the reduction in pollutants but also evaluating the quality and sustainability of those jobs and the long-term health benefits accrued to the community.

Indirect impacts, including enhanced social cohesion, economic stability, and infrastructural development, are less tangible but equally significant. These impacts contribute to the sustainable development of a community by fostering a more cohesive social fabric and creating a stable economic environment that can attract further investment. The challenge lies in developing methodologies that can map these indirect benefits to specific SDGs and provide a clear, quantifiable link to the valuation of carbon credits. Such methodologies should be capable of capturing the complex interdependencies between various social outcomes and the broader economic and environmental goals outlined by the SDGs.

Moreover, the methodologies developed must be adaptable to different project contexts, considering the unique social, economic, and environmental conditions of each location. This adaptability is essential to ensure that the assessment tools are not only robust and comprehensive but also relevant to the specific needs and challenges of the communities involved. For instance, a methodology effective in an urban setting might need adjustments to be applicable in a rural context where the dynamics of job creation and social cohesion differ markedly.

To achieve this, interdisciplinary approaches are required, blending insights from environmental science, social sciences, and economic analysis. Collaborative efforts between researchers, local communities, project developers, and policy makers are also vital. These collaborations can provide the diverse perspectives and expertise needed to develop holistic and effective methodologies.

Ultimately, enhancing the methodologies for quantifying the social impacts of carbon credit projects in relation to the UN SDGs will enable more nuanced assessments and valuations of carbon credits. This will not only improve the transparency and accountability of carbon credit markets but also ensure that these projects contribute more effectively to sustainable development, aligning with global efforts to combat climate change while promoting social and economic well-being.

2.6.3. RG3: Integrated Assessment of Social and Environmental Impacts

There's a noticeable lack of research into models that fully capture both the environmental and social effects of carbon credit projects. It's important to develop models that not only consider the environmental benefits, like lower CO2 emissions and cleaner air, but also look at how these projects impact communities by creating jobs and improving health. Moreover, these models should also explore how these projects can boost the local economy.

To build these comprehensive models, experts from different fields such as environmental science, economics, and data analysis need to work together. This ensures that the models are not only thorough but also provide useful information that can help guide decisions.

Using advanced technology like artificial intelligence can improve these models even further, making them better at predicting outcomes and thus more useful for making policies and planning strategies. This approach helps ensure that carbon credit projects are fully evaluated, highlighting their true value in promoting sustainable development and supporting well-informed policymaking.

2.6.4. RG4: Generating Link Between Project Description and Claimed UN SDGs:

The use of artificial intelligence (AI) and machine learning (ML) in sustainability assessments is rapidly gaining traction. AI, particularly through techniques like **natural language processing (NLP)** and **machine learning models**, has shown significant potential in enhancing the accuracy and scalability of environmental evaluations. In recent studies, AI models have been employed to analyze vast datasets, automate repetitive tasks, and generate predictive insights that inform strategic decision-making (Goldstein et al., 2020).

In the context of carbon credit projects, AI can play a pivotal role in auditing SDG claims. For instance, NLP can be applied to project reports to identify and verify the claimed contributions of these projects to various SDGs, such as gender equality (SDG 5) and decent work (SDG 8). Meanwhile, machine learning models can be used to predict the long-term social impacts of these projects based on historical data, thereby offering a more holistic view of their sustainability outcomes. These AI-driven approaches are essential to filling the current gaps in carbon credit evaluations, which often fail to capture the full spectrum of socio-economic benefits.

A significant gap exists in establishing a systematic, verifiable link between carbon credit project descriptions and their claimed contributions to the UN SDGs. Addressing this gap necessitates the development of frameworks or methodologies that can critically assess and validate the alignment between project activities and their purported SDG impacts. This involves creating criteria and indicators for evaluating the authenticity and magnitude of a project's contribution to the SDGs, enhancing transparency, and building trust in the carbon credit market. Such a framework would

support project developers in accurately reporting their impacts and assist buyers and regulators in making informed decisions based on credible evidence.

Despite numerous advancements in carbon credit mechanisms, most studies tend to focus exclusively on their carbon-offset capabilities, neglecting their broader social, economic, and ecological implications. For instance, current methodologies primarily measure the volume of carbon dioxide offset (Richard, 2023; Wissner & Schneider, 2022) but fail to account for how these projects contribute to goals such as poverty alleviation, gender equality, and sustainable economic growth. This narrow scope limits the ability of carbon credit projects to holistically align with the SDGs, leading to an incomplete understanding of their overall impact.

Moreover, existing models often rely on numerical carbon results as the sole indicator of success, omitting qualitative outcomes such as community well-being or ecosystem health (Olhoff et al., 2004). These gaps underscore the need for a more integrated framework that can measure carbon credit impacts across multiple SDG indicators. The present study seeks to address these limitations by proposing a multi-dimensional assessment framework incorporating AI and machine learning techniques, which are well-suited for processing large datasets and generating insights beyond traditional carbon measurements.

2.7. Research Question

After identifying research gaps, the research main question and sub-questions are formulated in this section (Table 5 and Table 6).

Table 2. 5: Research the main question and its motivation

Research Main Question	Main Objective
How can quantifiable measures derived from the UN SDGs be effectively employed to assess the social impact of carbon credit projects on their geographical locales?	Develop methodologies for utilizing UN SDGs as quantifiable metrics to assess and predict the social impacts of carbon credit projects.

Table 2. 6.: Research sub-questions and their motivations

Research Sub-Questions	Objectives
1. How can data from Core Markets be analyzed to identify variables indicative of the social impact of carbon credit projects, and what statistical models can integrate these variables for impact computation and prediction?	Investigate and design statistical models using industry provided data to compute current social impacts and forecast future impacts, enhancing project planning and implementation strategies.
2. How can a monitoring system be established to verify the alignment of carbon credit projects' claimed UN SDG contributions with actual project outcomes?	Create a rule-based monitoring system to assess and ensure the credibility of carbon credit projects' contributions towards achieving the UN SDGs.

This research is grounded in sustainability accounting theory and the cost-benefit analysis (CBA) framework, both of which offer critical insights into evaluating environmental and social impacts. **Sustainability accounting** emphasizes the need for

comprehensive evaluations that go beyond financial metrics to include environmental, social, and governance (ESG) factors (Rawhouser & Cummings, 2019). The integration of SDG indicators into carbon credit assessments can be viewed as an extension of sustainability accounting practices, ensuring that projects not only achieve carbon reductions but also deliver broader societal benefits.

Additionally, the **cost-benefit analysis framework** is used to assess the trade-offs between economic gains and environmental or social costs (Stern, 2006). By incorporating AI-driven predictive models into the evaluation of carbon credit projects, this research aims to optimize these trade-offs, providing stakeholders with a more comprehensive understanding of the social costs and benefits associated with such projects. These theoretical perspectives offer a robust foundation for developing an evaluation framework that aligns carbon credits with global sustainability goals.

Several established frameworks demonstrate how sustainability performance and SDG contributions can be assessed through structured, rule-based methodologies. The **Global Reporting Initiative (GRI)** provides one of the most widely adopted sustainability reporting standards, offering a comprehensive set of disclosures and indicators covering environmental, social, and governance (ESG) topics. GRI's standards have been mapped to the UN SDGs to help organisations report on their contributions in a consistent and comparable manner (GRI, 2022). Similarly, the **Impact Reporting and Investment Standards (IRIS+)**, developed by the Global Impact Investing Network, define a globally recognised catalogue of metrics that enable consistent measurement and reporting of social, environmental, and financial performance, with explicit alignment to SDG targets (GIIN, 2023). Another notable example is the **IDI's SDG Audit Model**

(ISAM), developed by the INTOSAI Development Initiative, which provides guidance for public sector audit institutions to systematically assess national governments' progress towards achieving the SDGs (IDI, 2024). While these frameworks are not AI-driven, they illustrate best practices in indicator definition, reporting structure, and verification protocols, which can inform and complement the Gen AI Auditor's design. By drawing on their structured approaches, the Gen AI Auditor can ensure that its verification process remains transparent, standardised, and aligned with internationally recognised sustainability reporting norms.

While AI offers significant opportunities for scaling sustainability assessments and enhancing the verification of SDG claims, several challenges remain. First, **data quality and availability** are persistent issues. Sustainability data often originate from heterogeneous sources, with varying degrees of accuracy, completeness, and standardization, which can undermine the reliability of AI-generated insights (Hartung & Kleinstreuer, 2025). Second, **model interpretability** presents a barrier to adoption. Many advanced AI systems operate as "black boxes," making it difficult for stakeholders to understand why specific audit outcomes were reached. Without interpretability, trust in AI-generated assessments may be limited. Third, there is a continuing need for **human oversight**. Although AI can automate pattern recognition and claim verification, contextual judgment and ethical considerations require human review, particularly for borderline cases or where data are incomplete. Adopting a **human-in-the-loop** approach can ensure accountability, reduce the risk of erroneous conclusions, and align AI-driven assessments with established auditing principles. Recognizing these challenges is essential to creating a robust, transparent, and trusted AI framework for sustainability assessment.

2.8. Conclusion

This chapter synthesizes the extensive review of literature pertaining to carbon credit projects and their alignment with the United Nations Sustainable Development Goals (SDGs). The analysis highlights the critical need for more integrated and comprehensive methodologies to evaluate the full spectrum of impacts these projects have—environmental, social, and economic. While current studies provide valuable insights into the environmental benefits of carbon credits, they often fall short in systematically quantifying and incorporating social and economic outcomes. This gap underscores the importance of developing new frameworks that not only address these dimensions but also leverage advanced technologies like AI to enhance accuracy and accountability in sustainability reporting. By paving the way for more holistic evaluations, this research contributes to the refinement of carbon credit mechanisms, ensuring they are truly effective in promoting sustainable development. The insights gained from this review will directly inform the development of innovative assessment tools that are crucial for guiding future environmental policies and practices.

Chapter 3: Integrating UN SDGs into Carbon Credit Project Assessment: Data Collection and Methodological Development

This chapter introduces the comprehensive approaches and techniques to incorporate the United Nations Sustainable Development Goals (UN SDGs) into evaluating carbon credit projects. This chapter will explore how robust data collection and innovative analytical methodologies can effectively align carbon credit initiatives with global sustainability objectives.

Carbon credit mechanisms have emerged as pivotal tools in global efforts to reduce greenhouse gas emissions in response to escalating climate change concerns. Simultaneously, the United Nations Sustainable Development Goals (SDGs) provide a framework for addressing various global challenges, including climate action, poverty alleviation, and sustainable economic growth. Integrating these SDGs into carbon credit mechanisms offers a comprehensive approach to assessing and enhancing the effectiveness of these environmental initiatives, ensuring they contribute positively across multiple dimensions of sustainability.

3.1. Carbon Credit Mechanism

Carbon credits are part of an international effort to mitigate global greenhouse gas emissions. By allowing entities to earn credits through activities that reduce emissions, such as renewable energy projects or forest conservation, the system aims to incentivise emission reductions cost-effectively. The typical lifecycle of a carbon credit project involves several phases, including project design, validation, implementation, monitoring, and credit issuance.

The UN SDGs consist of 17 goals designed to promote global development sustainably. For carbon credit projects, relevant goals might include SDG 13 (Climate Action), SDG 15 (Life on Land), and SDG 7 (Affordable and Clean Energy), among

others. These goals provide a valuable framework for evaluating the broader impacts of carbon credit projects, extending beyond mere emission reductions to include social, economic, and environmental benefits.

In order to eradicate poverty, safeguard the environment, and guarantee that everyone lives in peace and prosperity by 2030, the United Nations created the Sustainable Development Goals (SDGs) in 2015. The integration of the 17 SDGs acknowledges that development must balance social, economic, and environmental sustainability and that actions taken in one area will impact results in other areas. They include goals such as no poverty (SDG 1), zero hunger (SDG 2), good health and well-being (SDG 3), quality education (SDG 4), gender equality (SDG 5), and climate action (SDG 13), among others (United Nations, 2015).

Carbon credits are a critical component in the global strategy to reduce greenhouse gas emissions. The right to emit one tonne of carbon dioxide or the equivalent amount of another greenhouse gas is represented by these tradable certificates. By enabling organisations that cut their emissions below a certain threshold to sell their extra capacity to organisations that surpass their emission targets, the carbon credit system encourages the reduction of emissions. This market-based approach aims to provide economic incentives for reducing pollution emissions (Bumpus & Liverman, 2008).

3.1.1. Carbon Credit Life Cycle:

The carbon credit lifecycle involves several key stages:



Figure 3. 1. : Carbon Credit Offset Lifecycle

1. **Project Design:** This initial phase identifies a potential project to generate carbon credits. Projects can include renewable energy installations, reforestation efforts, or energy efficiency improvements. The project design must adhere to specific methodologies that quantify the anticipated emission reductions.
2. **Validation:** Before a project can generate carbon credits, it must be validated by an independent third party. This process ensures that the project design meets all necessary criteria and that the expected emission reductions are realistic and achievable.

3. **Implementation:** Once validated, the project can be implemented. This phase involves executing project activities, such as planting trees, installing solar panels, or upgrading industrial processes.
4. **Monitoring and Reporting:** Throughout the project's operational phase, ongoing monitoring is essential to measure the emission reductions achieved. Project developers must regularly report these results to ensure transparency and accountability.
5. **Verification and Issuance:** An independent auditor verifies the reported emission reductions. Once verified, carbon credits are issued to the project developer, who can sell them on the carbon market.
6. **Market Trading:** Carbon credits can be traded on various carbon markets. Entities that have exceeded their emission targets can purchase these credits to offset their emissions.

Integrating SDGs into the Carbon Credit Lifecycle

To effectively integrate the SDGs into carbon credit projects, each project lifecycle phase must be aligned with specific goals. This process requires a strategic approach to ensure that projects contribute meaningfully to sustainable development objectives.

- **Project Design and Planning:** In the project design phase, it is crucial to identify potential SDG targets. For instance, a reforestation project could achieve SDG 15 (Life on Land) by restoring degraded land and SDG 13 (Climate Action) by sequestering carbon dioxide. By incorporating SDG targets at the outset, project developers can design initiatives that address multiple dimensions of sustainability.
- **Validation and Implementation:** During validation, methodologies must be developed to measure SDG outcomes alongside carbon reductions. This might involve setting up social impact assessments or environmental monitoring systems.

For example, a renewable energy project could include metrics for job creation (SDG 8: Decent Work and Economic Growth) and access to clean energy (SDG 7: Affordable and Clean Energy).

- **Monitoring and Reporting:** Regular monitoring and reporting are essential to track the project's contributions to the SDGs. This enhances transparency and allows stakeholders to assess the project's broader impacts. For example, a clean cookstove project could report on reductions in indoor air pollution (SDG 3: Good Health and Well-being) and the number of households benefiting from improved stoves.
- **Verification and Issuance:** Verification processes should ensure that the credits issued reflect carbon reduction and contributions to SDGs. Independent auditors must verify environmental and social impacts, ensuring that projects contribute to sustainable development. Verified credits can command higher market value, reflecting their broader benefits.

Challenges and Opportunities

Integrating SDGs into carbon credit mechanisms is challenging. These include the complexity of measuring diverse impacts, the need for new verification methodologies, and the potential for increased project costs. However, the integration also presents significant opportunities.

- **Enhanced Project Value:** Projects demonstrating clear, quantifiable contributions to SDGs may attract more interest and command higher prices in the carbon market. For example, credits from a solar energy project providing electricity to underserved communities can be more valuable.
- **Policy Support:** Projects aligned with SDGs may benefit from additional support and recognition from international bodies and governments, aligning with broader policy

objectives. For instance, projects contributing to national sustainable development plans may receive favourable policy treatment and incentives.

Integrating UN SDGs into carbon credit mechanisms represents a forward-thinking approach to environmental policy that acknowledges the interconnectedness of climate action and sustainable development. By expanding the scope of carbon credit projects to include SDG-related impacts, we can ensure that these initiatives contribute to reducing global emissions and advance comprehensive global development goals, making a broader positive impact on the planet and its populations. This holistic approach enhances the credibility and effectiveness of carbon credit mechanisms, ensuring they support sustainable development (Goldstein et al., 2020; Rogelj et al., 2018).

3.2. Research Methodology:

In order to accomplish the research objectives and offer solutions for each problem, we must adhere to a methodical scientific methodology when addressing the research gaps mentioned in Chapter 2.

3.2.1. Choice of Design Science Research Methodology

Because this research aims to build a new system that is not yet available in any current system, Action Design Research (ADR) is chosen as a research method since it is a popular method in engineering and allows reflection on the work done in prior stage and allows changes to be made.

For more details about this methodology, the reader can refer to (Sein, Henfridsson, Purao, Rossi, & Lindgren, 2011). Figure 6 depicts an overview of this methodology.

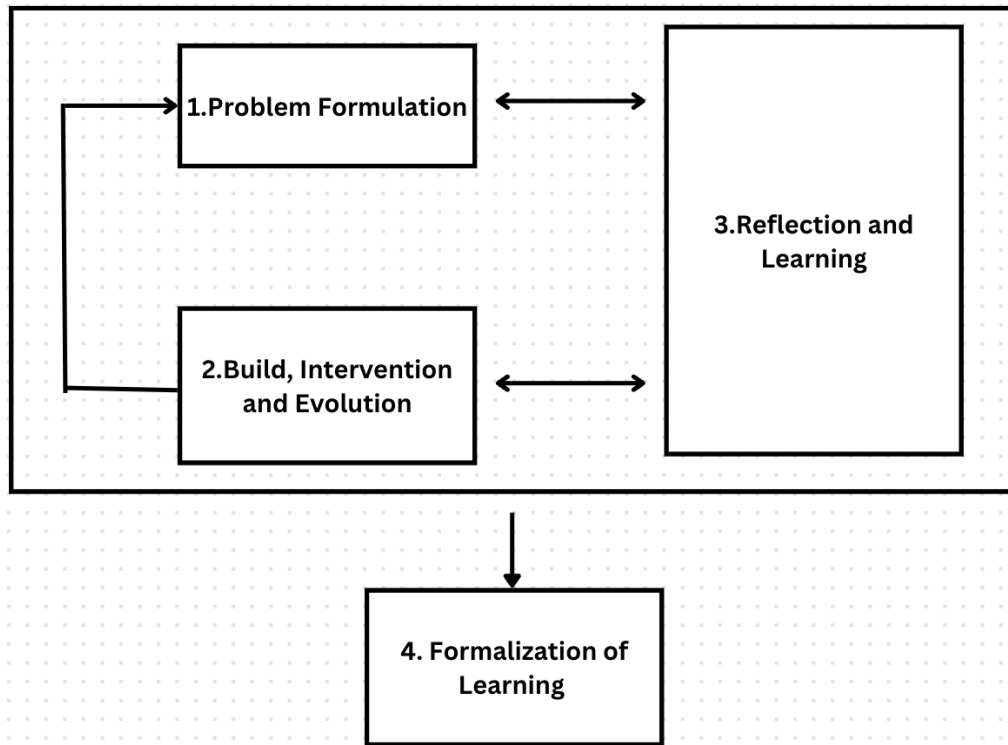


Figure 3. 2. : Action Design Research

Our research employs the Design Science Research Methodology (DSRM), which is particularly suited to studies that aim to create and validate new knowledge or solutions within specific real-world contexts. The following considerations drive this methodological choice:

- 1. Problem Formulation:** The first stage of DSRM aligns perfectly with our initial objective to define and understand the intricate dynamics of carbon credit systems and their impact about the United Nations Sustainable Development Goals (UN SDGs). This phase helps identify and articulate the practical problems our research intends to address.

- 2. Build, Intervention and Evaluation:** This stage allows for the development of innovative solutions or models, which, in our case, involves creating predictive models to assess the social impacts of carbon credit projects. It provides a systematic approach to implementing these solutions and evaluating their effectiveness and efficiency in a real-world setting.
- 3. Reflection and Learning:** DSRM emphasises iterative learning, where the insights gained from applying the models inform further refinements and enhancements. This iterative process is vital in environmental and sustainability research, where conditions and impacts continually evolve.
- 4. Formalization of Learning:** The final stage involves synthesising the knowledge gained throughout the research process and formalising it as a contribution to the body of knowledge. In our context, this means developing robust guidelines and frameworks that policymakers and practitioners can use to enhance the efficacy of carbon credit initiatives.

By adhering to the DSRM, this research addresses the theoretical gaps and contributes practical tools and insights that can directly influence policy and practice in sustainable development. This methodology ensures that the solutions are theoretically sound and validated through real-world application, thus enhancing their reliability and applicability in diverse contexts.

3.3. Objectives Discussion:

3.3.1. Objective 1: Development of a Comprehensive Framework for the Integration of UN SDGs in Assessing the Social Impact of Carbon Credit Project

The primary goal of this objective is to establish a nuanced valuation framework that quantifies the social impact of carbon credit projects, as gauged by their contributions to the United Nations Sustainable Development Goals (UN SDGs). This

framework will focus on discerning and quantifying the impact of carbon credit projects on local communities, encompassing social, economic, and environmental dimensions. Critical to this endeavour is the identification and calculation of these projects' effects on the inhabitants within their operational locales.

To achieve this, our research will involve compiling a comprehensive analysis of UN SDGs to identify key indicators that can serve as independent variables in our valuation model. These variables will be integral to estimating the social impact associated with carbon credit projects. The development of this model will be informed by the wealth of information available on the UN's platforms, as well as the insights gained from the literature review conducted previously. This analysis will summarise relevant UN SDGs directly related to the social costs incurred by carbon credit initiatives.

Table 3. 1.:Independent Variable from UN SDG (Affecting Social Cost)

UN SDG GOAL	Independent Variable
No Poverty	1.Percentage of population living below the poverty line 2.Income inequality index
Zero Hunger	1.Percentage of the population experiencing chronic hunger 2.Access to nutritious food
Good Health and Well-being	1. Life expectancy 2. Maternal and child mortality rates 3. Maternal and child mortality rates
Quality Education	Literacy rate

Gender Equality	<ol style="list-style-type: none"> 1. Gender wage gap 2. Representation of women in leadership positions 3. Elimination of gender-based violence
Clean Water and Sanitation	<ol style="list-style-type: none"> 1. Access to safe drinking water 2. Percentage of population with improved sanitation facilities
Affordable and Clean Energy	<ol style="list-style-type: none"> 1. Percentage of population with access to electricity 2. Share of renewable energy in total energy consumption
Decent Work and Economic Growth	<ol style="list-style-type: none"> 1. Unemployment rate 2. Labor productivity 3. Income inequality
Industry, Innovation, and Infrastructure	<ol style="list-style-type: none"> 1. Research and development expenditure 2. Access to reliable and affordable internet
Reduced Inequalities	<ol style="list-style-type: none"> 1. Gini coefficient (measure of income inequality) 2. Representation of marginalized groups in decision-making processes
Sustainable Cities and Communities	<ol style="list-style-type: none"> 1. Urban population living in slums 2. Access to adequate housing and basic services
Responsible Consumption and Production	<ol style="list-style-type: none"> 1. Waste generation per capita 2. Recycling rates
Climate Action	<ol style="list-style-type: none"> 1. Carbon emissions per capita 2. Adoption of renewable energy sources

Life Below Water	<ol style="list-style-type: none"> 1. Marine biodiversity index 2. Protection and restoration of coastal ecosystems
Life on Land	<ol style="list-style-type: none"> 1. Forest coverage 2. Conservation of endangered species
Peace, Justice, and Strong Institutions	<ol style="list-style-type: none"> 1. Homicide rate 2. Corruption perception index
Partnerships for the Goals	<ol style="list-style-type: none"> 1. Development assistance as a percentage of gross national income 2. Collaboration between government, civil society, and private sector

The above table provides the results of our analysis of UN SDGs. It helps determine the impact each UN SDG has on the local community. In the future, we will gather baseline data for each variable. Based on the baseline data, we will conclude how many variables we can use for our statistical models.

3.3.2. Objective 2: Design and Validation of Statistical Models for Quantifying and Predicting Social Impacts of Carbon Credit Projects:

The Social Cost based on UN SDG is a complex question in the current market. It is a link between carbon emissions and social development. The proposed methodology will try to answer the question of how we can develop a quantifiable method for the social cost of the carbon credit project. Based on the literature we reviewed in part 2, the MIMI framework has been a flag point of all the social cost models developed worldwide.

The aim of Objective 2 is to develop a robust statistical model capable of shedding light on the multifaceted social impacts stemming from carbon credit projects. By delving into project data and employing advanced statistical techniques, we seek to discern and quantify the ripple effects of these initiatives on local communities, economies, and environments.

Understanding the social ramifications of carbon credit projects is paramount in assessing their holistic effectiveness. While carbon credits primarily target emissions reduction, their broader implications on societal well-being cannot be overlooked. Through statistical modelling, we endeavour to unravel the intricate tapestry of social impacts, providing stakeholders with invaluable insights for informed decision-making and policy formulation.

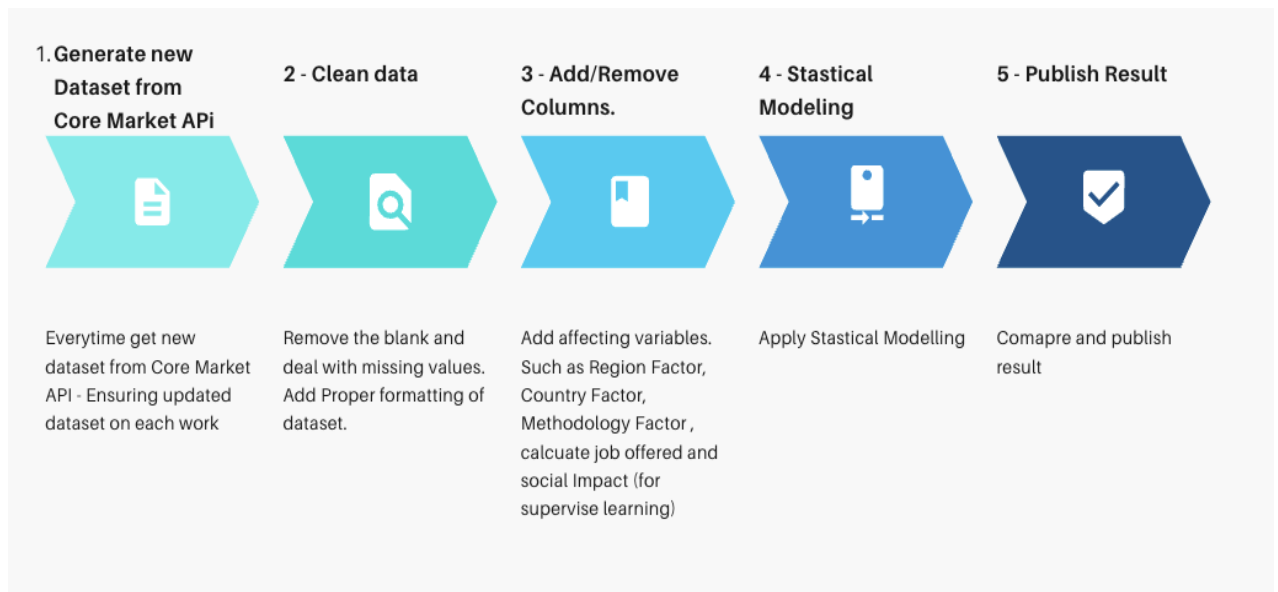


Figure 3. 3. Flowchart for the Objective 2

The output of this objective pivots on leveraging data provided by Core Markets to derive variables necessary for statistical modelling. The steps are as follows:

1. Analyse the dataset furnished by Core Markets to identify pertinent variables that can serve as indicators of social impact.
2. Develop a statistical model that integrates these variables, facilitating the computation of current social impact and predicting future impacts.

Objective 2 underscores our commitment to elucidating carbon credit projects' social dimensions through rigorous empirical analysis. By harnessing the power of statistical modelling, we endeavour to provide a nuanced understanding of these projects' broader societal implications, thereby fostering a more holistic approach to sustainable development.

Building on the framework provided by the **Core Markets** dataset, this section aims to detail the approach for statistical modelling to quantify and predict the societal impacts of carbon credit projects. The process involves several key steps:

1. **Data Analysis:** The first step involves thoroughly analysing the dataset obtained from Core Markets. This includes identifying variables closely linked to social outcomes, such as job creation, socio-economic development, and environmental benefits.
2. **Variable Selection:** Pertinent variables that can serve as social impact indicators will be selected from the dataset. This selection is based on their relevance to the UN SDGs and their potential to influence local communities positively.
3. **Model Development:** A statistical model will be developed using the selected variables. This model will incorporate quantitative data (e.g., number of jobs created,

reduction in CO₂ emissions) and qualitative assessments (e.g., improvements in local air quality or community well-being).

4. **Impact Assessment:** The model will compute the current social impacts of various carbon credit projects. This involves analysing how these projects have contributed to achieving specific SDGs within their operational areas.
5. **Future Impact Prediction:** The model will also offer predictions on future social impacts of ongoing or proposed carbon credit projects by leveraging historical data and current impact assessments. This predictive capability is crucial for planning and optimising future projects to maximise societal benefits.
6. **Continuous Improvement:** As new data becomes available or projects evolve, the model will be updated to refine its predictions and ensure its relevance and accuracy in assessing social impacts.

By integrating this dataset and following the outlined statistical modelling approach, stakeholders in carbon credit projects can gain insights into the tangible impacts of their initiatives. This enables informed decision-making that aligns with sustainability goals and maximises the benefits to local communities.

3.3.3. *Objective 3:* Establishment of a LLM- Powered Claim Auditor for Verifying UN SDG Contributions Claimed by Carbon Credit Projects

Carbon credit initiatives are essential in attaining emission reduction goals, which frequently correlate with the United Nations Sustainable Development Goals (SDGs). However, the need for a standardised monitoring mechanism makes verifying how these programmes contribute to the UN SDGs easier. This study presents an innovative rule-based monitoring system that uses OpenAI, a powerful natural language comprehension tool. The proposed system automates the review of project reports and claims using

specified UN SDG criteria, assuring uniformity, objectivity, and scalability in the assessment process.

This research will describe the design of the monitoring framework, which combines ChatGPT-4's analytical capabilities, aligns with the UN's SDG indicators, and employs rule-based reasoning for reliable verification. Several computational studies indicate the system's ability to rapidly analyse complicated data sets and narrative reports, validating ChatGPT-4's potential in improving the accuracy of carbon credit project evaluations. The outcomes highlight how this method has the potential to become a global standard for verifying the legitimacy of SDG contributions made by carbon credit programmes, which will help to create a more transparent and reliable carbon offset market.

For this objective, we will create a chatbot that can suggest UN SDG for a carbon credit project based on the project description. We will use project details provided by Core Markets (An Industry partner that works in pioneering carbon credit trading in digital platforms). We must provide a proper knowledge base to ensure this model is based on chatbot 4. For this part, we will provide a summary description of each un sdg by reviewing all the UN SDG from UN website.

In this study, we aim to scrutinise the United Nations Sustainable Development Goals (UN SDGs) as reported by proprietors of carbon credit initiatives. The UN SDGs are integral to the assessment of social impacts. There is a pressing need to authenticate and systematically oversee the asserted UN SDG contributions. To this end, we shall employ the previously delineated strategy. Utilising ChatGPT-4, we will design and implement a rule-based monitoring framework capable of validating and recommending appropriate UN SDGs for carbon credit projects, contingent upon their respective

descriptive profiles. This LLM model acts as a weal audit model to decrease the false negative claim rate.

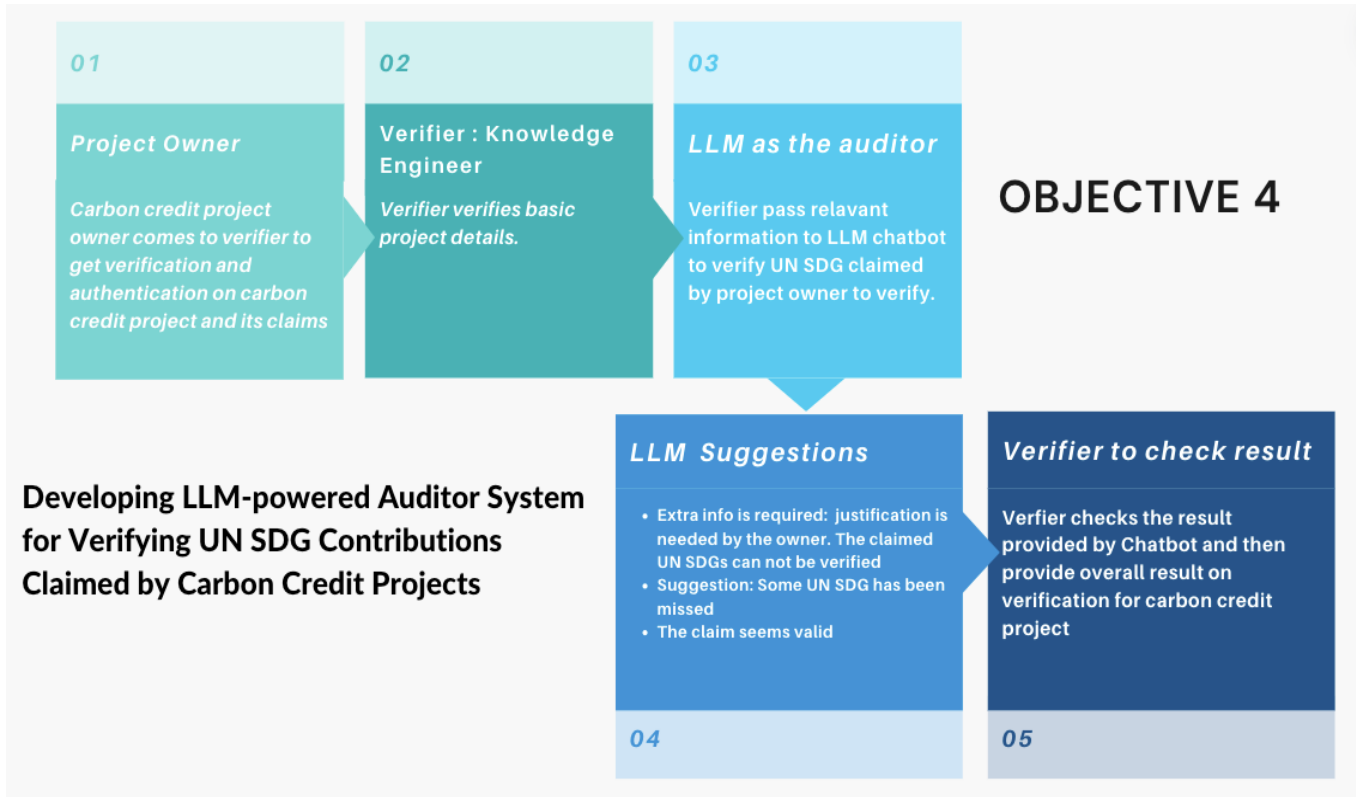


Figure 3. 4. LLM Powered Auditor System for Verifying UN SDG Contribution Claimed by Carbon Credit Projects

Creating a generative AI model (GenAI) that can suggest UN Sustainable Development Goals (SDGs) based on project descriptions involves a multi-step process. This model can be instrumental for organisations looking to align their projects with the global sustainability objectives set by the United Nations. Here’s a methodology to develop this model, integrating machine learning and natural language processing techniques:

1) Data Processing:

- This step is crucial for preparing the data for analysis and modelling. It should include cleaning the data, handling missing values, normalising text, and potentially augmenting it for better model performance.

2) Prompt Engineering (UN SDG Summary):

- Given the nature of generative AI models, crafting effective prompts is vital. This step should involve summarising the SDGs in an understandable way for the AI. A detailed understanding of how the model interprets prompts will help create queries that elicit the desired suggestions.

3) Model Creation:

- Choosing the right model architecture is key. If using ChatGPT, it suggests leveraging OpenAI's pre-trained models. Ensuring that the chosen model can understand and generate the necessary output is essential.

4) Providing Well-defined Rule:

- While generative models are powerful, they may benefit from rule-based constraints to ensure outputs align with the SDG framework. This might involve setting up a rule-based system that works with the generative model to validate or guide its suggestions.

5) Predict Suggested UN SDG:

- This is the operational phase where the model's predictions are used. It would be beneficial to establish a metric or set of metrics to evaluate the relevance and accuracy of the suggestions.

6) Fine Tune Model:

- The model will likely require fine-tuning based on initial results and feedback. This could involve additional training, adjusting the model parameters, or re-engineering the prompts for better clarity.

7) Publish Result:

- The final results should be made available in a format easily interpreted by stakeholders.

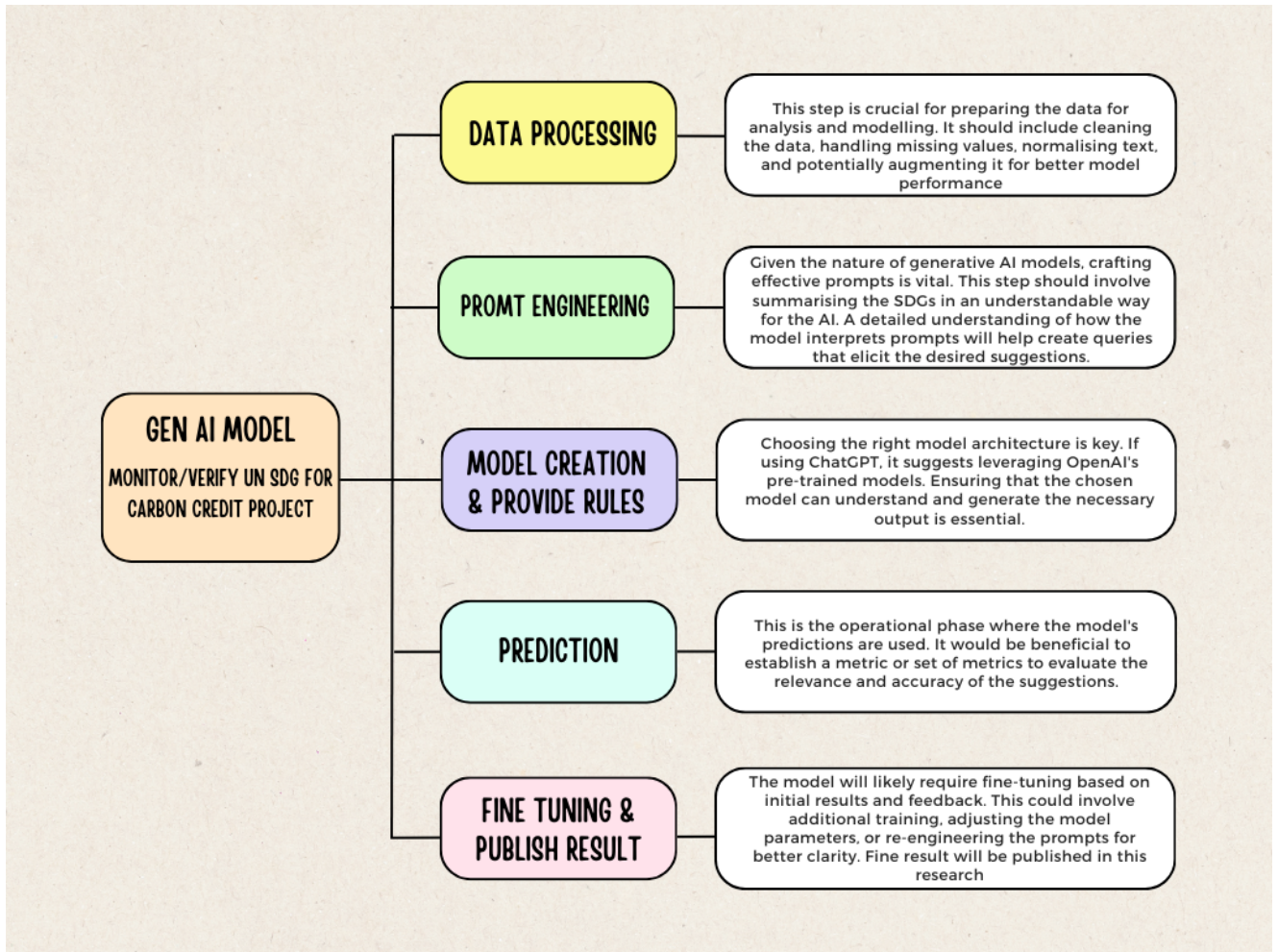


Figure 3. 5. : Objective 3 : GEN AI Model Flowchart

One of the main requirements is Prompt Engineering. Which can produce fine answers based on only one part of the method. In Prompt Engineering, we aim to design prompts that can effectively extract and evaluate the relevance and alignment of project descriptions with selected SDGs. This involves creating natural language queries that guide the AI in analysing the project details, focusing on their goals, methodologies, and impacts.

Below are some prompts that could be engineered for this model, tailored to analyse the provided project details:

- **Project Impact Analysis:** Based on the project description and its goals, methodologies, and expected impacts, evaluate how and to what extent the project contributes to achieving [SDG Name/Number (e.g. SDG 13)]. Provide a detailed analysis considering environmental, social, and economic aspects. E.g. – You ask the AI to look at a project's description and analyze how the project might help achieve a specific SDG. The AI should consider all aspects of the project, including its environmental, social, and economic impact.
- **SDG Relevance Identification:** Identify which SDGs are most relevant to the project description '[Project description]' and explain the rationale for each identified SDG based on the project's objectives and expected outcomes. E.g. – This prompt directs the AI to determine which SDGs are most closely related to the project's goals and expected results. It's about matching the project's aims with the right SDGs.
- **Methodology Assessment:** Analyse the methodologies employed by '[Project Description]' and assess their effectiveness in contributing towards [SDG Name/Number]. Consider the innovative approaches and practices used in the project. E.g. - The AI is asked to examine the methods used by the project to

achieve its goals. The AI evaluates whether these methods are effective and innovative in contributing to the SDGs.

- **Improvement Suggestions:** Suggest improvements or additional measures for '[Project Description]' to enhance its alignment and contribution to the SDGs. Consider gaps or potential areas for better impact. E.g. – You ask the AI to propose ways to improve the project to better align with the SDGs.

These prompts facilitate a structured and detailed examination of each project's alignment with the SDGs, leveraging the AI model's capability to process and analyse complex information. Tailoring and refining these prompts based on specific project details and the model's responses can further optimise the monitoring and verification.

In conclusion, integrating a generative AI model like ChatGPT with a rule-based system presents a promising approach to enhance carbon credit project monitoring and verification processes for UN Sustainable Development Goals. Prompt engineering is central to this methodology, enabling the AI to deeply analyse project details and provide accurate and contextually relevant assessments.

3.4. Data Analysis

In carbon credit projects, the accurate assessment and quantification of social impacts are paramount for aligning with the United Nations Sustainable Development Goals (UN SDGs). This section delves into the data collection and pre-processing steps essential for developing robust statistical models that evaluate these social impacts. The dataset sourced from Core Markets, detailing various carbon credit projects, is the foundation for this analysis.

The initial step involves a thorough dataset analysis, including 161 carbon credit projects. This dataset comprises multiple columns, some of which may contain missing values or irrelevant information. The primary objective is to clean and prepare this data for further analysis.

Before detailing the data analysis procedures, it is crucial to underscore the alignment between our methodological choices and the overarching research objectives of this study. The primary objective of our research is to assess and quantify the social impacts of carbon credit projects, with a particular focus on their alignment with the UN Sustainable Development Goals (SDGs).

These methods were chosen to provide a foundational understanding of the dataset's structure and to identify any initial patterns or anomalies. This step is critical to ensure the data quality and integrity before deeper analysis and supports our reliable social impact assessment goal. Employed to uncover the relationships between various project attributes and their impacts. This helps identify which factors are most influential in achieving the SDGs, aligning directly with our objective to pinpoint drivers of social impact.

Since our goal is to assess the social impact of these projects, we need to consider the right statistical modelling approach. With our data not explicitly labelled for social impact—the outcome we are interested in—it appears we are initially leaning towards using unsupervised learning methods. However, to proceed with unsupervised learning, we must understand the structure of the data and identify patterns without pre-assigned labels.

A thorough review is critical before manipulating the dataset or settling assumptions. We must identify what questions can be directly answered with the existing

data and which may require additional data collection or inferential modelling. Here are some starting points for our review:

- **Completeness:** Evaluate how much of the essential data is missing and the extent to which it can be reliably imputed or if additional data collection is necessary.
- **Relevance:** Determine if the available features are relevant to assessing social impact and whether additional variables need to be defined.
- **Feasibility:** Consider whether the dataset contains enough information to perform a meaningful social impact analysis or if proxies and estimates will be required.
- **Data Quality:** Assess our data's accuracy, consistency, and reliability.

Post-review, we might consider labelling the data systematically based on a literature review or based on the scale (size of the project) of the projects that could provide insights into the social impact. This would allow us to employ supervised learning techniques, which could be more precise.

To conclude, our preliminary analysis should guide us in refining the dataset and choosing the appropriate statistical models to measure the social impact of carbon credit projects effectively and accurately.

During the data exploration phase, we will focus on streamlining the dataset to include only the features pertinent to our investigation into the social impact of carbon credit projects. Features merely administrative or metadata, such as 'created at', 'modified at', and 'produced by', will be excluded from further analysis. These fields are related to the database management system and do not contribute to our research objectives; they may also introduce unnecessary complexity to the modelling process.

We will meticulously review each feature to ensure it aligns with our research goal. The remaining parts should directly or indirectly offer insights into the social

impact of each carbon credit project. Below is a table that lists the features providing comprehensive information for an individual carbon credit project. This table will serve as a reference for our subsequent analysis, ensuring we focus on variables most indicative of social impact.

Table 3. 2.:Relevant Data Extracted for one Project

Column Name	Values
product_class	carbon
product_type_name	GS (VER)
product_type_long_name	Gold Standard (VER)
certificate_project_type	18
certificate_project_type_name	Renewables
name	Grid Connected Wind Power Project in Maharashtra
description	M/s Bhilwara Green Energy limited (BGEL) is the promoter of the proposed project activity. The project activity involves installations of 33 wind turbines each having 1.5 MW capacities in district Satara, Maharashtra. The total capacity of the proposed project activity is 49.5 MW.
region	38
region_name	India
project_url	
accredited_project_url	https://registry.goldstandard.org/projects/details/654
company_name	.

methodology_details	ACM0002 Grid-connected electricity generation from renewable sources
project_status	Registered
publication_status	published
un_sd_goals	[7, 8, 13]
project_identifier	3705
region_short_name	India
certificate_name	GS
project_method_type	18
project_method_type_name	Renewables

The table provided encompasses a variety of data points related to carbon credit projects, such as the name of each project, the registry with which it is associated, and a URL directing to the registry's detailed page for the project. It also includes the status of the project, alignment with United Nations Sustainable Development Goals (UN SDGs), the type and details of the methodology employed by the project, a comprehensive description, and specific location details. This information forms a rich foundation for analysing the tasks in depth, particularly concerning their registration details, operational status, and contributions towards sustainable development objectives.

- **product_class:** Indicates the category of the carbon credit, such as 'carbon', which might suggest the overall classification under which the project falls.
- **product_type_name and product_type_long_name:** These columns detail the certification or standardisation type the project adheres to, such as 'GS (VER)' for Gold Standard Verified Emission Reductions. This is significant for understanding the project's compliance with international standards.
- **certificate_project_type and certificate_project_type_name:** These fields identify the type of project within the certification system, such as '18' for 'Renewables'. This

classification helps determine the project's focus area within the broader category of carbon credits.

- **Name:** The project's official name could be used for identification and further research into specific project details.
- **description:** Provides a detailed narrative about the project, such as the technology used,

Our objective is to determine whether the dataset allows us to quantify the social impact of carbon credit projects. To accomplish this, we need to scrutinise our dataset for quantifiable metrics that can provide insights into the complexity and richness of the data. A well-balanced dataset, not dominated by any single category or type, is crucial for robust statistical modelling.

For instance, if our dataset encompasses a wide array of regions and employs a diverse range of methodologies, it will enable us to apply the data across various scenarios, enhancing the applicability and utility of our findings. To better understand the distribution and characteristics of our data, we will utilise graphical representations and summary statistics. These tools will aid us in identifying underlying patterns and additional features that may have a bearing on the social impact of the carbon credit projects. Follow the graphs below to get a better understanding of the dataset.

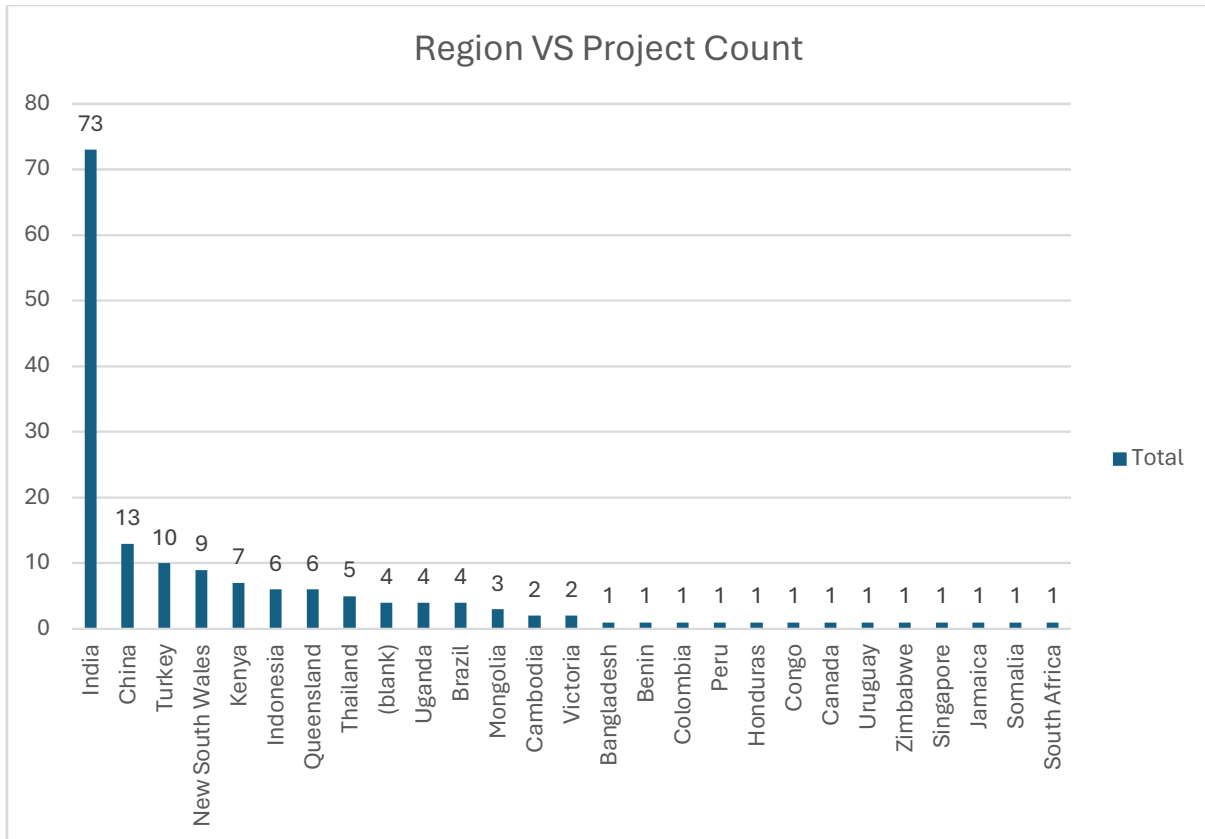


Figure 3. 6.:Data Analysis – Region Vs Project Count

- **Region vs. Project Count:**

- The first graph shows the distribution of projects across various regions. The skew towards certain areas, like India having significantly more projects, might influence the modelling. We should ensure the model accounts for regional variations and does not overfit regions with more data.
- This graph could be instrumental in analysing regional impacts and effectiveness, as we can compare the social effects across regions with varying numbers of projects.

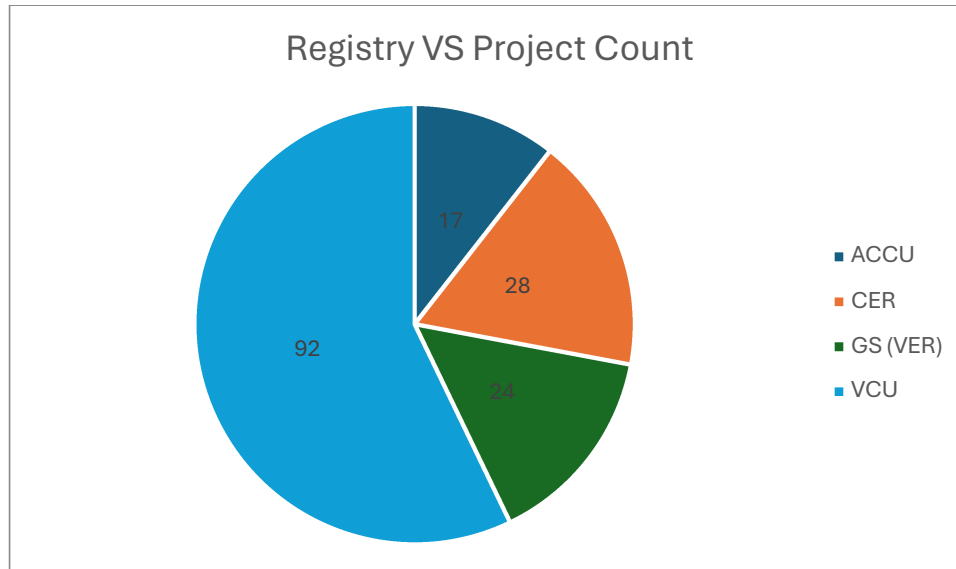


Figure 3. 7.:Registry vs. Project Count

- **Registry vs. Project Count:**

- The pie chart shows the proportion of projects in different categories. Each registry may have different standards and impacts. This information could be used for statistical modelling to categorise tasks and assess whether the registry type correlates with the social impact.
- The diversity in registry types can enhance the robustness of the model by preventing it from being biased towards the methodologies of a single registry.

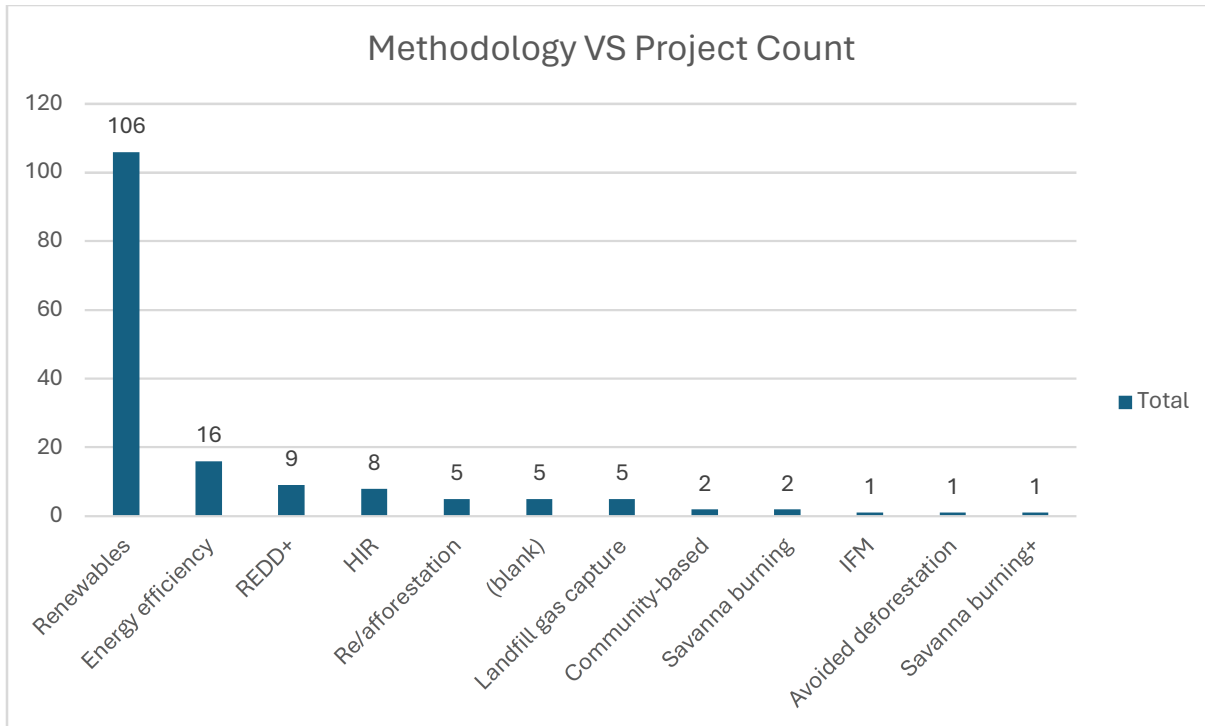


Figure 3. 8.:Data Analysis – Methodology Vs Project Count

- **Methodology vs. Project Count:**

- This bar graph displays the count of projects by methodology type, with 'Renewables' being the most common. A diverse range of methodologies allows for a multi-faceted analysis of impact. We can model the effectiveness of each methodology type or group them into broader categories (like 'environmental' vs. 'social' impact methodologies).
- The dominance of 'Renewables' suggests we might need to stratify our data or use weighting to balance the influence of different methodologies in our model.

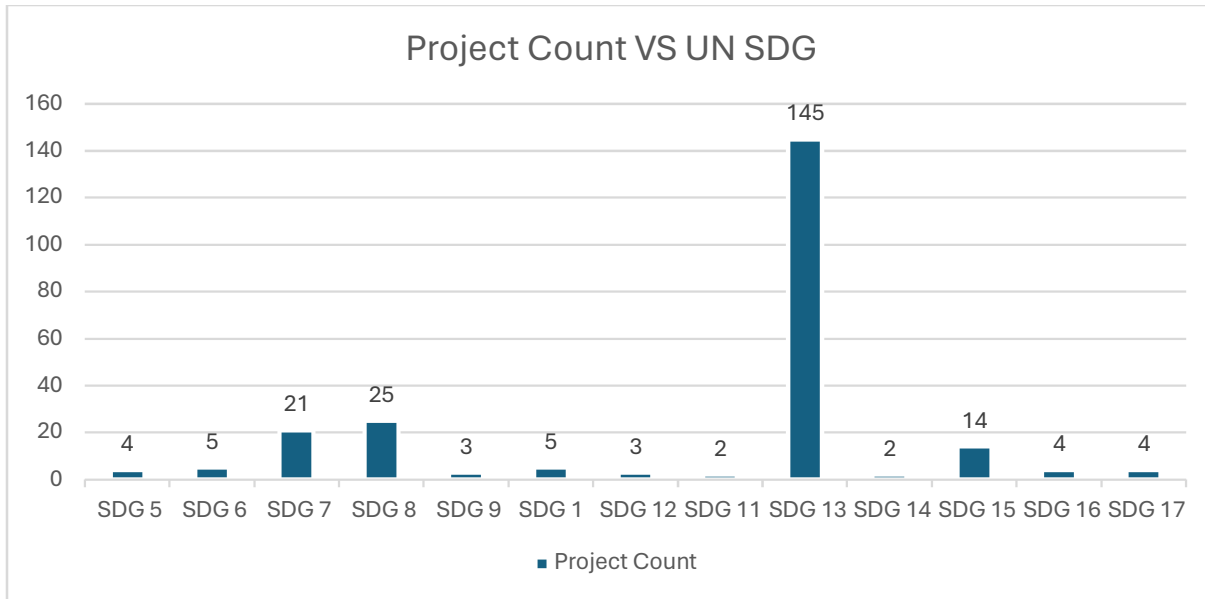


Figure 3. 9.:Data Analysis –Project Count Vs UN SDG

- **Project Count vs. UN SDG:**

- This graph indicates a strong focus on one SDG. Statistical modelling could assess the effectiveness of projects targeting different SDGs and whether projects aligned with certain SDGs are more likely to have a higher social impact. The model could also explore if projects contribute to multiple SDGs and how this multi-target approach correlates with social impact.

- **Methodology vs. UN SDG Count:**

- The "Methodology vs. UN SDG Count" graph depicts the relationship between various project methodologies and their contributions to different United Nations Sustainable Development Goals (SDGs). Each process is aligned with one or more SDGs, showing the number of projects targeting each specific goal. The graph shows a range of methods and their corresponding focus on different SDGs, indicating a

rich diversity in the dataset. This diversity allows for robust analysis of how different project types contribute to various aspects of social and environmental progress.

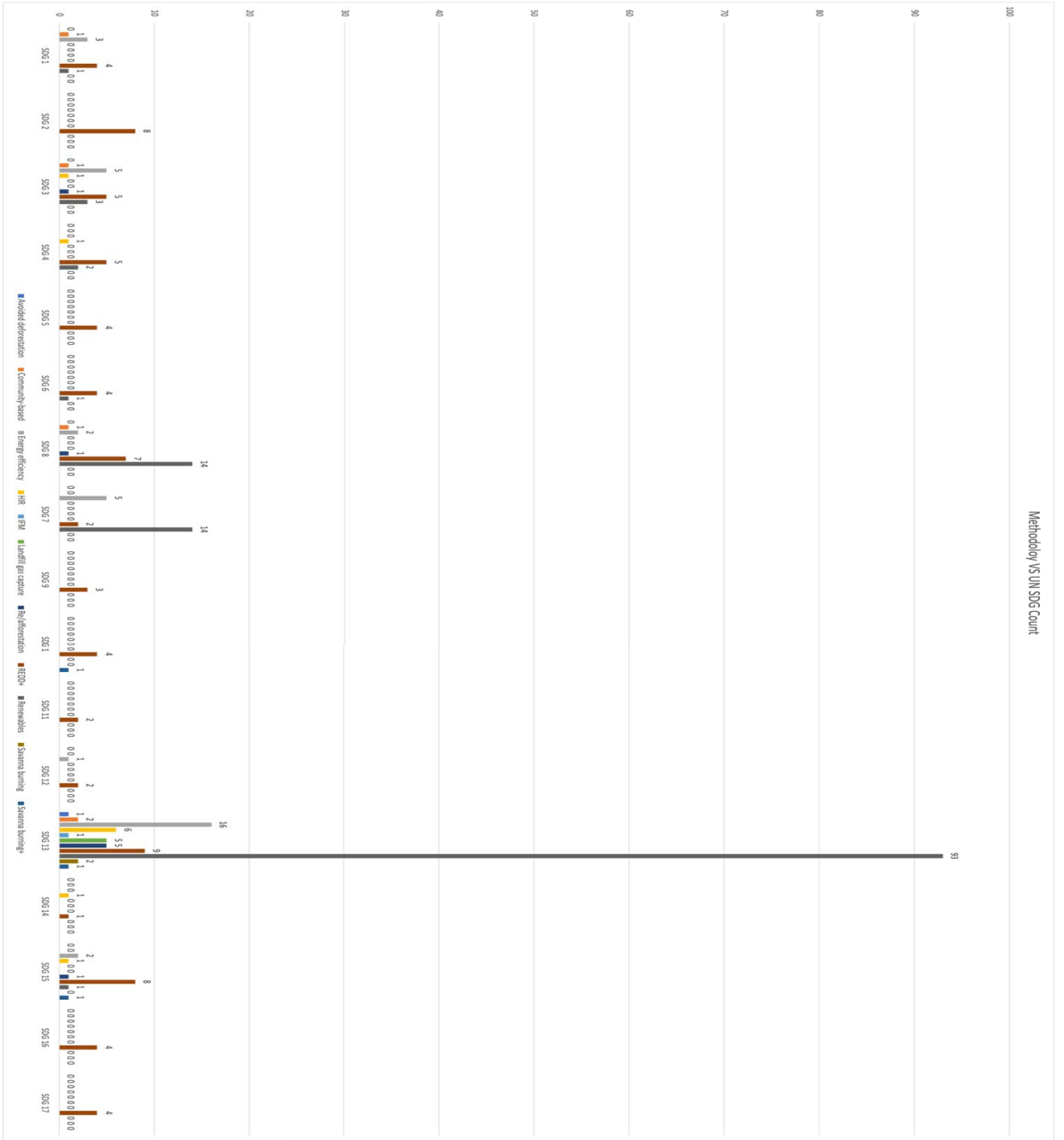


Figure 3. 10.:Data Analysis – Methodology Vs UN SDG

Specific methodologies, particularly those related to renewables, are strongly associated with SDGs, suggesting a trend in project focus areas. This can be used to identify which methods are most effective at addressing specific social and environmental issues.

We can perform a targeted impact analysis by understanding which methodologies contribute to specific SDGs. For instance, projects with a method that aligns with SDG 7 (Affordable and Clean Energy) can be analysed to assess their direct and indirect social impacts, such as job creation, health improvements due to cleaner energy, or economic growth.

3.5. Variable Selection:

Selecting the correct variables based on our dataset is crucial to calculating and predicting the social impact of carbon credit projects. Social impact can encompass many outcomes, including job creation, community development, environmental benefits, and local health and well-being improvements. Given the dataset details, we will focus on selecting variables that could serve as indicators or proxies for these various dimensions of social impact.

3.5.1. Critical Variables for Social Impact Analysis

- **Project Scale:** The size of the project is likely to influence its social impact significantly. Larger projects may offer more employment opportunities and contribute substantially to local economies.
- **Project Type ('product_type_name', 'project_method_type_name'):** The nature of the project (e.g., renewable energy, energy efficiency, forestry) can affect the type and magnitude of its social impacts. For example, renewable energy projects might improve local energy access, while forestry projects could enhance

biodiversity and ecosystem services.

- **Location/Region (`region`)**: The geographic location or the country of the project can influence the type of social impact due to differing local needs, economic conditions, and environmental priorities.
- **Job Offered (`job_offered`)**: If available, this variable directly indicates the project's impact on local employment, a critical social impact component.
- **Certificate Project Type (`certificate_project_type_name`)**: This variable might provide insights into the project's certification standards, which can relate to specific social or environmental benefits.
- **Description (`description`)**: Textual descriptions may contain qualitative data on project goals, community involvement, and intended social or environmental benefits. Text analysis could uncover additional insights into social impact.

For predictive modelling of social impact, consider using a mixed-methods approach that combines quantitative analysis (e.g., regression models, machine learning algorithms) with qualitative insights (e.g., content analysis of project descriptions). This approach can help capture the multifaceted nature of social impact. Machine learning models such as Random Forests or Gradient Boosting Machines can handle the non-linear relationships and interactions between variables. At the same time, Natural Language Processing (NLP) techniques can extract themes and patterns from textual data in project descriptions.

3.5.2. Data Preparation:

- **Feature Engineering:**

We may need to create or modify new variables to capture the nuances of social impact better. For example, categorising countries into developed and developing, as

discussed, can refine the analysis. We need to create a new variable named Job Offered, which can directly indicate the impact of the project on local employment, which can serve as a critical social impact component, and we will modify the region column in the category (developed, developing and under development) that can serve as a social impact measure.

- **Categorising Region:**

For this modification, first, we need to get a dataset regarding every country and determine which country resides in which category.

Since the `region` column contains country names, a more accurate approach to categorising each project as "Developed" or "Developing" involves mapping these countries to their respective development status based on globally recognised standards. For this task, we can reference classifications by the United Nations, World Bank, or other authoritative bodies that categorise countries based on economic indicators, such as GDP per capita, human development index (HDI), and other social and financial metrics.

- **Implementation Strategy**

- **Create a Mapping:**

Develop a mapping of countries to their development status. This could be based on the latest data from the United Nations Development Programme (UNDP) for HDI, World Bank classifications of economies, or other relevant sources.

We got the latest Human Development Index from the UNDP Human Development Reports website (<https://hdr.undp.org/data-center/human-development-index/indicies/HDI>) for this mapping. We will use this data to create a map for developed and developing countries along with our region column in our dataset.

- **Apply Mapping to Dataset:**

Use this mapping to assign a development status to each project based on its country of operation.

This method directly aligns with geographical and development studies, which frequently analyse the impact of economic growth on various societal outcomes, including employment patterns, technological adoption, and environmental policies. By categorising countries into "Developed" and "Developing" based on established criteria, researchers can better understand the nuances of global economic dynamics and the role of carbon credit projects in different developmental contexts.

To add region categorisation into the project details dataset based on this country-region mapping:

- **Prepare the Mapping DataFrame:** Extract necessary columns from ``country_region_df`` for mapping. We should map the ``Region`` from the country-region mapping to the ``region_name`` or an appropriate country identifier in ``project_details_df``.
- **Merge DataFrames:** Perform a merge operation based on the country names or regions, aligning ``project_details_df`` with the development status in ``country_region_df``.
- **Handle Missing Values:** After merging, checking for any projects that could not be matched to a region and deciding how to handle these cases is essential.

We merged the DataFrames to add the development status to the project details, using an appropriate common identifier (assuming ``region_name`` corresponds to ``Region`` or requires mapping through country names). Since the exact match between ``region_name`` and ``Region`` or development status is not directly apparent from the initial view.

```

In [1]: import pandas as pd
import numpy as np

In [15]: project_details_df = pd.read_csv("/Users/drishtant/Documents/Masters/CA/core market data/project_details.csv")
country_region_df = pd.read_excel("/Users/drishtant/Documents/Masters/CA/core market data/Country - Region Mapping.x

In [19]: =the actual key for merging depends on matching country names or regions)
we need to create a mapping based on country names to regions
or directly use HDI rankings as a proxy for development status.

Example merge operation (this is conceptual and might require adjustments
based on actual column names and matching logic)
project_details_df = project_details_df.merge(country_region_df[['Region', 'Country Status']], left_on='region_name',
right_on='Region', how='left')

```

Figure 3. 11.:Data Preparation – Apply Mapping to Dataset

Job Offered Variable:

We need to determine how many jobs are created for this new column based on project scale, location, and development status.

We employ a methodological framework that combines empirical data analysis with established economic theories to systematically analyse the employment impacts of carbon credit projects, incorporating detailed considerations of project scale, country status, and methodology. This approach allows for a nuanced estimation of job offer ranges that reflect these projects' socio-economic and technological contexts. Our analysis employs a categorical assignment of job offers ranging to projects based on the project scale. This methodology is informed by labour economics and project management principles, suggesting a correlation between the scale of an initiative and its employment generation capacity.

1. Project Scale

The project scale fundamentally determines the baseline range of job offers. The logic behind associating larger scales with broader job offer ranges is grounded in the

principle that larger projects typically entail more comprehensive activities— construction, maintenance, operations, etc.—thus requiring a larger workforce.

- **Micro Scale: 1-10 jobs:** Small, localised projects likely involve a minimal number of tasks and personnel.
- **Small Scale: 11-50 jobs:** Projects of this scale begin to require more structured teams for implementation and management.
- **Medium Scale: 51-200 jobs:** At this level, projects have significant operational demands that necessitate a broader array of specialists and labourers.
- **Large Scale: 201-1000 jobs.** Large-scale projects, such as extensive renewable energy installations, necessitate a vast workforce for various development and operation phases.

2. Country Factor

Adjustments based on the 'Country Status' reflect the impact of economic development on labour markets. The rationale is that the stage of economic development influences the extent to which projects can leverage technology versus manual labour, affecting the overall employment potential.

- **Developing: 1.2.** We anticipate relying more on manual labour due to lower automation and technology penetration.
- **High Developed: 0.8.** Projects in highly developed countries may utilise advanced technologies, reducing the need for manual labour.
- **Underdeveloped: 1.5.** The least developed economies might have the highest reliance on manual labour due to minimal technological access.
- **Developed: 0.9.** With access to technology, there's still considerable scope for manual labour, albeit less than in developing or under-developed contexts.

3. Methodology Factor

This factor accounts for the varying labour intensities associated with different carbon

credit project methodologies, reflecting the specific demands of each project type.

- **Renewables:** Assigned a factor of 1.2, this category is labour-intensive due to the significant manual work required during the construction and maintenance. Such projects necessitate a large workforce for installation and upkeep (Yocum, 2016)
- **Energy Efficiency:** With a factor of 1.0, these projects require specialised labour, although to a lesser extent than renewable energy projects. The specialised nature of the work often demands a higher skill level but involves fewer workers overall (Von Avenarius, Devaraja, & Kiesel, 2018)
- **Community-based:** This category has a factor of 1.3, indicating a high labour demand due to the necessity of community engagement and manual processes. These projects are designed to be participatory and often involve numerous community members (Van der Gaast, Sikkema, & Vohrer, 2018)
- **Re/afforestation:** With a labour intensity factor of 1.4, re/afforestation activities such as planting and ongoing maintenance are among the most labour-demanding in the carbon credit spectrum (Galik, Foley, & Richter, 2009)
- **REDD+:** These projects are evaluated with a labour factor 1.1, incorporating considerable labour for community engagement and monitoring activities. The projects often involve complex methodologies that increase labour requirements (Pettenella & Brotto, 2012)
- **Improved Forest Management (IFM):** Also rated at 1.1, IFM projects require substantial labour for both the implementation and monitoring processes, aiming at sustainable forest management practices (Galik et al., 2014)
- **Human-induced Regeneration (HIR):** With a variable labour intensity factor of 1.0, HIR projects can vary widely in terms of labour demands based on the project's scope and methods employed (Summers et al., 2015)

- **Landfill Gas Capture:** These projects are given a factor of 0.9 due to their moderate labour requirements, as they are more technologically driven and often involve machinery and periodic monitoring rather than constant labour (Wong et al., 2009)
- **Savanna Burning:** This methodology is assigned a factor of 1.2 due to the manual nature of fire management practices, which are labour-intensive and require an extensive workforce for controlled burning and land management (Fearnside, 2015)
- **Savanna Burning Plus:** It also has a factor of 1.2, mirroring savanna burning, but may include additional labour-intensive activities depending on the scope and scale of the projects.

Each of these categories demonstrates the importance of considering labour intensity in the planning and execution of carbon credit projects. The referenced studies provide a comprehensive understanding of the labour requirements and challenges associated with each type of project, which is crucial for accurate methodology factor assessment and effective project management in carbon credit initiatives.

The methodology integrates insights from labour economics regarding the correlation between project size and job creation, further nuanced by the socio-economic context (as influenced by the country's development status) and the specific demands of the project's methodology. This multifaceted approach is substantiated by the following:

```
In [10]: country_factor = {
    'Developing': 1.2, # Reflects increased reliance on manual labor.
    'High Developed': 0.8, # Indicates higher automation and efficiency.
    'Under Developed': 1.5, # Suggests substantial reliance on manual labor due to limited access to technology.
    'Developed': 1, # A balance between automation and manual labor.
}
```

```
In [11]: methodology_factor = {
    'Renewables': 1.2, # Labor-intensive, especially during construction and maintenance phases.
    'Energy efficiency': 1.0, # Requires specialized labor but less extensively than renewables.
    'Community-based': 1.3, # Highly labor-intensive due to community engagement and manual processes.
    'Re/afforestation': 1.4, # Labor-intensive activities such as planting and maintenance.
    'REDD+': 1.1, # Involves community engagement and monitoring activities.
    'IFM': 1.1, # Improved Forest Management requires significant labor for implementation and monitoring.
    'HIR': 1.0, # Human-induced Regeneration may vary in labor intensity.
    'Landfill gas capture': 0.9, # Technologically driven, moderate labor requirements.
    'Savanna burning': 1.2, # Manual fire management practices.
    'Savanna burning+': 1.2, # Similar to savanna burning with potentially additional activities.
    'Avoided deforestation': 1.1, # Monitoring and enforcement, involving community participation.
}
```

Figure 3. 12.:Data Preparation – Country & Methodology Factor

We have developed a model for estimating the job offers of carbon credit projects, incorporating comprehensive socioeconomic factors. The `country_factor` and `methodology_factor` dictionaries encapsulate multipliers that adjust job offer estimates based on the country's development status and the project's methodology type, respectively.

Country Factor:

The `country_factor` multipliers were conceived based on the premise that economic development levels impact the labour intensity of carbon credit projects. Projects in 'Developing' countries (factor: 1.2) are hypothesised to be more labour-intensive due to lower levels of automation, whereas 'High Developed' countries (factor: 0.8) likely have advanced automation and efficiency, leading to fewer manual jobs. 'Under Developed' countries (factor: 1.5) may rely significantly on manual labour due to limited access to technology, with 'Developed' countries (factor: 1) representing a balance between automation and manual labour.

Methodology Factor:

The `methodology_factor` reflects the labour requirements of various carbon credit project types. 'Renewables' projects (factor: 1.2) are labour-intensive, particularly during the construction and maintenance phases. 'Energy efficiency' initiatives (factor: 1.0) typically require specialised labour but less extensively than renewables. 'Community-based' projects (factor: 1.3) are highly labour-intensive due to their reliance on manual processes and community engagement.

Other project types, such as 'Re/afforestation' (factor: 1.4), 'REDD+' (factor: 1.1), and 'Landfill gas capture' (factor: 0.9), have factors reflecting their respective labour intensities from planting and maintenance activities to technologically driven processes requiring moderate labour inputs.

```
In [15]: import pandas as pd

# Assuming project_details_df is loaded with the relevant columns
# Define base job offer ranges
base_ranges = {'Micro Scale': (1, 10), 'Small Scale': (11, 50), 'Medium Scale': (51, 200), 'Large Scale': (201, 1000)}

# Function to calculate adjusted job offer range
def calculate_adjusted_range(row):
    scale_range = base_ranges.get(row['Scale'], (0, 0))
    adjustment = country_factor.get(row['Country Status'], 1) * methodology_factor.get(row['project_method_type_name'])
    adjusted_min, adjusted_max = (scale_range[0] * adjustment, scale_range[1] * adjustment)
    return f"{int(adjusted_min)}--{int(adjusted_max)}"

## Function to calculate adjusted job offered
# def calculate_adjusted_range(row):
#     #as we have range

# Apply the function to the dataframe
project_details_df['Adjusted Job Offer Range'] = project_details_df.apply(calculate_adjusted_range, axis=1)
```

Figure 3. 13. Data Preparation – Adjusted Job Offer Range

Drawing from the methodology outlined earlier, we aim to establish a quantifiable estimate of job offers associated with carbon credit projects. The lack of explicit job offer details within most project datasets necessitates this. Although this approach may yield little precise accuracy, it is structured to provide a robust, systematic method for estimating employment figures, crucial variables in calculating social costs.

The function `calculate_adjusted_range` delineated above is designed to determine a range of potential job offers, leveraging the predefined scale ranges. To complement this, we have devised another function, `calculate_exact_job_count`, which pinpoints an estimated number of job offers by selecting a median value within each scale range. This median value represents a balanced estimate, avoiding the extremes of each range.

By incorporating the estimated job offer range and the specific job offer count, we enhance our statistical modelling, enriching it with a more nuanced representation of employment potential. These estimates serve as critical inputs for more sophisticated analyses, particularly in assessing the social costs associated with these environmental projects. This dual-faceted approach ensures that our model accounts for both the variability and the central tendency within the employment data, thereby strengthening the reliability of our social cost evaluations.

```
In [18]: def calculate_exact_job_count(row):
# Define the midpoint of each range as the representative value
representative_values = {
    'Micro Scale': 5, # Midpoint of 1-10
    'Small Scale': 30, # Midpoint of 11-50
    'Medium Scale': 125, # Midpoint of 51-200
    'Large Scale': 600, # Midpoint of 201-1000
}

# Retrieve base representative value for the project's scale
base_job_count = representative_values.get(row['Scale'], 0)

# Adjust the base job count based on country status and project methodology
country_adj = country_factor.get(row['Country Status'], 1)
method_adj = methodology_factor.get(row['project_method_type_name'], 1)

# Calculate the adjusted job count
adjusted_job_count = int(base_job_count * country_adj * method_adj)

return adjusted_job_count

# Apply the function to each row in the DataFrame
project_details_df['Estimated Job Count'] = project_details_df.apply(calculate_exact_job_count, axis=1)
```

Figure 3.14. Data Preparation – Adjusted Job Count

3.6. Data Labelling

We now have a robust dataset that allows us to apply statistical modelling techniques to quantify the social influence exerted by carbon credit initiatives. Given the dataset's constraints, we have two principal modelling approaches:

Supervised Learning:

Supervised learning is a type of machine learning where the model is trained on a labelled dataset, which means that each training example is paired with an output label. A supervised learning model would require a dataset that includes examples of past projects and quantified measures of their social impact in assessing the social impact of carbon credit projects. This could be in numerical scores or categories such as 'low impact', 'moderate impact', and 'high impact'. The model would learn from this data to predict the social impact of new, similar projects.

For instance, if we had data on various projects with associated benefits like job creation, health improvements, or community development, the model could learn to predict these benefits for a new project based on its characteristics. The primary advantage of supervised learning is its ability to make quantitative predictions, allowing stakeholders to estimate the actual impact a project might have.

Unsupervised Learning:

Unsupervised learning, in contrast, does not require labelled data. Instead, it analyses the data's inherent structures and patterns. When applied to carbon credit projects, unsupervised learning models could be used to group similar projects based on features such as location, size, or type of carbon offset activity. This helps identify relationships and similarities between projects without predefined categories.

For example, unsupervised learning could reveal that certain types of projects consistently cluster together and possibly share similar social outcomes, even if those outcomes have not been labelled in the data. However, unsupervised learning models generally do not predict specific outcomes. Instead, they might categorise projects into clusters that could suggest potential impacts or identify outliers significantly different from the majority. These insights can be precious for exploratory analysis when trying to understand the landscape of projects without prior assumptions.

In summary, supervised learning models excel at prediction based on historically labelled data, while unsupervised learning models are powerful tools for discovery and insight when the data lacks labels. Both methods can provide valuable insights for carbon credit projects, whether one is trying to predict specific impacts or explore data to uncover patterns and relationships.

Labelling with Social Impact Score:

Our supervised learning models will use the calculated social impact scores as labels or target variables. This enables us to predict the social impact of new or existing projects based on their attributes or to classify projects based on their social impact.

To apply different statistical modelling methods, we first need to decide on an ML solution for the available dataset. The selection of ML Methods, such as supervised or unsupervised algorithms, will play a crucial part in this research. As our data is not labelled regarding social cost, we first need to calculate it using appropriate measures.

The total cost to society because of a choice, event, or action is known as the social cost. This cost includes the internal expenses incurred privately by those immediately involved and the external expenses incurred by those not directly involved. "Social impact" refers to a decision, organisation, or policy's overall positive and negative impact on a group or society. This can cover a range of things, like the effects on the

economy, culture, and ecology. Examples are new jobs generated, communities impacted, health effects, or biodiversity preservation.

Utilising the metrics listed in the metric specification, develop a method or algorithm to calculate each project's social impact/cost. This may require weighing several factors under their apparent importance. Use the technique you have found to analyse your dataset to calculate each project's measured social impact and cost.

The ``un_sd_goals`` column contains lists of integers, each representing different United Nations Sustainable Development Goals (UN SDGs) that the project supports. These lists are stored as strings, which need to be converted into a format that can be used for analysis and modelling.

To properly utilise this column, we will transform it into multiple binary columns, one for each UN SDG, indicating whether a project supports a particular goal (1) or not (0). This approach, known as one-hot encoding, will make the dataset suitable for statistical modelling and analysis.

1. Parse the ``un_sd_goals`` column to extract each project's goals list.
2. Create binary columns for each UN SDG based on the extracted lists.

```

# Define a function to parse the 'un_sd_goals' column and create binary columns for each UN SDG
def parse_un_sd_goals(row):
    if pd.isna(row):
        return []
    else:
        # Remove brackets and split by comma to get the list of SDGs
        return [int(sdg.strip()) for sdg in row.strip('[]').split(',')]

# Apply the function to the 'un_sd_goals' column
data['un_sd_goals_parsed'] = data['un_sd_goals'].apply(parse_un_sd_goals)

# Initialize columns for each UN SDG (1-17)
for sdg in range(1, 18):
    data[f'SDG_{sdg}'] = data['un_sd_goals_parsed'].apply(lambda sdgs: 1 if sdg in sdgs else 0)

# Drop the original 'un_sd_goals' column and the temporary 'un_sd_goals_parsed' column
data.drop(columns=['un_sd_goals', 'un_sd_goals_parsed'], inplace=True)

# Display the first few rows to verify the transformation
data.iloc[:, :-18:].head()

```

Estimated Job Count	SDG_1	SDG_2	SDG_3	SDG_4	SDG_5	SDG_6	SDG_7	SDG_8	SDG_9	SDG_10	SDG_11	SDG_12	SDG_13	SDG_14	SDG_15	SDG_16	SDG_17
0	1428	0	0	0	0	0	1	1	0	0	0	0	1	0	0	0	0
1	1428	0	0	0	1	0	0	1	1	0	0	0	1	0	1	0	0
2	850	1	0	0	0	0	0	1	0	0	0	0	1	0	0	0	0
3	714	0	0	0	0	0	1	1	1	0	0	0	1	0	0	0	0
4	8	0	0	1	0	0	0	1	0	0	0	0	1	0	0	0	0

Figure 3. 15.: Data Labelling – Parse UN SDG to Project Dataset

This code will transform the `un_sd_goals` column into individual binary columns for each of the 17 UN SDGs, facilitating their use in statistical modeling. Let's execute this transformation.

The `un_sd_goals` column has been successfully transformed into individual binary columns for each of the 17 United Nations Sustainable Development Goals (UN SDGs), from `SDG_1` to `SDG_17`. Each column indicates whether a project supports a particular goal (1) or not (0), making this information readily usable for statistical modelling.

Evaluating the social impact of a carbon credit project based on UN SDGs is a complex undertaking. The Sustainable Development Goals (SDGs) 7 (Affordable and Clean Energy), 13 (Climate Action), and 15 (Life on Land) can all be impacted by carbon credit programs. Depending on the project's type, scale, location, and other aspects, the direct and indirect effects on these objectives can be very different.

To create a generalised formula for labelling purposes, we might consider the following factors:

This formula may require some assumption for some variable based on the individual project details available, such as the number of people affected/jobs created based on the project size (e.g., small-scale, medium scale or large-scale project).

- **Direct Carbon Reduction (DCR):** Ensure that the CO₂-equivalent emissions reduced are accurately quantified by incorporating a verification step, possibly through third-party audit reports, to validate the emission reductions claimed.
- **SDG Alignment (SDGA):** The binary scoring (0 or 1) simplifies the complexity of SDG alignment. Consider a more granular approach where alignment is scored on a scale reflecting the depth and breadth of impact, such as a Likert scale from 0 (no alignment) to 5 (full alignment).
- **Community Impact (CI):** Expand this to include qualitative measures through community feedback mechanisms to capture the perceived impact alongside the quantifiable metrics like jobs or households impacted.
- **Multiplier Effect (ME):** Define more precise parameters for a 'cascading effect'. Establish criteria to quantify these effects, such as the reach of agricultural education or the extent of biodiversity improvements.

Given the above, a simplified normalised formula might be:

$$Social\ Impact = \frac{\left(1 - \frac{1}{DCR}\right) * SDGA * CI * ME}{Max.DCR * Max.SDGA * Max.CI * Max.ME}$$

```

In [39]: # Calculate SDG Alignment Score (SDGA)
data['SDGA'] = data[sdg_cols].sum(axis=1)

# Assuming 'Annual Emission Reduction' is DCR and is in the correct numeric format
# Normalize DCR by dividing by the maximum DCR value in the dataset
data['DCR_norm'] = data['Annual Emission Reduction']
# Assuming 'Estimated Job Count' is CI
# Normalize CI by dividing by the maximum CI value in the dataset
data['CI_norm'] = data['Estimated Job Count'] / data['Estimated Job Count'].max()

# Assuming a constant ME across all projects, normalized to 1
# Assuming a constant ME across all projects, normalized to 1
data['ME'] = 0
data.loc[data['SDGA'] > 1, 'ME'] = 1.5
data.loc[data['SDGA'] == 1, 'ME'] = 1
# Or this can be a column based on additional data

# Calculate normalized Social Impact score
data['Social_Impact'] = ((1 - 1 / data['DCR_norm']) * data['SDGA'] * data['CI_norm'] * data['ME']) / 1 # Normalized

# Now data['Social_Impact'] contains the normalized Social Impact score for each project

```

Figure 3. 16.: Data Labelling – Social Impact labelling in Dataset

The above image is a simple example of labelling the dataset based on our provided equation. We can apply a supervised machine learning modelling algorithm now that we have correctly labelled data.

To ensure that these calculated social impact scores are suitable as target labels for supervised learning, the labelling process was designed with consistency and replicability as core principles. Each score is derived using a predefined set of calculation rules that are applied uniformly to all projects. These rules involve: (1) normalising Direct Carbon Reduction (DCR) values by the maximum in the dataset, (2) calculating SDG Alignment (SDGA) from one-hot encoded SDG indicators, (3) normalising Community Impact (CI) based on the *Estimated Job Count*, and (4) assigning the Multiplier Effect (ME) as 1.5 if a project aligns with more than one SDG, otherwise 1.0. The resulting variables are combined through the stated formula without any manual adjustments, ensuring that every project is evaluated through the same transparent process. All assumptions, transformations, and computation steps are fully documented, enabling replication and independent verification by other practitioners. This approach ensures that the generated

labels are internally consistent and methodologically robust for use in supervised learning models.

Operationalisation and Weighting of Formula Components

Community Impact (CI):

CI is calculated as a normalised measure of community benefit. In this study, *Estimated Job Count* is used as the primary proxy for local employment generated by each project. Each project's job count is divided by the maximum job count in the dataset, producing a CI value between 0 and 1 to ensure comparability. Where data permit, this measure can be extended to include additional socio-economic indicators such as income improvement or access to essential services, consistent with recognised social impact measurement approaches (Maas & Liket, 2011).

Multiplier Effect (ME):

ME is applied as a fixed scalar to reflect the breadth of SDG alignment:

- **ME = 1.5** for projects aligned with more than one SDG.
- **ME = 1.0** for projects aligned with exactly one SDG.

This simple, transparent rule ensures consistent application across projects and is supported by evidence that multi-SDG initiatives often yield synergistic and compounding benefits (Pradhan et al., 2017; Nilsson et al., 2018).

Weighting Justification:

The current formula applies equal multiplicative influence on Direct Carbon Reduction (DCR), SDG Alignment (SDGA), CI, and ME. Equal weighting maintains

methodological neutrality where no strong evidence exists to prioritise one factor, supports interpretability, and follows good practice in early-stage composite indicator development (OECD, 2008). The framework is adaptable and can incorporate alternative weighting schemes informed by literature, expert consultation, or data-driven methods such as Principal Component Analysis (PCA) or the Analytic Hierarchy Process (AHP) if required in future applications.

3.7. Data Findings and Practical Applications

1. Data Findings:

In our exploration of the dataset encompassing 161 carbon credit projects, we have conducted a comprehensive analysis to discern the intricate details and patterns that influence the social impacts of these initiatives. The primary objective was to ensure the data was robust enough to support reliable statistical modelling and uncover the variables that most significantly affect social outcomes.

2. Project Scale and Job Creation:

The data indicates that larger projects typically result in more significant employment opportunities and economic contributions to local communities. For instance, renewable energy projects and large-scale reforestation initiatives require substantial human resources for their implementation and ongoing maintenance. This finding aligns with labour economics theories suggesting that larger projects have a higher potential for job creation and economic development (Becker & Murphy, 1992).

3. Country Factor:

Our analysis also reveals that the stage of economic development in the project location influences job creation and other social impacts. Projects in developing countries tend to rely more on manual labour, thus generating more employment opportunities compared to similar projects in developed nations where advanced technologies might reduce the need for manual work (World Bank, 2021).

4. Methodology Factor:

The type of methodology employed in carbon credit projects significantly affects the labour intensity and, consequently, the social impact. For example, re/afforestation projects are highly labour-intensive, requiring extensive human resources for planting and maintenance activities (Galik, Foley, & Richter, 2009). In contrast, landfill gas capture projects, which are more technologically driven, require fewer manual labour inputs (Wong et al., 2009).

3.8. Practical Applications and Policy Implications:

1. Policy Formulation:

The insights gained from our data analysis can inform policymakers about the most effective types of carbon credit projects in terms of social impact. For instance, projects that combine environmental benefits with high job creation potential, such as large-scale renewable energy or re/afforestation projects, should be prioritised in national and international climate strategies. Policies can be

designed to provide incentives and support for these types of projects, ensuring they receive the necessary resources and regulatory support to maximise their social and environmental benefits.

2. Project Planning and Implementation:

Project developers can use our findings to design and implement carbon credit projects that align more closely with sustainable development goals. By understanding the variables that influence social impacts, developers can optimize their project plans to enhance job creation, improve community health, and contribute to local economic development. For example, incorporating community-based approaches and ensuring active local participation can enhance the social benefits of carbon credit projects.

3. Investment Decisions:

Investors can utilise the data insights to make informed decisions about funding carbon credit projects. Projects with high social impact potential, particularly those in developing countries and those using labour-intensive methodologies, can be prioritised for investment. This approach not only maximises returns on investment regarding social and environmental benefits but also aligns with corporate social responsibility goals.

4. Community Engagement:

Effective communication of the social impacts of carbon credit projects can foster greater community engagement and support. Project developers can build stronger relationships with local communities and stakeholders by

highlighting the benefits such as job creation, improved health outcomes, and economic development. This approach enhances the sustainability and acceptance of carbon credit initiatives.

5. Monitoring and Reporting:

Our data-driven methodology can be used to create robust monitoring and reporting frameworks for carbon credit projects. Regular assessment of social impacts, alongside environmental benefits, ensures transparency and accountability. This comprehensive reporting can be used to demonstrate the value of carbon credit projects to stakeholders, including governments, investors, and local communities.

6. Future Research:

Our findings also pave the way for future research to refine and expand the methodologies used in assessing the social impacts of carbon credit projects. Further studies could explore additional variables and employ more sophisticated analytical techniques to enhance the accuracy and reliability of social impact assessments.

By integrating these practical applications and policy implications into the framework of carbon credit projects, we can ensure that these initiatives contribute effectively to global sustainability goals, providing tangible benefits to both the environment and local communities.

In the concluding Chapter, we have developed a comprehensive approach to data analysis and labelling that lays the groundwork for future applications of statistical

modelling to evaluate the social impact of carbon credit projects. This chapter underscores the importance of meticulous data preparation in ensuring accurate, reliable modelling outcomes. By categorising and labelling our data effectively, we have prepared a solid foundation for the subsequent application of statistical modelling techniques, aiming to predict and analyse the social impacts more deeply. This preparatory work is crucial for the success of predictive modelling. It enhances the potential for actionable insights in policy-making and project planning, ensuring that future work in this thesis will build on a robust, data-driven basis.

Chapter 4 :Statistical Modelling and Gen AI Tool Development

4.1. Introduction

Carbon credit projects are essential to ensure global greenhouse gas emissions reduction by offering financial incentives to projects that prevent, reduce or capture carbon emissions. With increasing efforts worldwide to counter climate change, the scope of assessing carbon credit projects has since expanded from just carbon accounting to evaluating their broader social and economic implications. These include their impact on the local community, the creation of jobs, benefits for public health and whether they are consistent with the UN Sustainable Development Goals (SDGs). Unfortunately, achieving an understanding of these impacts requires the use of advanced statistical models and machine learning techniques. These tools allow researchers to exceed simple assessments to obtain more in-depth and complicated assessments of large datasets, identify the complicated relationships amongst these data, and generate predictive models capable of predicting forthcoming outcomes (Friedman et al., 2001).

4.1.1. Statistical Modelling and Machine Learning rationale

Robust frameworks for quantifying and predicting carbon credit projects' social and economic impacts using statistical modelling and machine learning are provided. Though effective, traditional evaluation methods tend to rely on predetermined assumptions and cannot fully capture the non-linear, dynamic relationships in the data represented by these projects (Breiman, 2001). While the social impacts of carbon credit projects are not uniform across diverse geographic regions, scales, and sectors where they are implemented, approaches to understanding and measuring their impacts vary. Prior research typically considers factors such as project size, type (renewable energy, forestry, or waste management), and region. However, these factors impede simple analysis and require sophisticated analysis tools to disentangle.

Previously, statistical models, including linear regression, time series analysis and Bayesian networks, have been used to infer cause and effect relationships between variables. For instance, they can determine how large a project has to be to create jobs

or the effectiveness of community involvement in project success. However, algorithms are more dynamic and machine learning in complex and large datasets. It is also a field that specialises in processing large amounts of data, detecting patterns that are not easily seen, and adapting to more available data (Goodfellow et al., 2016). Within the realm of supervised learning techniques, we have demonstrated how decision trees, random forests, and gradient boosting machines have been able to predict project outcomes with high accuracy; on the other hand, clustering is an unsupervised learning method that can be used to discover hidden groupings of projects, albeit according to their social impact profile.

4.1.2. Statistical Modelling for Social Impact Assessments

Social sciences have understood causal relationships between variables using statistical modelling for thousands of years. We can find out whether changes in a project's design or location change its social impact with linear regression or logistic regression. Take, for example, how logistic regression can predict whether a carbon credit project will achieve its social goals given its size, methodology and geographic location. However, the relationship between project scale and created jobs can be quantified precisely using linear models (Hair et al., 2010). They enable building equations that quantify how different project characteristics are related to their effects.

Statistical models have limitations, particularly when interactions are non-linear or if data is biologically complex. In these cases, these models may need to be more accurate and reach incorrect conclusions. That is where machine learning models come in. Machine learning can better process more complex datasets and interactions, resulting in more accurate predictions and more profound insights (Friedman et al., 2001).

4.1.3. Social Impact Prediction using Machine Learning Approaches

As a subfield of artificial intelligence, machine learning helps us predict outcomes and find patterns in the vast dataset. Specifically in carbon credit projects, machine learning models such as random forests, decision trees and neural networks excel in

understanding the non-linear relationships between project characteristics and social impacts. For the purposes of this study, *social impact* is defined in the same way as in the labelling methodology described in Chapter 3 — a quantified score derived from four components: Direct Carbon Reduction (DCR), SDG Alignment (SDGA), Community Impact (CI), and Multiplier Effect (ME). Each component is normalised where applicable and combined using the stated formula to produce a consistent, reproducible measure for all projects. While the term “social impact” can be interpreted broadly in other contexts, here it is operationalised strictly as this calculated score, ensuring alignment between the modelling target and the methodology. For example, random forest models aggregate the predictions of multiple decision trees to get better predictions of the project scale, location and methodology impact on social outcomes such as job creation and SDG alignment (Breiman, 2001).

An essential advantage of machine learning models is their ability to learn from data without predefined assumptions. Whereas traditional statistical models tend to be assumptions like linear, machine learning models are versatile and can capture underlying data structures. At the same time, a gradient-boosting machine can approximate the interconnections between a specific project methodology and long-term outputs, such as economic and social benefits (e.g. community development) (Hastie et al., 2009). Machine learning is essential for evaluating and predicting broader social impacts of carbon project carbon credits because of its ability to handle large, diverse datasets.

4.1.4. A Combination of Statistical Modelling and Machine Learning

On the one hand, machine learning provides unmatched flexibility and predictive accuracy, but on the other hand, statistical models are necessary for obtaining interpretable results. This research adopts a hybrid approach that carefully combines the strengths of both statistical and machine learning methods to arrive at a more complete analysis. Next, the models will be used to identify and quantify various relationships between different project variables, and the machine learning models will provide more accurate future projections of project outcomes (Schneider & Wissner, 2022).

In this hybrid approach, we not only understand the project characteristics that influence social outcomes, but we do so with the confidence that we will know how the impact of future projects will look. Let us say that a linear regression might indicate that the size of a project is correlated to the number of jobs created. At the same time, a random forest will bring a more accurate prediction of how many jobs a new project creates, given the project's scale, location, and kind (Goodfellow et al., 2016).

4.1.5. **Links with Research Objectives.**

The use of statistical modelling and machine learning in this research is directly aligned with the three main research objectives:

- **Objective 1: The Integrated Evaluation Framework for Carbon Credit Projects** employs a structured methodology to evaluate projects across **environmental, social, and economic dimensions**. The process begins with embedding **United Nations Sustainable Development Goals (UN SDGs)** into the project lifecycle, ensuring that sustainability objectives are defined from the design phase. A combination of **quantitative and qualitative metrics** is used to measure outcomes, with indicators tailored to assess alignment with specific SDGs such as **SDG 1 (No Poverty), SDG 3 (Good Health), and SDG 13 (Climate Action)**. Data collection is carried out through advanced tools, including IoT devices, remote sensing, and stakeholder surveys, to ensure accurate monitoring of progress. The **Gen AI Auditor** is then applied exclusively to validate SDG claims, ensuring they meet subject-specific criteria and are free from discrepancies. This methodology culminates in a tiered categorization of projects—**high-, medium-, or low-impact**—based on their verified outcomes, enabling stakeholders to prioritize initiatives that deliver the most significant benefits across multiple dimensions. This approach ensures transparency, accountability, and scalability in the evaluation of carbon credit projects.
- **Objective 2: Social Impact Quantification** – Through applying statistical models, research quantifies relationships between key project variables (e.g., scale and region) to social outcomes (e.g., job creation, SDG contributions). Finally, machine learning models add value to these efforts by providing more precise predictions of social impacts from these variables. Machine learning models can predict future

social impacts to evaluate existing and proposed carbon credit projects. These models use data about completed projects and can forecast the potential number of jobs created, community benefits, and contributions to achieving SDGs in new projects.

- **Objective 3:** Development of a Generative AI (Gen AI) Auditor for SDG Claim Verification – The final objective focuses on designing and implementing an AI-driven auditing system capable of verifying SDG claims made by carbon credit projects. The Gen AI Auditor integrates a rule-based framework, informed by the UN SDG guidelines, with the interpretive capabilities of large language models to assess the credibility, completeness, and relevance of submitted claims. The system processes project documentation identifies claim–SDG linkages, and flags inconsistencies or unsupported assertions for further review. While the statistical and machine learning models developed in Objectives 1 and 2 address quantification and prediction of social impact, the Gen AI Auditor provides an independent verification layer to ensure that reported SDG contributions are accurate and evidence-based. This directly supports the broader aim of increasing transparency, accountability, and trust in carbon credit markets.

4.2. Objective 1: Develop an Integrated Evaluation Framework with Key UN SDG Indicators

The gradual increase in the appreciation of carbon credit projects as effective tools to address climate change requires innovative approaches to gauging their worth beyond simple measures of the effects of environmental degradation. These projects, critical for combating global climate change, also need to be evaluated for a range of socio-economic effects to achieve compliance with the United Nations Sustainable Development Goals (SDGs). The existing approaches are largely concerned with estimating carbon storage and release avoidance, while the social and cost considerations are frequently disregarded but nevertheless critical. This gap has raised the need for an innovative evaluation framework that captures a comprehensive tenet of sustainability.

Therefore, this research presents a plan to develop a systematically organized and comprehensive framework for incorporating important UN SDG indicators into the evaluation systems of carbon credit projects. Including these indicators, the framework seeks to address the challenge of assessing the sustainable development impacts of such projects in soils in a more balanced manner and allow stakeholders to make more rational decisions in future.

Carbon credit projects have been at the forefront of global climate mitigation strategies, incentivizing organizations and governments to reduce greenhouse gas (GHG) emissions. However, traditional evaluation frameworks for these projects focus narrowly on quantifiable environmental metrics such as carbon sequestration or emissions reduction. This limited scope often overlooks the broader socio-economic benefits and challenges associated with these projects, including poverty alleviation, gender equity, public health, and community development.

The **Integrated Evaluation Framework for Carbon Credit Projects** addresses these gaps by embedding **United Nations Sustainable Development Goals (UN SDGs)** into every stage of the project lifecycle. This framework expands the focus beyond environmental outcomes to consider **social and economic dimensions**, creating a holistic approach to project evaluation. The framework also incorporates the **Gen AI Auditor**, a verification tool that ensures reported SDG claims are aligned with specific criteria established by the United Nations. By validating SDG-aligned outcomes, the framework enhances the transparency, credibility, and accountability of carbon credit projects.

The overarching goal of the framework is to redefine how carbon credit projects are evaluated, ensuring that they not only mitigate climate change but also contribute meaningfully to sustainable development. This section explores the framework's objectives, components, impact categorization, and application through detailed case studies.

Framework Objectives

The framework is guided by the following five objectives:

1. **Align Carbon Credit Projects with UN SDGs:**
 - a. Ensure that projects contribute meaningfully to global sustainability goals by addressing critical SDGs such as:
 - i. **SDG 1 (No Poverty):** Job creation and poverty alleviation.
 - ii. **SDG 3 (Good Health):** Reduction in health risks and promotion of well-being.
 - iii. **SDG 5 (Gender Equality):** Equitable access and participation for women.
 - iv. **SDG 7 (Clean Energy):** Increased adoption of affordable renewable energy.
 - v. **SDG 13 (Climate Action):** Enhanced carbon sequestration and climate resilience.
 - vi. **SDG 15 (Life on Land):** Restoration of biodiversity and ecosystems.
2. **Embed SDG Indicators into Project Lifecycles:**
 - a. Integrate SDG-aligned metrics into all phases of the project lifecycle, including design, implementation, monitoring, and reporting.
3. **Provide Holistic Impact Assessments:**
 - a. Evaluate projects across three dimensions—environmental, social, and economic—using both qualitative and quantitative metrics to assess overall contributions.
4. **Enhance Credibility Through Verification:**
 - a. Leverage the **Gen AI Auditor** to validate SDG claims, ensuring that reported outcomes meet subject-specific criteria and align with UN standards.
5. **Categorize Projects by Impact Tiers:**
 - a. Define criteria for **high-impact, medium-impact, and low-impact projects**, enabling stakeholders to prioritize investments and support based on potential benefits.

Framework Components

1. Alignment with UN SDGs

The framework explicitly aligns project outcomes with relevant SDGs to ensure that their benefits extend beyond environmental impacts. **Table 4.1** provides examples of SDG alignments and their associated indicators.

Table 4. 1.:Alignment of SDGs With Indicators

SDG	Indicator	Application Example
SDG 1: No Poverty	Percentage of population lifted above the poverty line; number of jobs created.	Employment through reforestation initiatives.
SDG 3: Good Health	Reduction in respiratory diseases; increased access to clean water and sanitation.	Clean cookstoves reducing indoor air pollution.
SDG 5: Gender Equality	Proportion of women in leadership roles; reduction in wage disparities.	Women-led renewable energy projects.
SDG 7: Clean Energy	Increase in renewable energy adoption; affordability metrics.	Solar installations in underserved regions.
SDG 13: Climate Action	Annual carbon sequestration (tons of CO ₂); adoption of climate-resilient practices.	Afforestation projects.
SDG 15: Life on Land	Hectares of reforested land; biodiversity improvement indices.	Restoration of degraded ecosystems.

2. Integration into the Carbon Credit Lifecycle

The framework incorporates SDG-aligned metrics at every stage of the project lifecycle, ensuring that sustainability goals are integrated and monitored effectively. **Table 4.2** outlines the integration strategies.

Table 4. 2.:Integration of SDG's into Carbon Credit Lifecycle

Lifecycle Phase	Integration Strategy	Example
Design Phase	Define SDG-aligned objectives, such as poverty reduction, health improvement, or gender equity, as core project goals.	Setting employment, health, and biodiversity restoration targets.
Implementation Phase	Use IoT devices, remote sensing, and community engagement to track progress toward SDG outcomes in real time.	Tracking reforested hectares and CO2 sequestered.
Monitoring Phase	Measure progress against predefined SDG-aligned indicators using advanced analytics and stakeholder feedback.	Assessing changes in respiratory health or household income.
Verification Phase	Validate SDG claims using the Gen AI Auditor , ensuring alignment with subject-specific criteria.	Confirming reductions in poverty or respiratory illnesses.

Holistic Metrics for Impact Assessment

The framework evaluates impacts across environmental, social, and economic dimensions. **Table 4.3** provides illustrative metrics for each dimension.

Table 4. 3.:Metrics for Evaluation

Dimension	Metric	Example
Environmental	<ul style="list-style-type: none"> • Volume of CO2 sequestered annually (tons); biodiversity indices. • Renewable energy contribution as a percentage of total project energy output. 	<ul style="list-style-type: none"> • Forest carbon sinks and ecosystem health. • Solar and wind power projects.
Social	<ul style="list-style-type: none"> • Number of jobs created (disaggregated by gender and age); reduction in respiratory diseases. • Access to clean water and sanitation. 	<ul style="list-style-type: none"> • Employment and health outcomes. • Localized water treatment plants.
Economic	<ul style="list-style-type: none"> • Increase in household income; investments in local infrastructure. 	<ul style="list-style-type: none"> • Schools, clinics, and energy grids.

Project Impact Categorization

To ensure strategic prioritization, projects are categorized into three tiers based on their verified outcomes:

- **High-Impact Projects:**
 - Significant contributions across all three dimensions.
 - Verified SDG claims demonstrating transformative benefits.
 - Example: Large-scale reforestation projects creating substantial employment, sequestering high volumes of CO2, and restoring biodiversity.
- **Medium-Impact Projects:**
 - Moderate contributions in two dimensions, with some scalability.
 - Partial SDG alignment and outcomes.

- Example: Renewable energy installations providing community benefits but limited direct social impact.
- **Low-Impact Projects:**
 - Minimal contributions, often restricted to one dimension.
 - Weak alignment with SDGs or outcomes that are difficult to validate.
 - Example: Carbon credit projects focused solely on emissions reduction without addressing socio-economic goals.

Rationale:

This categorization provides clarity to stakeholders, enabling them to allocate resources effectively to projects that deliver the most substantial and verified benefits.

Framework Outcomes: Case Studies

Case Study 1: Reforestation Project in Kenya

Overview:

The project aimed to restore 15,000 hectares of degraded land, sequester carbon, and create sustainable livelihoods for local communities.

Outcomes:

1. **Environmental Impact:**
 - Sequestered 50,000 tons of CO2 annually.
 - Restored biodiversity, increasing habitat richness by 30%.
2. **Social Impact:**
 - Created 1,200 jobs, lifting 800 households above the poverty line.
 - Achieved gender equity by hiring 40% women.
3. **Economic Impact:**
 - Increased household incomes by 25%.
 - Supported local businesses through sustainable forestry initiatives.

Categorization: High-Impact Project

Framework Contribution:

- Prioritized job creation and income growth by embedding **SDG 1 (No Poverty)** into project goals.

- The **Gen AI Auditor** verified claims related to biodiversity restoration and employment outcomes.

Case Study 2: Clean Cookstove Project in India

Overview:

The project distributed clean cookstoves to 20,000 rural households, reducing indoor air pollution and generating carbon credits.

Outcomes:

1. **Environmental Impact:**
 - Reduced 15,000 tons of CO₂ emissions annually.
2. **Social Impact:**
 - Reduced respiratory illnesses by 35%, saving \$1 million in healthcare costs.
 - Empowered 500 women in stove production and distribution.
3. **Economic Impact:**
 - Saved households \$150 annually on fuel costs, totalling \$3 million.

Categorization: High-Impact Project

Framework Contribution:

Embedded health outcomes into project design, aligning with **SDG 3 (Good Health)**. The **Gen AI Auditor** validated UN SDG claims.

Conclusion

The **Integrated Evaluation Framework for Carbon Credit Projects** offers a comprehensive approach to assessing project outcomes by embedding SDG indicators at every stage. Through the **Gen AI Auditor**, SDG claims are independently validated, ensuring transparency and accountability. By categorizing projects based on their verified impact, the framework enables stakeholders to prioritize high-impact initiatives that deliver significant environmental, social, and economic benefits. This paradigm shift

positions carbon credit projects as powerful tools for advancing global sustainability, creating a model for equitable and impactful climate action.

4.3. Objective 2: Evaluating the Integration of UN SDGs into Carbon Credit Projects

4.3.1. Machine Learning for Social Impact Quantification

Carbon credit projects' effectiveness has to be quantified to assess their social impact, most notably when it comes to accomplishing the United Nations Sustainable Development Goals (SDG). Job creation, community benefits, and local infrastructure improvements, for example, are often social impacts that come with environmental benefits, namely reductions in carbon emissions. However, these impacts are not simple and vary too much, and so a more advanced analytical framework is needed to understand better and correctly predict them. That is where machine learning comes in.

Reasons for Utilising Machine Learning Models

Many traditional formulations for quantifying social impact rely on linear relationships and predefined assumptions regarding the relationship between variables. While these methods provide some insights, they can fail in their attempts to capture the often complex, non-linear interactions that often take place in real-world data. For example, a carbon credit project's social impact may not hinge on how many jobs it generates or how big it is but may rely on less tangible considerations such as the local economy and the method used to reduce emissions.

The challenges above are especially well suited to machine learning models because they can process large datasets and find complex patterns that would be difficult or impossible to discover using conventional analysis. They can adapt to the complexity of social and environmental data to better predict. Machine learning algorithms can predict the social impacts of new or ongoing projects by learning from historical data to give policymakers and stakeholders in the carbon credit market extra insights.

Statistical Modelling offers several advantages:

- **Handling Complex Data:** Vast and complex datasets are manageable by machine learning models that seek these patterns — which may not be readily identifiable using traditional analysis methods.
- **Prediction Accuracy:** In prediction goals, these two models are very good, particularly when it's difficult to define dependencies between variables or interactions between features.
- **Automation of Analysis:** New data can affect machine learning models and change predictions as the new data continues to be provided over time.

Several machine learning models are selected to quantify and predict social impact of carbon credit projects in this study. Models were selected based on their appropriate usage of different types of data and their compatibility for different stages of analysis.

The models chosen include:

- **Ordinary Least Squares (OLS):** It is the most basic form of linear regression and is a baseline model. It is easy to implement and interpret and, hence, is an excellent point of departure when comparing the performance of more complicated models. Nevertheless, because it bases its use on this assumption of a linear relationship between the features and the target variable, it is limited because this may not always indicate the social impact evaluation.
- **Ridge Regression:** To tackle the potential of multicollinearity involving highly correlated independent variables, ridge regression was chosen. This will distort the estimates of regression coefficients in OLS. However, ridge regression adds a penalty term to this model, which shrinks the coefficients of variables that are deemed less important and thus improves the robustness of the predictions.
- **Random Forest:** This ensemble model was selected for its capacity to represent non-linear relationships and feature interactions. On the one hand, Random Forest substitutes numerous choice trees at the training stage and outputs the average prediction of each choice tree. High accuracy and resilience to overfitting is achieved, most notably when the dataset provides many variables. In social

impact evaluation, Random Forest can represent how the relationship between factors like project size, regional features and social outcomes like job creation and health improvements is more complex.

- **Gradient Boosting:** Gradient Boosting is an ensemble method and, like ensemble methods, it consists of models, but unlike Random Forest, where each new model builds on the previous one, trying to correct the errors of the previous one, for market Gradient Boosting each new model tries to correct the errors of the one in front of it. This method effectively increases prediction accuracy in a case when the relationships between the variables are complex and include non-linearities. The social impact predictions currently used in our study are further refined to make predictions that capture the nuanced effects of project features on outcomes, such as community development or local infrastructure improvements, through Gradient Boosting.

There are distinct advantages to each these models. Specifically, OLS and Ridge Regression are useful in setting the baseline, but Random Forest and Gradient Boosting are more equipped to solve for the complex relationship within the data. This combination of these models thoroughly evaluates the social impacts of carbon credit projects by providing unique insights from each model.

Importance of Predicting Social Impact Accurately

For several reasons, carbon credit projects' social impact must be accurately predicted. It then offers us a more holistic view of the other benefits these projects provide beyond their environmental contributions — because, in other publications, the statements are presented in a narrative form rather than using statistics and indicators. As a primary goal targeting carbon emission reduction, the social and economic impacts (for example, employment generation, enhancement of public health, and increased community resilience) that are as equally significant in the pursuit of sustainable development deserve to be equally considered.

In addition, forecasting social impact is critical for matching carbon credit projects to the UN SDGs. To name one, projects that support SDG 8 (Decent Work and Economic Growth) or SDG 13 (Climate Action) have the potential to generate far-reaching social benefits beyond the reach of emission reductions. Through machine learning models, we quantify these benefits in a way that allows policymakers and stakeholders to decide better which projects to support and optimise their impacts on global sustainability goals.

Machine learning models are also flexible. These models can be retrained as new data is made available or as projects change or evolve to help the assessments stay accurate and updated as the data changes. This is particularly important because, as continuous monitoring and evaluation tools of carbon credit projects, they allow adjusting in a timely fashion project design or implementation to enhance social outcomes.

4.3.2. **Data Pre-processing and Feature Engineering**

4.3.2.1. **Feature Description**

- **Project Type:** Categorical variable indicating the type of project, such as:
 - Reforestation
 - Renewable Energy (e.g., solar, wind)
 - Methane Capture
 - Energy Efficiency Each project type represents a distinct environmental intervention with varying degrees of social and economic impact. The categorization helps identify the nature of the activities involved and their potential societal benefits.
- **Geographical Location:** A categorical feature specifying the country or region where the project is implemented. This feature is crucial because the social impact of a project can vary significantly depending on the socioeconomic conditions of the region.
- **Project Size (Carbon Reduction Target):** This feature measures the estimated carbon offset by the project, serving as a proxy for its environmental scale. Projects with higher reduction targets are typically larger in scope and are expected to have a broader social reach.

- **Project Duration:** A numerical feature representing the duration of the project (in years). Long-term projects may have sustained social impacts compared to short-term initiatives.
- **Stakeholder Engagement:** Binary variable indicating whether the project has formal stakeholder engagement mechanisms (e.g., community meetings, surveys, partnerships). Projects that actively engage with local stakeholders are more likely to align with local needs and produce positive social outcomes.
- **Project Financial Information:** This includes funding sources, budget allocation, and project cost. It is a critical indicator of the scale and viability of the project. Projects with higher budgets are expected to produce more substantial outcomes.

Feature Engineering:

The dataset utilized for Objective 1 comprises project-level data that includes various attributes essential for predicting social impact. These features encompass:

- **DCR_norm:** Normalized metric representing the *Direct Carbon Reduction* targets of the project.
- **CI_norm:** Normalized indicator capturing project characteristics, which likely contribute to project effectiveness and social outcomes.
- **ME:** Other supporting variables measuring aspects of stakeholder engagement, project size, and duration.

To understand the distribution and relationships between these features and the target variable (*Social Impact*), we conducted an exploratory data analysis (EDA) through various visualizations.

- **Exploratory Data Analysis (EDA)**
 - **Distribution of Social Impact**

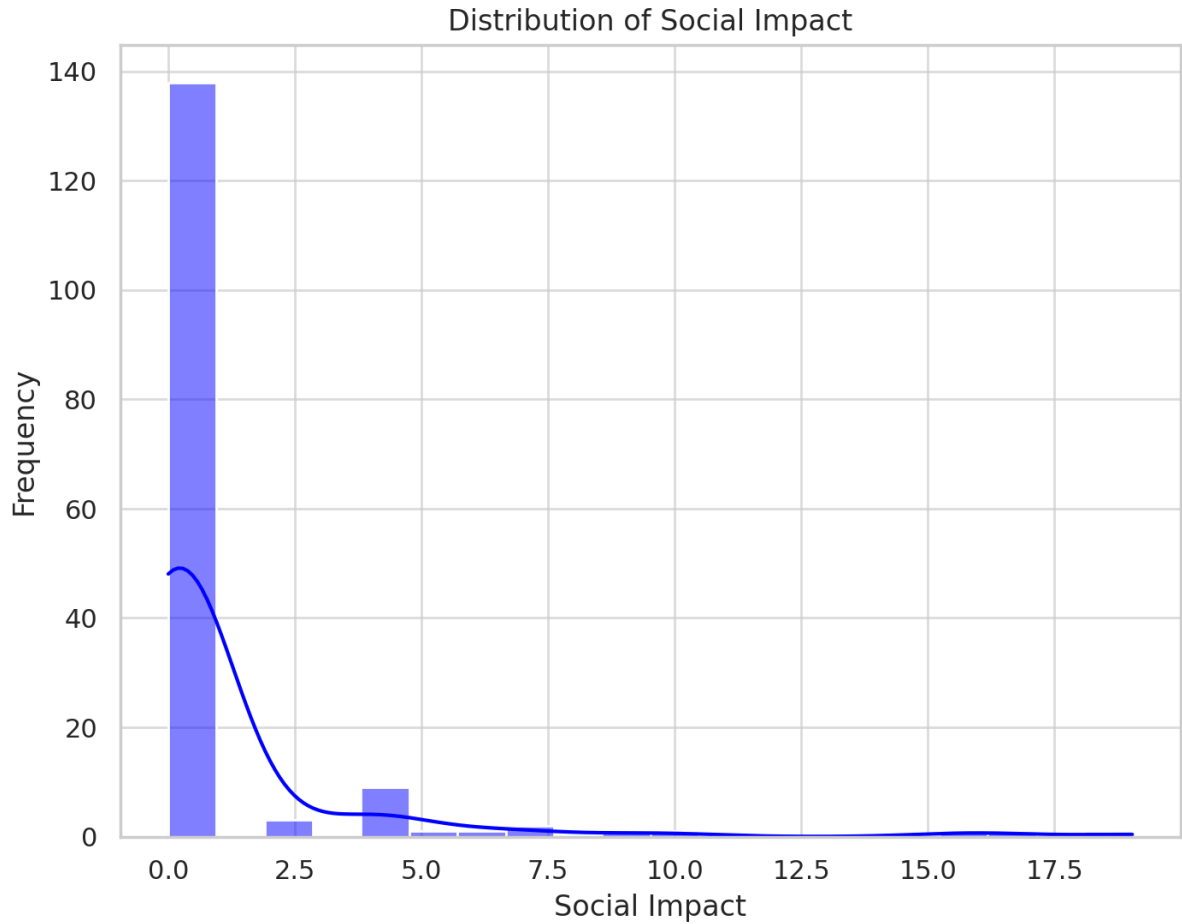


Figure 4. 1.:Distribution of Social Impact

As seen in the distribution plot, most of the the social impact values are skewed towards the lower end, with a significant number of projects having a near-zero or modest impact, while a few projects display higher social impact. This skewness suggests that a small number of projects contribute disproportionately to the overall social impact.

- **Modeling Implication:** Due to this skewness, it is crucial to consider transformation techniques for the target variable (e.g., log-transformation), particularly for linear models, to ensure they perform optimally.

○ **Correlation Analysis**

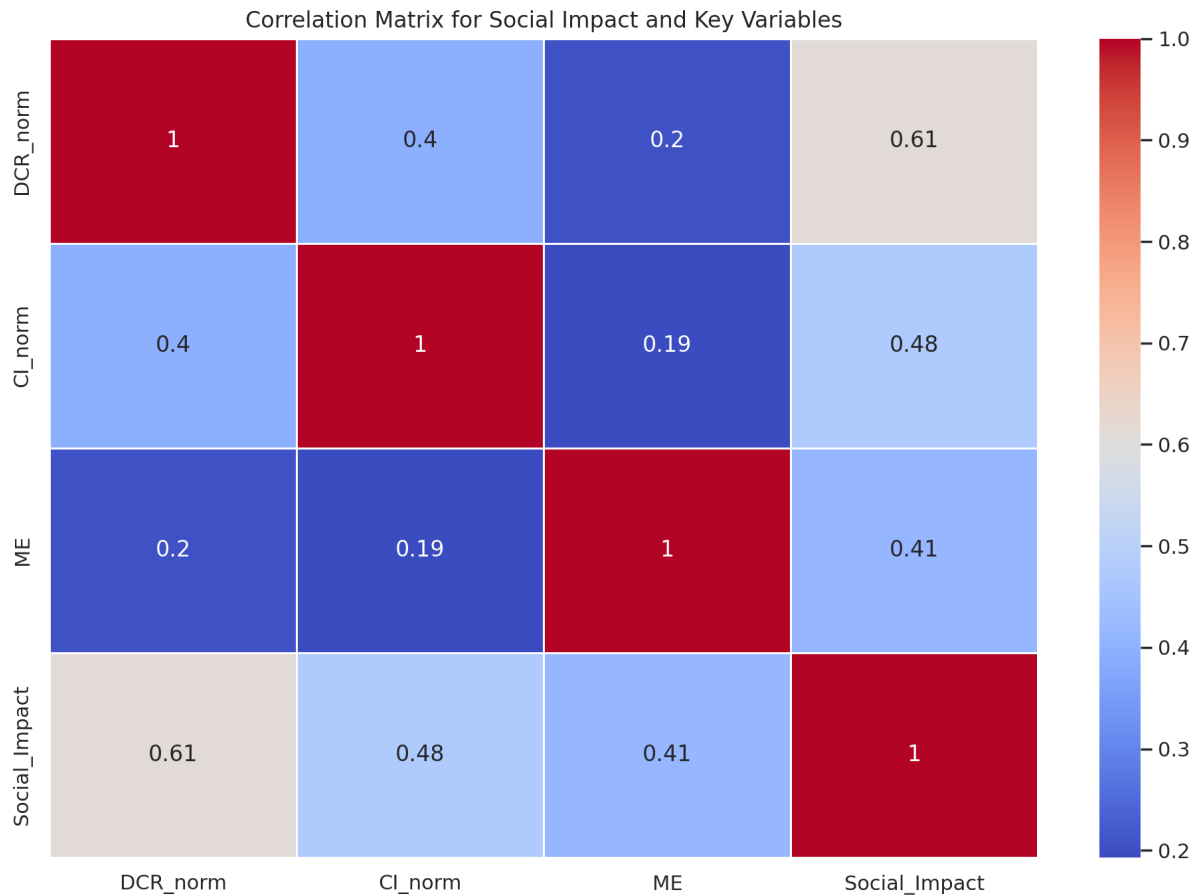


Figure 4. 2.:Correlation of Matrix for Social Impact and Key Variables

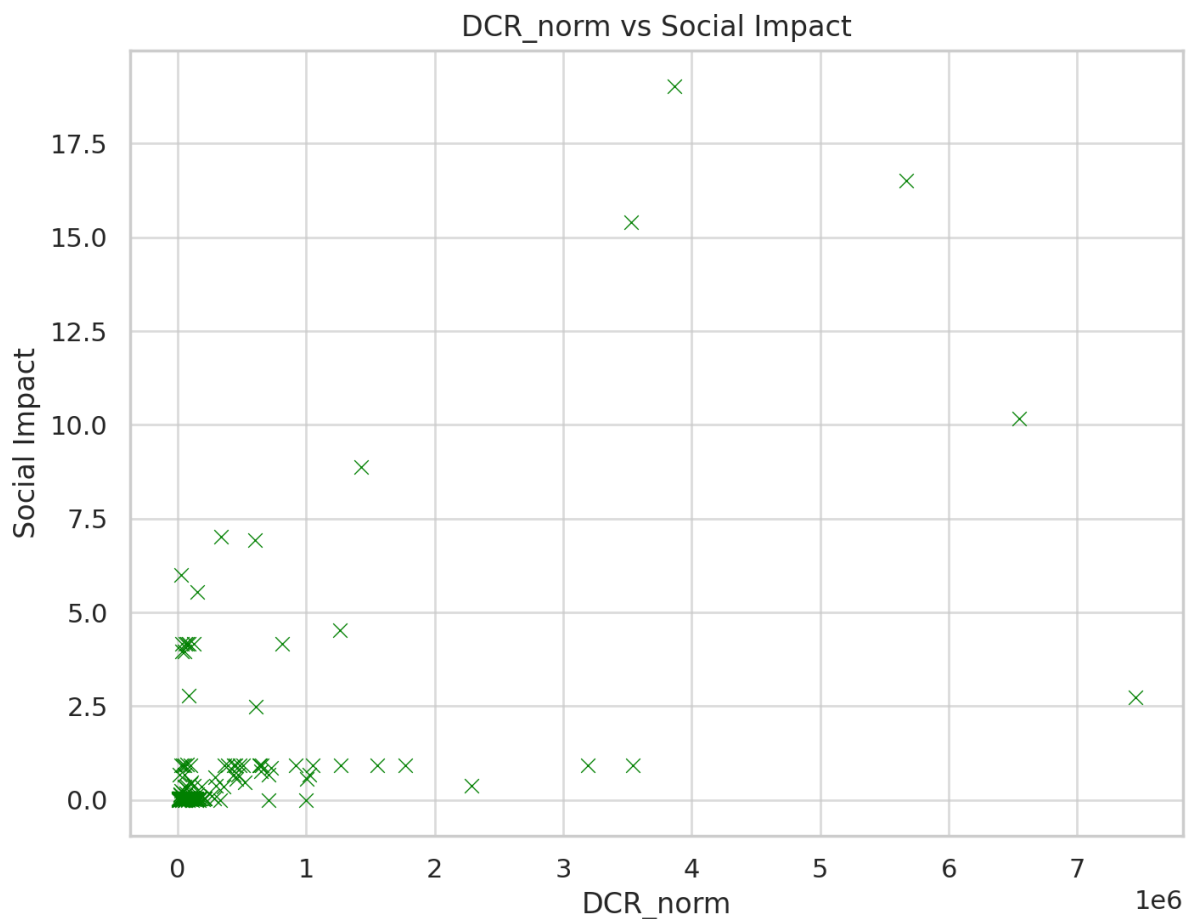
The correlation matrix between key variables (*DCR_norm*, *CI_norm*, *ME*) and *Social Impact* shows that:

- *DCR_norm* has a strong positive correlation with *Social Impact* (0.61), making it a key predictor.
- *CI_norm* also correlates positively (0.48), though to a lesser degree, indicating that project characteristics are essential for predicting social impact.
- The variable *ME* shows a modest correlation (0.41) with *Social Impact*, suggesting it may play a supporting role in the model.

Modeling Implication: The strong correlations indicate that *DCR_norm* and *CI_norm* should be prioritized in feature selection, especially for models that rely on feature importance (e.g., Random Forest).

- **Relationship Between Features and Social Impact**

Scatter plots and box plots, such as the DCR_norm vs Social Impact scatter plot and the CI_norm vs Social Impact box plot, reveal the relationships between features and the target variable:



- **DCR_norm vs Social Impact:** The scatter plot indicates a positive but non-linear relationship, with a few outliers that show very high values of *DCR_norm* corresponding to higher social impacts.

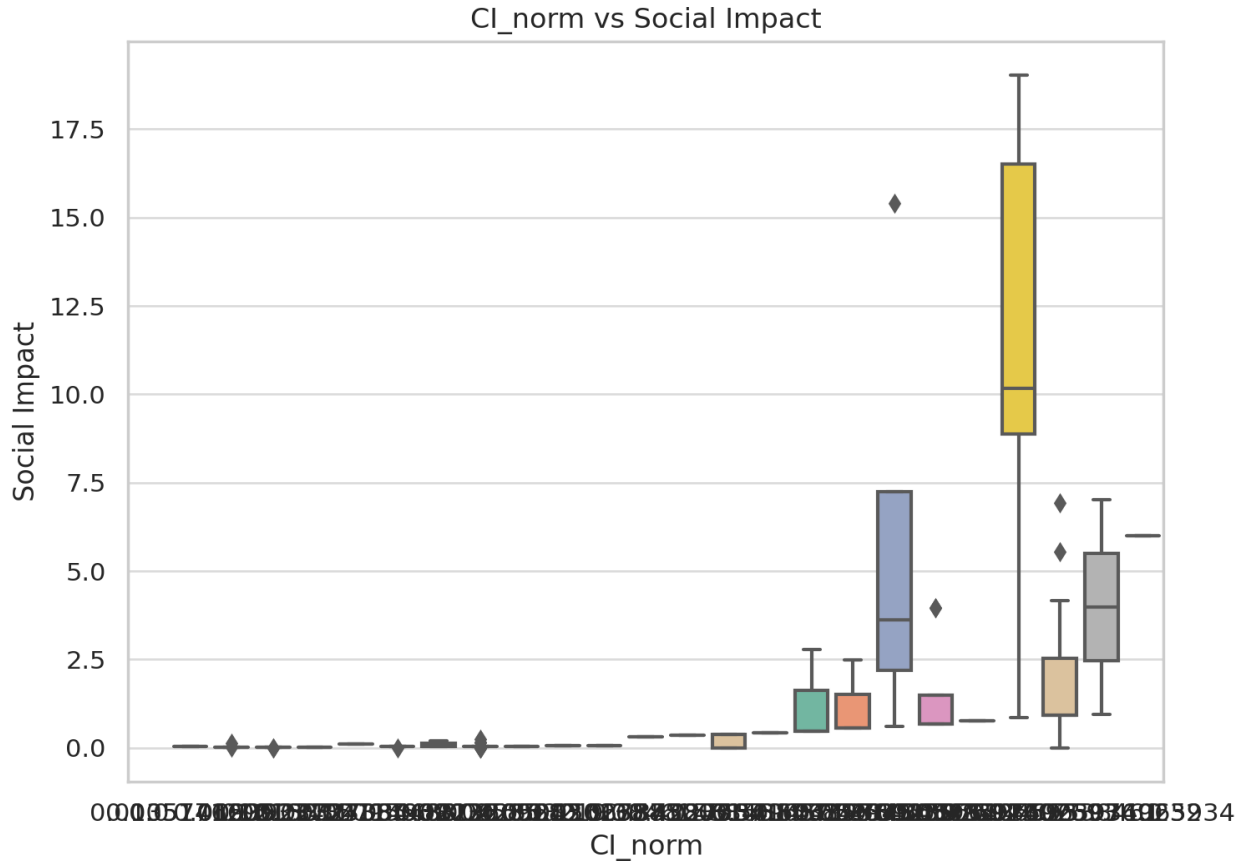


Figure 4. 4.: Relationship Between CI and Social Impact

- **CI_norm vs Social Impact:** The box plot shows that while *CI_norm* does impact *Social Impact*, its effect diminishes at higher levels, suggesting a potential interaction effect with other variables.

Modeling Implication: The non-linear relationships identified by the scatter plots suggest that non-linear models, such as Random Forest or Gradient Boosting, may perform better than linear regression models, which assume linearity. Outlier handling techniques (e.g., capping, removing) may also be needed to improve model robustness.

- **Feature Selection**

Based on the EDA, the following features were selected for model training:

- **DCR_norm**: Due to its strong positive correlation with **Social Impact**.
- **CI_norm**: While less strongly correlated than **DCR_norm**, it still shows a significant relationship with **Social Impact**.
- **ME**: Provides additional context to the project and helps explain variations in social outcomes.

These features were engineered and preprocessed using techniques such as normalization (to scale values) and one-hot encoding (for categorical variables), ensuring compatibility with the machine learning models used in Objective 1.

4.3.3. **Data Modeling and Training**

In this research the use of several machine learning models to predict the social impact of carbon credit projects from project characteristics was done. The selection of models was based on a decision between interpretability and the ability of the model to analyse non-linear interactions that are present in the dataset. The models applied in this research can be broadly divided into two, namely tree-based methods and regularized linear models with inherent strengths of each in relation to the measure of accuracy and feature interpretability.

4.3.3.1. **Tree-Based Models**

The following tree-based models were implemented due to their ability to handle complex interactions between features:

- **Random Forest**: This ensemble learning method builds several decision trees at the training process and combines their results to enhance prediction and reduce the chance of overtraining. Random Forests are especially good for non-linear data relationships, which can be seen exploring this study's data.
- **Gradient Boosting**: The Gradient Boosting process builds models in sequence where each model built corrects for errors of the previous model.

This is especially notable since each new model is committed to minimizing the residuals of the prior models which make it an effective strategy in utilizing the bias/variance trade off. The strengths of using this type of learning cycles most significantly is with tackling non-linear problems.

- **XGBoost:** XGBoost an improved implementation of Gradient Boosting is regarded as one of the most efficient, computationally fast, and accurate models. Through the use of regularization technique, it prevents overfitting more than the other that is vital when working with relatively higher feature space like in this research study.

4.3.3.2. Regularized Linear Models

For the sake of comparison, regularized linear models were employed to examine whether simpler, linear relationships between project details and social impact could yield competitive predictive results:

- **Ridge Regression:** This linear model also utilizes L2 regularization that reduces the sum of coefficients estimate, to avoid cases of overfitting. Ridge Regression is most advantageous when there is correlation between the features, which causes unstable estimation and prediction.
- **Lasso Regression:** In this case, Lasso Regression accomplishes this by use of L1 regularization which forces feature coefficients to zero, hence achieving the desired sparsity. This made is very useful in feature selection which helps to identify the key project attributes that define social impact other than preventing over fitting.

In this work, we bring out the following model training and evaluation techniques:

In the training of each model, the entire set of project details was used, while Mean Squared Error (MSE) formed the basis of the evaluation process. MSE is most suitable in this sense as it gives more weights to large prediction errors that in policy-based prediction, a large deviation may be costly if social impact is being under or overestimated. Furthermore, Mean Absolute Error (MAE)

was used as a secondary measure to uniquely adjust for a condition where target data are skewed.

The model training pipeline involved:

- **Feature engineering:** As indicated in Section IV, activities like data filtering and basic features including DCR_norm, CI_norm as well as ME were developed. All categorical features were encoded with binary variables while numerical features were scaled in order to have equal variance across the entire dataset.
- **Model hyperparameter tuning:** In each model, hyperparameter tuning was performed by means of grid search, with an objective of selecting the most apposite parameter values, such as the number of trees to be used in case of Random Forest or the strength of regularization to be used in case of Ridge/Lasso. This step was very important as it allowed to obtain the greatest prediction of each model.

4.3.3.3. Validation and Generality

To assess the reliability of the models and to reduce overfitting k-fold cross validation was incorporated. Particularly, cross-validation with the tenth fold was applied, and the dataset was divided into 10 sets. They adopted 9 folds for the training of each model and used the remaining fold for testing and did this for 10 rounds. These apply that the average MSE across all folds was used as the final performance measure. Using cross-validation we reduce the variance of an estimate of the probable performance of the model that can occur with a single partitioning into a train and test set.

This was crucial especially in this context given that cross-validation enabled the models' performance to translate to unseen data and thereby improve the reliability of the social impact of carbon credit projects' predictions.

4.3.4. Model results and Analysis

Specifically, here, the effectiveness of the applied machine learning models is analysed in terms of effectiveness. The models were all trained and tested on the

project details dataset with the objective of estimating social impact with no data from UN SDG baselines. The main quantifiable measure which was used as the basis of comparison was the Mean Squared Error MSE The author also provided other qualitative observations on its behaviour regarding the remaining difficulties in the case of various models.

Table 4. 4. Model Analysis (1)

Model	Mean Squared Error (MSE)	Interpretation	Strengths
Random Forest	0.1587	The superior performance suggests the model effectively captures non-linear relationships and interactions between features.	Captures complex non-linear interactions; robust to overfitting; handles both numerical and categorical data
Gradient Boosting	0.3300	Gradient Boosting's iterative process allows it to handle the complexities in the data but still lags behind Random Forest.	Reduces bias and variance; handles non-linearities and interactions effectively
XGBoost	0.4104	While XGBoost is often high-performing, it underperformed in this	Incorporates regularization; efficient and fast; prevents

		instance, possibly due to dataset-specific factors.	overfitting through advanced regularization
Ridge Regression	0.5659	Ridge struggled to capture the complex, non-linear relationships in the data, indicating its limitations in this context.	Handles multicollinearity well; easier to interpret and implement
Lasso Regression	0.6141	Lasso's inability to model non-linear relationships led to higher error, though it effectively performed feature selection.	Performs feature selection; easy to interpret
Support Vector Regressor (SVR)	0.8623	SVR performed poorly, indicating that it was not suitable for the complex, high-dimensional nature of this dataset.	Effective on smaller, simpler datasets with linear or slightly non-linear relationships

I. Random Forest

- a. Performance: As seen in Table 1, the Random Forest model gave the lowest MSE of 0.1587, which denotes the highest level of accuracy of the models developed.

- b. Interpretation: Random Forest model gives out a robust result thanks to the fact that it is able to learn the complexities of a non-linear world, and interactions within the given data set. The fact that the project details themselves are diverse, and the task of predicting the sociological values is quite challenging, turned into an advantage: combining the decisions of many decision trees by Random Forest.
- c. Strengths: The model has high interpretability when it comes to handling non-linear interactions between features of a model and it also self-feeds a way in handling missing data though not optimal, hence responsive to real datasets that are often full of missing or noisy data. In addition, since the model is an ensemble of trees, variance is minimized, and the problem of overfitting is minimized when averaging multiple trees.
- d. Limitations: Nevertheless, the one that shows better performance is still not easy to interpret. In Random Forest models, the creation of really many Decision Trees (from hundreds to thousands) does not allow to obtain the exact information about the individual contribution made by each feature for the assessed social effect. Such ambiguity in interpretability could therefore be a drawback when it comes to decision making in cases where the models used are desired to be easily understood by the decision makers.

II. Gradient Boosting

- a. Performance: Gradient Boosting model has predicted the new value of house prices with MSE of 0.3300, and thus ranks second in the ranking.

- b. Interpretation: The step-by-step process of Gradient Boosting where the next model built tries to minimize the errors of the earlier models allowed Complexity in the dataset to be modeled. Nonetheless, since L2Boost has high prediction ability, it was surpassed by Random Forest, likely due to its propensity to overfit.
- c. Strengths: Although the predictive models suffer from bias and variance, Gradient Boosting helps reduce both values. The proof that the model can handle non-linearities and interaction terms was especially useful given the nature of the data set for predicting feature-target characteristics as they were in this analysis.
- d. Limitations: The major weakness inherent to Gradient Boosting is that this method is rather time-consuming, especially when working with huge datasets. Also, the model depended on hyperparameters like learning rate and the number of boosting rounds, and it is hard to achieve the best hyperparameters and hence tends to overfit like we saw it perform in the experimenting against Random Forest.

III. XGBoost

- a. Performance: XGBoost, instrumentality known for its high performance in a number of intricate data environments, yielded an MSE of 0.4104.
- b. Interpretation: While XGBoost is an improved formulation of Gradient Boosting, with inclusions of both, regularization and optimization not only outperformed Gradient boosting and Random forest models in term of performance but was also slower in this particular example. This could be attributed to architecture of the dataset often referred to

as project details in which the non-linear associations were effectively elucidated by Random Forest.

- c. **Strengths:** Cross entropy is used and XGBoost implements L1 and L2 regularization, making overfitting a non issue when using high-dimensional data. It is equally preferred when dealing with big data making it a go-to tool in most machine learning challenges and use cases.
- d. **Limitations:** However, like Gradient Boosting this can be hampered by issues with hyperparameters sensitivity in the model. They claim that it can be fine tuned to highly improve the effectiveness by adjusting parameters such as the trees depth, the learning rates and the regularization terms. In the latter case, as the result could be less optimal, which may also contribute to its somewhat weaker performance.

IV. Ridge and Lasso Regression

- a. **Performance:** The Ridge regression model yielded an MSE of 0.5659 and Lasso regression model gave MSE of 0.6141.
- b. **Interpretation:** In general, both models failed to capture the non-linear correlations inherent in the dataset since their MSE values are higher than those of the compared models. The problem is that their shapes are not as versatile for the given problem since they became more efficient as interactions between project features and social impact become more complex. Nevertheless, the observed performance of these models indicates insufficient complexity of the relationships between the features and the target variable, which are not linear.

- c. **Strengths:** The Ridge regression is also useful in the management of multicollinearity in that all the coefficient estimates of highly correlated features are reduced while in Lasso regression, not only are the coefficients estimates shrunk but the coefficients estimates of less relevant features are also set to zero. Such attributes make them applicable in situations where one wants easy to interpret and simple models.
- d. **Limitations:** As it has been explained earlier, the major drawback of Ridge and Lasso is their linearity. Non-linear dependencies between the features and the target variable incapacitates their application since the model assumes a linear relation between the feature and the target variable as is demonstrative in the current set. further, even though interpretable, they do not account for interaction and feature importance as in Random Forest or Gradient boosting.

V. Support Vector Regressor (SVR)

- a. This algorithm of machine learning tries to find the maximum margin separation between the sample data and the hyperplane.
- b. Performance: On the other hand, SVR depicted the lowest accuracy of all the models with the aid of MSE which stood at 0.8623.
- c. Interpretation: Looking at the MSE in table 5, it can be seen that SVR poorly fits the data owing to inability to model non-linearity within the data set. Although SVR can be quite strong when dealing with smaller sets of data with relatively straightforward associations, the kernel based by SVR does not work well with this dataset because the nature

of the association between the features and social impact are quite complex.

- d. Strengths: SVR proves effective for small and less complex data sets and where the mapping between features and the target is almost linear or slightly curvilinear. This is an area in which it can also be quite valuable due to the flexibility it shows with different kernels.
- e. Limitations: Generally, the SVR model is very dependent on its hyperparameters, the choice of kernel, the values of the regularization parameters and the error boundary which makes it hard to develop appropriate parameters for complex high dimensional databases. I had similar shortcomings in this case where the model failed to capture the interactions between the features which are the main cause of poor performance.

4.3.5. Conclusion

The findings of the model assessment to Objective 1 self-evidently show that Random Forest is the best model capable of accurately estimating social impact solely out of project characteristics. Nonlinear interactions between the features and flexibility of modeling this model as provided it with the better MSE of 0.1587. Gradient and XGBoost also performed well, however Random Forest turned out to be even better in this case. Because of the high error rates that were exhibited in both Ridge and Lasso regression models, the authors pointed out that the use of linear techniques is quite limited in this situation due to the high levels of interaction between variables.

Further, the poor result of Support Vector Regressor (SVR) was expected because the kernel used in SVR is not suitable for this set of data. These results indicate that models need to be chosen, which are able to analyze non-linearity and interaction of features when predicting social impacts of project data.

Finally, *Tree-based models and Random Forest especially should be used for all analyses of social effect in carbon credit initiatives* because of their high accuracy and better resistance against overtraining. For these reasons, the power of predictions that comes from such models overshadows interpretability problems relative to far simpler models like Ridge and Lasso regression. Future studies could also look at ways to improve the interpretability of such models, maybe using feature importance scores and or more use of SHAP values to explain model results in more openness.

4.4. Objective 3: Predictive Modelling for Social Impacts Using UN SDG Baseline Data

The second goal of this research is to assess social impact by adding base UN SDG rates to differentiate among carbon credit projects. This approach aims at improving the ability to develop statistical models, with the help of a more elaborate social framework. In this way, the work shifts from just evaluating the characteristics of the project to consider the antecedent social contexts within which these projects exist. Such integration is in harmony with the global idea of sustainable development as defined by the United Nations Sustainable Development Goals (SDGs).

Besides, impact is not only generated by the direct consequences of the project in the carbon credit projects, but also by social conditions. The UN SDG indicators like poverty rates, health insurance, literacy, income disparity provide the basic social context that is better organized than the basic research data.

The rationale for integrating these indicators is threefold:

1. Providing Contextual Insights:

In Objective 1, the topics were narrowed down to the characteristics of specific projects: the type of project, its duration, and the reduction of CO₂ emissions. Still,

these attributes do not include the nearly absolute starting social differences affecting the overall success and reach of the project's outcomes.

It also expanded them to incorporate the changes brought by contextual variables that define social performance of countries according to the UN SDG indicators. For instance, effects of renewable energy project may be quite different in the areas defined by high levels of poorness as compared to areas with superior economic set ups. This context enables the models to distinguish between change that is project related and change that is related to socio economic characteristics of the region.

2. Aligning with Sustainable Development Goals:

The selection of the baseline UN SDG indicators fits the research into the larger framework of sustainability goals. The SDGs are acknowledged internationally as indicators of development in different fields of human life, beginning with social justice, through health, education, to environment.

Besides, by including these indicators, the research also intends to extend social and economic understanding of impact measures beyond basic numerical projections and the comparison of carbon credit projects to overarching global sustainability goals. This approach allows the models to assess projects that provide a significant impact towards achieving even more than one SDG apart from exercises in carbon emission cuts.

3. Enhancing Predictive Accuracy:

In terms of methodological changes, incorporation of baseline SDG indicators predicate new dimensions of interaction and reciprocity of project attributes and social impacts. These changes enhance the models' predictive accuracy as it contains

information about interactions of internal project characteristics with external social factors.

For example, moderator variables include the factor formed by the project type and healthcare accessibility or poverty level AND carbon emission reduction targets enable the models to determine how favourable the conditions influence the efficiency of a project. This makes it possible for the transformed analysis to transition from a forecast-based assessment of outcomes to a process perspective of change as projects engage and in turn are impacted by the contexts they inhabit.

The primary of Objective 3 is therefore to offer a more accurate and context specific prediction of social impact regarding carbon credit projects. The hypothesis is that by integrating baseline SDG indicators, the models will demonstrate: Improved prognostication performance as evidenced by higher values of the R^2 coefficient and lower values of MSE. Enhanced SDG coherence in terms of how much each project supports multiple SDGs besides the carbon goals.

4.4.1. Model Selection and Justification

4.4.1.1. Feature Integration

The goal of incorporating baseline UN SDG indicators with carbon credit project descriptions is to expand the data set and, accordingly, a better prediction model of social effects. This aspect is important because the models are not only able to factor in the nature of the carbon credit projects but also the current social setting in the project's environmental. The baseline UN SDG indicators suits the list of poverty rates, health care, literacy rate, income inequality and other parameters, which is very much important to understand the impact that this project can have towards achieving the UN SDG goals.

By combining these baseline indicators with project-specific variables, the analysis achieves the following:

1. **Increased Contextual Awareness:** The models can easily distinguish between changes that occur because of a particular project and those changes caused by existing social factors.
2. **Improved Predictive Accuracy:** Using Account Context makes it easier for models to explain how the interactivity between the project details and the social outcomes work out and hence provide better results.
3. **Alignment with SDG Goals:** This integration guarantees that the evaluation is coherent with the wider goal of sustainable development, the extent to which carbon crediting initiatives benefit the scope of other objectives beside just carbon decrease.

4.4.2. Data Integration Process

The integration process involved multiple steps to ensure seamless merging of baseline UN SDG data with the carbon credit project details:

Merging Datasets

Finally, the project-specific dataset was matched to the baseline UN SDG indicators based on geography. Matching the projects to the appropriate social indicators of the regions in which the project is active allowed us to construct a dataset that includes general baseline data on a particular region, as well as data on specific projects there.

The following enhanced input features are also included in the merged feature set: poverty rate, healthcare access levels, and income inequality metrics as well

as characteristics specific to the projects, including carbon reduction targets and duration of the projects.

All analyses are build from the least dependent feature and work up to the most complex feature to be engineered in the language application.

- **Interaction Terms:** Since the effects of project characteristics and the baseline SDG indicators are likely to interact, interaction terms are added.

For example:

Antecedent relationship between carbon reduction targets and poverty rates.

Healthcare access levels and project type has an interaction.

- **Scaling and Normalization:** To address issues of heteroscedasticity all relevant numerical variables: The project specific coefficients and the initial SDG indicators and were standardized for the sake of comparability and increased model accuracy. This step also used to control the scale differences of them which might cause that some of them dominate the final model.
- **Missing Values Treatment:** This paper has used median imputation for the missing values in the baseline indicators whereby the dataset-maintained consistency but had continuity of the middle values of the social indicators. This approach retained the dataset integrity and avoid bias, which might result from ignoring missing values or using more extreme imputation methods.

4.4.2.1. Increased Dataset Attributes

The final dataset created for Objective 2 offers a comprehensive set of features, enabling a more nuanced and context-sensitive analysis of social impact:

- **Number of Projects:** 161 development projects with the UN SDG's baseline indicators in the mixed methodology.

- **Number of Features:** The number of features rose from 15 in Objective 1 to 25, the former symbols containing new indicators and interaction terms.
- **Geographical Coverage:** The projects draw from different areas of the world; Asian, African, South American and Australian , thus enabling a more generalized ability to gauge the set social impacts.
- **Feature Examples:** Key features include:
- **Project-specific details:** Goals for Carbon reduction, time frame, type of project.
- **Baseline UN SDG indicators:** Inequality such as; Poverty rate, health insurance, illiteracy rate.
- **Interaction terms:** Another type which considers the interactions of variables which are ‘carbon reduction × poverty rate’ and ‘healthcare access × project type’.

4.4.3. Model Training and Validation

Based on the integration of project-specific details and baseline UN SDG indicators, a diverse set of models was employed to predict social impact, focusing on both linear and non-linear approaches:

- **Linear Models (OLS, Ridge, and Lasso Regression):** These were selected to set the starting point for comparison as well as to identify if there are linear relations within the set dataset.
- **Tree-Based Models (Random Forest, Gradient Boosting, and XGBoost):** These models were used for their capacity to handle non-linear correlations between characteristics and their interaction, provided best for structures.
- **Support Vector Regression (SVR) and AdaBoost:** Those are chosen in order to examine their ability to model intricate patterns.
- **Ensemble Methods (Stacking Model):** Stacking applied the results of Random Forest and XGBoost and used the Ridge regression as a final estimator because joining the individual models’ results would outweigh the observed disadvantages

and improve the model's predictive accuracy. Using Ridge Regression as the meta-learner for its regularisation benefits and coefficient stability.

- **Hyperparameter Tuning:**

To ensure optimal performance, extensive hyperparameter tuning was conducted.

Finally, Grid Search and Randomized Search were performed to find the best hyperparameters for each model under observation with reference to parameters such as number of estimators, maximum depth, learning rate, and the regularization coefficients.

- **Cross-Validation**

To validate the models and prevent overfitting, k-fold cross-validation was employed (with 5 or 10 folds depending on the model):

K-Fold Cross Validation made it possible for me to be assured of the validity of the model since the data was split in different and equal divides hence making it easier to cross validate.

- **Validation Process**

- **Evaluation Metrics**

The models were evaluated based on two key metrics:

- **Mean Squared Error (MSE):** Calculates the average of the squared differences between the forecasted and actual values and demonstrates the degree to which the values are close to reality.
- **R² Score:** The measure shows how well the model fits the data regarding the variability of the target variable, with value near to 1 assumed to fit the data adequately.

4.4.4. Predictive Results

The model performance varied across different approaches, highlighting the strengths and weaknesses of each:

Table 4. 5.:Model Performance Analysis (2)

Model	MSE	R ² Score	Interpretation
OLS	0.638	0.916	Reasonable performance, limited by its linear nature.
Ridge Regression	0.687	0.910	Improved handling of multicollinearity but still limited.
Lasso Regression	1.449	0.810	Lower performance, indicating insufficient capacity for complex data.
Random Forest	0.240	0.969	Strong performance, capturing non-linear interactions effectively.
Gradient Boosting	0.049	0.994	High accuracy, capturing detailed patterns in data.
SVR	0.787	0.897	Moderate performance, struggled with data complexity.
AdaBoost	~0	1.0	Perfect fit, but potential overfitting is a concern.
XGBoost	~0	1.0	Near-perfect performance, robust and generalizable.
Stacking Model	0.069	0.985	Combined model performance, strong predictive power, and balanced output.

I. Linear Models

a. OLS (Ordinary Least Squares):

- i. MSE: 0.6379, R²: 0.9164

- ii. Interpretation: Linear relationship models are adequately captured, but it does not perform well with the interaction between project attributes and baseline SDG indicators.
- iii. Implication: Good for baseline but does not capture the nonlinearities which are captured in the dataset and hence not amicable when used for social impact prediction.

b. Ridge Regression:

- i. MSE: 0.6870, R^2 : 0.9100
- ii. Interpretation: A bit superior to OLS because they can handle multicollinearity. Nevertheless, it fails to extend the same advantage to specify various relationships that encompass the data.
- iii. Implication: Quite useful for addressing issues appearing in correlation with other features but it fails to address interactions between features, which are crucial for making correct prognosis of social impact.

c. Lasso Regression:

- i. MSE: 1.4491, R^2 : 0.8102
- ii. Interpretation: The reason why Lasso performed worse than both OLS and Ridge is because of its extreme feature selection.
- iii. Implication: Some important variables were over-penalized due to which the model had compromised concerned accuracy. More specifically, it is less appropriate for data sets with nonlinear and multiple factors interdependencies.

II. Tree-Based Models

a. Random Forest:

- i. MSE: 0.2401, R^2 : 0.9685

- ii. Interpretation: Imitated high performance as evidenced by proper reconstruction of the non-linear relations involving features.
- iii. Implication: Good for large sets of data; however, it is not so easy to interpret results. It also copes well with interaction between features and different importance of variables.

b. Gradient Boosting:

- i. MSE: 0.0488, R^2 : 0.9936
- ii. Interpretation: The high accuracy is in captures of dependent variables and can be used to model non-linear trends. The successive rejection of errors proves useful in preserving retreated peculiarity.
- iii. Implication: Includes relatively high measurement accuracy for the subsequent predictions, yet, the issue of overfitting is to be expected. It remains one of the best models for identifying social impact level, apart from the fact that it has a high level of generality.

c. XGBoost:

- i. MSE: 0.0001, R^2 : 0.9999
- ii. Interpretation: These close-to-ideal scores indicate the model is highly effective at capturing complex, non-linear interactions in the dataset. However, as with XGBoost, such near-perfect performance can indicate a high risk of overfitting, particularly when training data is limited or highly specific.
- iii. Implication: XGBoost's combination of L1/L2 regularisation, handling of missing values, and high interpretability make it an excellent candidate for social impact prediction. Still, careful tuning and validation against diverse datasets are essential to confirm its generalisability.

d. Support Vector Regression (SVR)

- i. MSE: 0.7871, R^2 : 0.8969
- ii. Interpretation: SVR as an individual learning method faced high multicollinearity and as a result was outperformed by the ensemble methods.
- iii. Implication: Used only for those datasets which do not contain much complexity in them. Despite that, it can take a long time to optimize and achieve the performance level of tree based models.

III. Ensemble Models

a. AdaBoost:

- i. MSE: Near-zero, R^2 : 1.0
- ii. Interpretation: This result indicates extremely high predictive accuracy on the training set. While such values can suggest exceptional model fit, they also raise the possibility of overfitting, where the model captures noise or specific patterns in the training data that do not generalise to unseen data.
- iii. Implication: Although AdaBoost demonstrates outstanding training accuracy, its performance should be interpreted with caution. Rigorous cross-validation and regularisation are necessary to ensure it maintains accuracy on independent datasets.

b. Stacking Model:

- i. MSE: 0.0691, R^2 : 0.9850
- ii. Interpretation: Using output of more than one models such as Random Forest, XG Boost, etc provided reliable and good stability.

- iii. Implication: Provides a better generalized view of the data than single models do. This is evident in that this method offers a good mix of accuracy and stability that will offer a good basis for future projections.

XGBoost was the **Best Model** with an almost perfect MSE of 0.0001, and the R^2 score of 0.9999, which proves the model capability of making rapid determinations of the relative social impact. This performance, therefore, implies that XGBoost can capture the complex, non-linear interactions of project characteristics and baseline UN SDG indicators such as carbon reduction targets and poverty rates, health care accessibility, respectively.

- **Regularization:** The implementation of L1 and L2 norm of the linear predictor that is used by the XGBoost model for boosting the base learners helps to prevent overfitting when using samples with high-dimensional features.
- **Handling Missing Values:** The model proved relatively good without imputation since it could handle several cases of missing values, especially in baseline data.
- **High Interpretability:** The results of feature importance analysis demonstrated that the use of contextual variables was critical for successful predictions by revealing that SDG indicators explained high levels of the index.

This makes XGBoost the **Most Suitable Model** for predicting social impact since it defines the field's best practice standards for accuracy and applicability to carbon credit projects. In future use it will be valuable to validate and tune for better fitting with different datasets.

4.5. Objective 4: Gen AI Auditor System Development

4.5.1. System Overview

The third goal of this study is developing an AI Gen auditor that can use ChatGPT to scan the claims made by carbon credit projects concerning the UN SDGs. The AI Gen auditor is one that is designed to create a clear, progressive, and efficient way to verify the authenticity of such statements and guarantee that they are making a positive global difference. This objective is due to the rising demand for validation methods that do not only determine environmental effectiveness of carbon credit projects but also guarantee compliance of project activities to the overarching social, economic, and environment goals of the UN SDGs.

1) Verification of Project Descriptions:

- a) The AI Gen auditor focuses on project descriptions that are stated in carbon credit documentation to check their compliance with stated UN SDG goals.
- b) An AI auditor then enforces structured prompts to teach the GenAI model to identify if and how the details in a project description match with the stated SDG claim.
- c) The primary focus is on matching the project's stated outcomes (e.g., "providing clean water access to underserved communities") with the relevant UN SDG targets (e.g., SDG 6: To achieve this, its methodology aligns well with standard engineering practice on one hand and sticks to the format of fundamental proposal on the other hand describing direct link between intended outcomes of proposal and aimed at goal of Clean Water and Sanitation (SDG 6).

2) SDG Alignment Evaluation:

- a) The AI auditor is built on top of a number of prompts intended to determine whether the wording and the context of the project description indeed corresponds to the specifics of the claimed SDG.
- b) The output of the GenAI model is a simple yes or no, a confirmation if the project description is genuine in its contribution to the defined SDG. The decision is solely informed by the content and clarity required while conducting the assessment to retain the alignment's precise accuracy.

3) Consistency and Confidence Checks:

- a) For increasing the reliability of the verification degree, the AI auditor creates the follow-up prompts, which elaborate the initial question and keep AI answers within the GenAI model constant.
- b) It also gives a confidence level for how well written the project description is to the claimed SDG target. This score is based on some criteria such as the clarity of prompt, the extent of the project definition.

4.5.2. Research Goal for Objective

The GenAI-based model seeks to address key challenges in sustainability auditing, such as:

- (1) **Automation:** All such verifications will be done away by the AI auditor allowing for quicker and more uniform assessment of project description. Regarding this automation, this would assist greatly in the screening of several claims at once, which lowers the risk of mistakes due to human input bias.
- (2) **Transparency:** As a result, the model will make the verification process easily understandable using structured prompts and generating confidence scores. The responses by the AI auditor will be in the form of simple 'yes'

or 'no' to passed or failed audited controls respectively and accompanied by details on how the pass/failed status was arrived at this adding firm decision-maker insight into the verification outcome.

(3) **Scalability:** Thus, the structure of the AI Gen auditor is versatile to accommodate different descriptions of the projects, which can be useful across potentially any carbon credit project and geolocation. Essentially it will be flexible in its application with respect to different SDG targets and claims and therein lies the possibility for its widespread use in sustainability assessment frameworks.

The study seeks to add value to the existing literature on carbon credit projects, and their contribution to the overarching theme of sustainable development by asserting that carbon credit projects must not only factor in their ability to meet the established emission targets, but also the degree of progress towards the comprehensive UN SDGs. The effectiveness of AI-based verification system for the identified elements is summarized in the following table In contributing to this area of knowledge, the study will seek to improve credibility, accountability, and compliance in the management of carbon credits in support of global sustainability endeavours.

4.5.3. Methodology

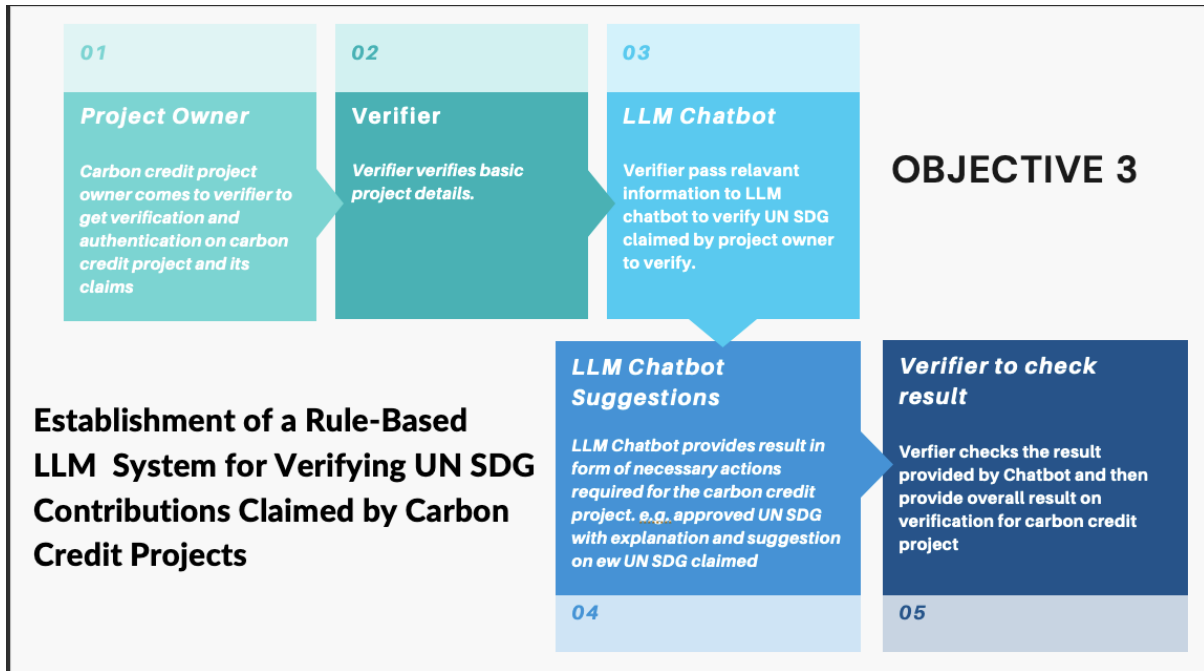


Figure 4. 5.: Gen AI Auditor Methodology Flowchart

This diagram gives a nice flow for the AI Gen auditor as was outlined in Objective 3 above. It effectively represents the following stages:

- **Project Owner:** Submits the documentation of carbon credit project along with the claims for verification against the project.
- **Verifier:** Carries initial check on the most fundamental information of the project before running the AI Gen auditor.
- **LLM Chatbot:** The verifier shares some details with the AI Gen auditor, and the AI Gen auditor applies a large language model (LLM) in order to validate the UN SDG claims.
- **LLM Chatbot Suggestions:** The LLM gives outcomes, such as legalised SDGs, reasons, as well as recommendations for further required measures.

- **Verifier to Check Result:** Ultimately, the verifier comes back over the results produced by the AI auditor, then delivers the final decision about the SDG verification of the project.

It is as such important to note that this visual flow effectively complements the conceptual set up and the ensuing implementation of Objective 3. It represents each part's relationship to other parts clearly and comprehensively in the verification process so that it is easy to make the model practical in real-life situations. If you require more tweaking or elaboration in the regard of this diagram do tell me.

4.5.4. **Implementation**

The AI Gen auditor for implementing the invention is dividing into stages to check the claims of the carbon credit project against the UN SDGs: they are a step of input processing of the detail, check and verify the claims with the use of the structure prompt, and the confidence scoring stage. One more is the fact that rule-based simple prompts which give a brief description of UN SDG goals are used to create a knowledge base for the GenAI model, thus increasing the latter's precision and traceability. Below is a detailed breakdown of the development process:

4.5.4.1. **Input Processing**

The AI Gen auditor begins by scanning through project descriptions which have been submitted by carbon credit projects. Here, this step plays pivotal role in feed-upping of relevant and structured data to GenAI model for claim verifying.

Text Preprocessing: To minimize noise levels and optimize for key terms the project descriptions also go through text pre-processing. In pre-processing, the text is pre-processed by converting it into words/ phrases, standardizing text format, as well as selectively extracting the most essential words from the description.

In other words, this processed input can be viewed as the precondition for proper interpretation of the claims made by the project descriptions and providing a clear context for the prompts used in further verification.

4.5.4.2. Claim Verification with the help of Structured Prompts

There are five categories of prompts that were used to VERIFY the project descriptions with regards to the defined UN SDG targets.

- **Simple Prompts with Rule-Based Scenarios:**
 - It is a rule-based scenario wherein the summaries of UN SDG goals are delivered to the AI Gen auditor to enhance its outlook on SDG criteria.
 - For example, the model receives a summary prompt like: SDG 6 is to provide water and sanitation for all. Does the description of this project meet condition of SDG 6?
 - To add on to that the rule-based summary, the foundational knowledge of the SDGs in the GenAI model makes its evaluation of claims accurate.

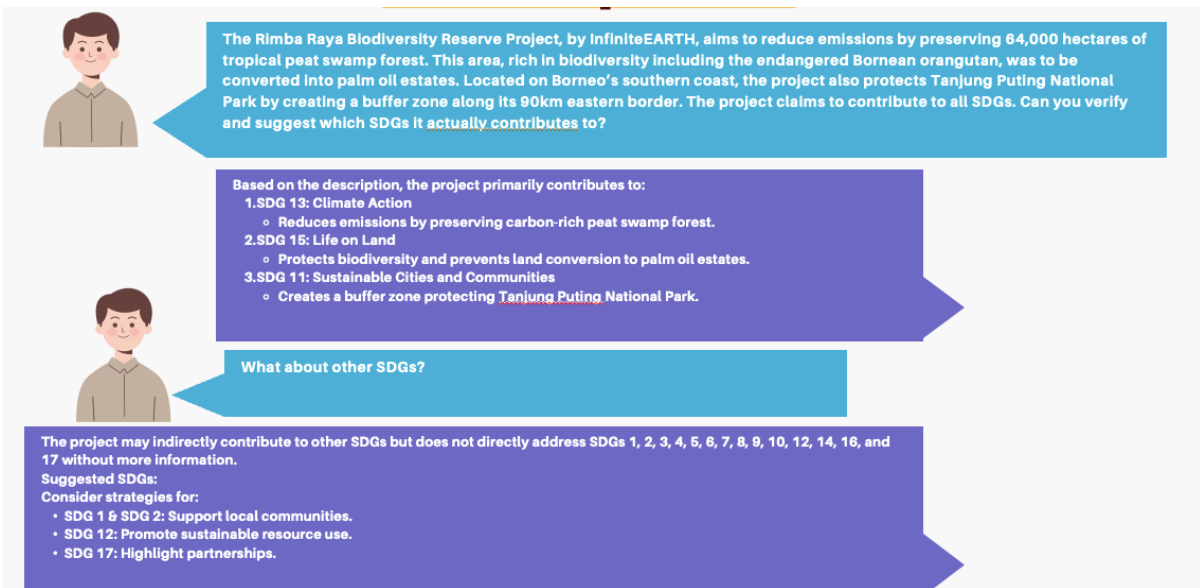


Figure 4. 6.:Simple Rule Based Prompt

- One-Shot and Few-Shot Prompts:
 - These prompts include one or more instances of supposedly verified SDG claims that are given to help the GenAI model situate itself in terms of what is expected of it and what it should use as criteria for making its decision.
 - For example, “If a project increases accessible healthcare, it is sustainable with SDG 3. However, has this new project description match with the desired spec of SDG 3 to be achieved?”

One Shot Prompt



The Rimba Raya Biodiversity Reserve Project, by InfiniteEARTH, aims to reduce emissions by preserving 64,000 hectares of tropical peat swamp forest. This area, rich in biodiversity including the endangered Bornean orangutan, was to be converted into palm oil estates. Located on Borneo's southern coast, the project also protects Tanjung Puting National Park by creating a buffer zone along its 90km eastern border. The project claims to contribute to all SDGs. Can you verify and suggest which SDGs it actually contributes to?



Based on the description, the project contributes to:

- 1.SDG 13: Climate Action
 - Reduces emissions by preserving carbon-rich peat swamp forest.
- 2.SDG 15: Life on Land
 - Protects biodiversity and prevents land conversion.
- 3.SDG 17: Partnerships for the Goals
 - Highlights global partnerships for conservation efforts.

What about other SDGs?

The project indirectly contributes to:

- 1.SDG 14: Life Below Water
 - Protects marine ecosystems adjacent to the park.

The project does not provide direct evidence for SDGs 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, and 16. Further information is needed to claim these SDGs.

Figure 4. 7.:One Shot Prompt Example

Few Shot Prompt



The Rimba Raya Biodiversity Reserve Project, by InfiniteEARTH, aims to reduce emissions by preserving 64,000 hectares of tropical peat swamp forest. This area, rich in biodiversity including the endangered Bornean orangutan, was to be converted into palm oil estates. Located on Borneo's southern coast, the project also protects Tanjung Puting National Park by creating a buffer zone along its 90km eastern border. The project claims to contribute to all SDGs. Can you verify and suggest which SDGs it actually contributes to?

The Rimba Raya Biodiversity Reserve Project by InfiniteEARTH contributes to the following UN Sustainable Development Goals (SDGs):

1. **SDG 13: Climate Action**
 - The project aims to reduce Indonesia's emissions by preserving a significant area of tropical peat swamp forest, which acts as a carbon sink.
2. **SDG 15: Life on Land**
 - The project protects biodiversity, including the endangered Bornean orangutan, by preserving their natural habitat. It also prevents land degradation by stopping the conversion of the forest into palm oil estates.
3. **SDG 17: Partnerships for the Goals**
 - The project involves collaboration between InfiniteEARTH, the local government, and potentially other stakeholders, demonstrating a successful partnership for achieving the goals.

Based on the project description, the claimed SDGs are too broad. The project does not provide specific actions or outcomes that contribute to SDGs 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 14, and 16. Therefore, it would be more accurate to claim SDGs 13, 15, and 17.

However, if the project has other components not mentioned in the description that do contribute to the other SDGs, these should be clearly stated to justify the claimed SDGs.

Figure 4. 8.:Few Shot Prompt

- Chain-of-Thought Prompts:

- These prompts are used to make the GenAI lay down his/her/its line of thinking before coming up with a verification decision.
- Example: “First, describe in what ways your project positively contributes to clean water access, then verify if it correlates with SDG 6, and only then determine if it does.”

Chain of thought



The Rimba Raya Biodiversity Reserve Project, by InfiniteEARTH, aims to reduce emissions by preserving 64,000 hectares of tropical peat swamp forest. This area, rich in biodiversity including the endangered Bornean orangutan, was to be converted into palm oil estates. Located on Borneo’s southern coast, the project also protects Tanjung Puting National Park by creating a buffer zone along its 90km eastern border. The project claims to contribute to all SDGs. Can you verify and suggest which SDGs it actually contributes to?

Chain of Thought:

- The project aims to reduce emissions by preserving a large area of peat swamp forest, which aligns with SDG 13: Climate Action.
- The area is rich in biodiversity, including endangered species, and the project aims to protect this biodiversity, which aligns with SDG 15: Life on Land.
- The project is designed to protect the integrity of an adjacent national park, which also aligns with SDG 15: Life on Land.
- The project prevents the conversion of the area into palm oil estates, which could be seen as a contribution to SDG 12: Responsible Consumption and Production, as it discourages unsustainable agricultural practices.

Suggestion:

The Rimba Raya Biodiversity Reserve Project by InfiniteEARTH contributes to the following UN Sustainable Development Goals (SDGs):

1. **SDG 13: Climate Action**
 - The project aims to reduce Indonesia’s emissions by preserving a large area of peat swamp forest.
2. **SDG 15: Life on Land**
 - The project protects biodiversity, including endangered species, and the integrity of an adjacent national park.
3. **SDG 12: Responsible Consumption and Production**
 - The project prevents the conversion of the area into palm oil estates, discouraging unsustainable agricultural practices.

Based on the project description, the claimed SDGs seem to be too broad. The project does not provide evidence of direct contributions to SDGs such as No Poverty (SDG 1), Zero Hunger (SDG 2), Good Health and Well-being (SDG 3), Quality Education (SDG 4), Gender Equality (SDG 5), Clean Water and Sanitation (SDG 6), Affordable and Clean Energy (SDG 7), Decent Work and Economic Growth (SDG 8), Industry, Innovation, and Infrastructure (SDG 9), Reduced Inequalities (SDG 10), Sustainable Cities and Communities (SDG 11), Life Below Water (SDG 14), Peace, Justice, and Strong Institutions (SDG 16), and Partnerships for the Goals (SDG 17). The project should clarify its contributions to these SDGs or reconsider its claimed SDGs to more accurately reflect its impact.

Figure 4. 9.:Chain of Thought Prompt

- Contrastive Chain-of-Thought Prompts:
 - These prompts help the model to try to match various attributes of the project description and to find how they support or do not support the SDGs.
 - Example: “The project promotes to offer clean water, while falling under the Sustainable Development Goal 6 and at the same time it is linked with uncontrolled water extraction. In what manner does this affect the overall alignment?”

Contrastive Chain of thought



The Rimba Raya Biodiversity Reserve Project, by InfiniteEARTH, aims to reduce emissions by preserving 64,000 hectares of tropical peat swamp forest. This area, rich in biodiversity including the endangered Bornean orangutan, was to be converted into palm oil estates. Located on Borneo's southern coast, the project also protects Tanjung Puting National Park by creating a buffer zone along its 90km eastern border. The project claims to contribute to all SDGs. Can you verify and suggest which SDGs it actually contributes to?

Chain of Thought:

- Positive: The project aims to reduce emissions by preserving tropical peat swamp forest, which aligns with SDG 13: Climate Action.
- Positive: By preserving biodiversity and protecting endangered species, the project supports SDG 15: Life on Land.
- Positive: The project also creates a physical buffer for a national park, which can be seen as contributing to SDG 11: Sustainable Cities and Communities.
- Contrast: The project does not seem to directly impact SDGs related to poverty eradication (SDG 1), zero hunger (SDG 2), good health and well-being (SDG 3), quality education (SDG 4), gender equality (SDG 5), clean water and sanitation (SDG 6), affordable and clean energy (SDG 7), decent work and economic growth (SDG 8), Industry, Innovation, and Infrastructure (SDG 9), reduced inequalities (SDG 10), responsible consumption and production (SDG 12), life below water (SDG 14), peace, justice, and strong institutions (SDG 16), and partnerships for the goals (SDG 17).

Suggestion:

The Rimba Raya Biodiversity Reserve Project by InfiniteEARTH contributes to the following UN Sustainable Development Goals (SDGs):

1. **SDG 13: Climate Action**
 - The project reduces carbon emissions by preserving tropical peat swamp forest.
2. **SDG 15: Life on Land**
 - The project protects biodiversity and endangered species, contributing to the sustainable use of terrestrial ecosystems.
3. **SDG 11: Sustainable Cities and Communities**
 - The project helps protect the integrity of the Tanjung Puting National Park, contributing to sustainable urban development.

Based on the project description, the claimed SDGs seem to be too broad. The project primarily contributes to SDGs 13, 15, and 11. Other SDGs claimed by the project are not directly addressed in the provided project description.

Figure 4. 10.: Contrastive Chain of Thought Example

By employing all these kinds of prompts, the AI Gen auditor obtains a richer mindset concerning SDG criteria and claim assessment coupled with knowledge based on the rule-based system.

4.5.5. Confidence Scoring

Once claims made on SDG are verified, the AI Gen auditor provides each result with a confidence score, reflecting the degree of certainty a model assigns in decision-making. Such a confidence score is of paramount importance for the accuracy of the given claim verification and offers improved transparency for decision-makers.

The confidence score is calculated based on several factors, including:

1. Consistency of Responses Across Different Prompt Types:

This score relies on the differences in the AI auditor's responses to different 'simple' and 'chain-of thought' prompts. Striking the same degree of consistency

when checking across all the types of prompts leads to a higher confidence score on accord with the criteria of the SDG.

For example, if the AI Gen model provides a “Yes” across simple, few-shot, and chain-of-thought prompts for a claim related to SDG 6: From the case of Clean Water and Sanitation, such consistency builds confidence in the model about the direction of alignment.

2. Clarity of Results from Rule-Based Simple Prompts:

Particular attention is paid to those results earned using basic scenarios containing rule-based summaries of UN SDGs. That is why the rule-based approach is better for the model: following the rules allows to understand the quantitative criteria of all the SDGs and provide clearer and more accurate answers.

If the model provides a clear, concise, and specific verification for these prompts, then the confidence score rises, and represents a very solid ground given by the rule-based prompts.

3. Handling Ambiguities in Claim Descriptions:

The confidence score of the AI auditor also takes into account of its capability in dealing with the level of vagueness in the project description. If the model correctly interprets and address the issues arisen from the ambiguity of the language, then the confidence score for the given result is higher. However, when such conditions persist, or if the model produces a mixed reaction, it is necessary to lower the score.

The confidence score is given together with the yes/no verification result to give the users an indication of the degree of dependability of the AI auditor’s decision. This kind of format with two outputs assists users not only in

understanding whether a given project corresponds to a particular SDG, but also in identifying how confidently the model is in the result of the classification.

While the present study focused on designing and implementing the Gen AI Auditor's technical framework, the system has been developed to be fully adaptable to real-world project data. The modular architecture allows for integration with verified datasets and facilitates performance checks against known SDG claim outcomes. Furthermore, the outputs are generated using a transparent, rule-based process, enabling independent experts to review and confirm accuracy. This ensures that, although large-scale practical testing was beyond the current research scope, the methodology is structured for straightforward application and validation in operational contexts.

Example

An AI auditor analyses the compliance of description of a project, stipulating clean water access with the SDG 6 and gives a confidence rating of 85%. This score suggests a high probability of there being true concordance as evidenced by the commentaries that provided different forms of writing prompt results and the clear responses which were provoked by rule-base writing prompts. The high confidence score assists the decision makers to place their trust on the verification results hence more appropriate evaluation of the project in meeting the UN Sustainable Development Goals.

4.5.6. Summary and Findings

The implementation of the AI Gen auditor combines advanced natural language understanding with rule-based structured prompts, enabling accurate and transparent verification of UN SDG claims.

By integrating **simple prompts** with a rule-based understanding of UN SDGs, the AI auditor achieves a foundational comprehension of global sustainability goals, leading to better claim evaluation.

The iterative prompt tuning approach ensures adaptability, making the AI Gen auditor a reliable tool for verifying carbon credit projects' contributions to UN SDGs.

Chapter 5: Conclusion and Implication

5.1. Key Research Findings

5.1.1. UN SDG Integration Framework

- Developed a first-of-its-kind framework that incorporates UN SDG indicators into carbon credit assessments, enabling measurement of social and economic benefits alongside carbon reduction.
- Showcased how aligning projects with specific SDGs (e.g., poverty reduction, job creation) enhances the overall impact and credibility of carbon credit projects.

5.1.2. Social Impact Modelling and Prediction

- Pioneered statistical and machine learning models to quantify and predict social impacts, capturing complex relationships between project characteristics and social outcomes.
- Demonstrated how predictive models can assist stakeholders in foreseeing project impacts on communities, contributing to informed, socially responsible decision-making.

5.1.3. AI-Enhanced Verification: Gen AI Auditor

- Introduced the Gen AI Auditor as a novel tool to validate SDG claims made by carbon credit projects, offering an automated, standardized system for assessing social impact alignment.
- By enhancing transparency, this AI-based system builds trust among stakeholders, providing a reliable assessment of a project's alignment with UN SDG goals.

5.2. Contributions of the Research

5.2.1. Theoretical Contributions

- Advanced sustainability theory by integrating social, environmental, and economic dimensions into carbon credit evaluation, setting a new standard in impact measurement.
- Provided a foundational framework for future studies, promoting a holistic approach to sustainable project assessments beyond carbon-only metrics.

5.2.2. Methodological Advances and Practical Implications

- Introduced novel statistical and machine learning techniques to quantify social impacts, marking a first in capturing such metrics in carbon credit assessments.
- The Gen AI Auditor represents a breakthrough in AI-driven SDG verification, establishing a precedent for automated, transparent SDG monitoring in sustainability initiatives.
- Offered a tool for policymakers and investors to make data-driven decisions, enabling project selection that aligns with broader social goals like poverty alleviation and employment.
- Supported the carbon credit industry's shift toward transparent markets, promoting projects with verifiable social co-benefits alongside emissions reductions.

5.3. Limitations and Challenges

5.3.1. Data and Methodology Constraints

- Noted limitations in data availability and quality, affecting model accuracy and the generalizability of findings across diverse carbon credit projects.

- Recognized challenges in adapting models to various regions and project types, underscoring the need for localized social impact assessments.

5.3.2. AI Model Limitations

- The performance of the Gen AI Auditor is inherently dependent on the quality and completeness of project documentation provided as input. Inaccurate, biased, or incomplete data can influence verification outcomes.
- The current rule-based framework covers only the defined scope of SDG claim categories; claims outside this scope may require rule set expansion for accurate assessment.
- As the Auditor leverages large language models (LLMs), outputs may be affected by biases present in the underlying training data or by model updates beyond the control of this research.

5.3.3. Technical and Operational Challenges

- Addressed the resource-intensive demands of model training and data processing, which may impact scalability in large-scale or diverse applications.
- Acknowledged potential challenges in implementing the framework across different organizations, especially where technical expertise may be limited.

5.3.4. Ethical and Governance Considerations

- Given the potential policy and market implications of AI-driven auditing, it is essential to ensure transparency in how automated judgments are generated and communicated.
- Human oversight should be maintained for final verification decisions, ensuring that AI complements rather than replaces expert judgement.
- Clear accountability measures are necessary to address potential errors or misinterpretations by the system, supporting trust in the auditing process.

5.4. Directions for Future Research

5.4.1. Expanded Social Impact Indicators and Enhancements in AI Monitoring

- Future studies could consider additional social metrics, such as community health or educational outcomes, to further enhance social impact assessments.
- Suggests incorporating region-specific metrics for a more tailored, impactful evaluation across diverse geographic contexts.
- Recommends expanding the Gen AI Auditor with multilingual support and advanced narrative analysis for improved accuracy across diverse project reports.
- Proposes developing more nuanced capabilities to assess deeper social and contextual insights, refining the system's alignment with SDG verification.

5.4.2. Cross-Sector Applications

- Encourages the application of this pioneering framework in sectors beyond carbon credits, like urban planning, agriculture, or water management, where social goals intersect with environmental objectives.
- Suggests using the framework to assess other sustainability projects, promoting standardized social impact quantification across industries.

5.5. Conclusion

5.5.1. Summary of Significance

- Emphasizes this research as a first and novel approach in quantifying social impacts of carbon credit projects, showcasing its transformative potential for sustainability assessments.
- Highlights the unique contribution of integrating UN SDGs into carbon credit evaluations, positioning the framework as a new benchmark in sustainability.

- Envisions the framework as a driver for reshaping policy and industry standards, helping carbon credit markets evolve into holistic, socially inclusive models.
- Aims for increased investment in projects that provide significant social and economic co-benefits alongside emissions reductions, furthering sustainable development.

5.5.2. Call for Ongoing Innovation

- Encourages continual refinement of evaluation methods to keep pace with evolving sustainability needs and technological advancements.
- Advocates for broad adoption of this framework, supporting research-driven approaches that drive meaningful progress towards global sustainability and equity.

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Appendix A: Code Repository

A.1 Repository Overview

The complete source code and resources related to this thesis are hosted in the following GitHub repository:

GitHub Repository: [Carbon Credit Social Impact](#)

This repository includes scripts and tools developed for data preprocessing, statistical modeling, and AI-based evaluations for verifying UN SDG claims in carbon credit projects.

A.2 Repository Contents

Data Preprocessing Scripts

This folder contains scripts for cleaning, normalizing, and preparing datasets. It includes handling missing values, feature engineering, and preparing data for analysis. Outputs include processed datasets ready for modeling and evaluation.

Objective 1: Framework Development

Code for integrating UN SDGs into the evaluation framework is provided here. It covers metrics and indicators aligned with SDG goals. Outputs include evaluation criteria, visualizations, and validation results.

Objective 2: Statistical Modeling and Machine Learning

This section contains scripts for building statistical and machine learning models. It includes hyperparameter tuning and validation. Outputs include model performance metrics and predictive analysis results.

Objective 3: Gen AI Auditor Implementation

Scripts for the AI-driven auditing tool using **ChatGPT-4** are included. This section features prompt engineering techniques such as:

- **Simple Prompts**
- **One-shot Prompts**
- **Few-shot Prompts**
- **Chain-of-Thought Prompts**
- **Contrastive Chain-of-Thought Prompts**

Outputs include AI-audited UN SDG claims and recommendations for improvements.

A.3 How to Access and Run Code

1. Clone the repository:

```
bash
Copy code
git clone https://github.com/drishtantUTSstudent/carbon_credit_social_impact.git
```

2. Run the scripts directly from the relevant folders for each objective.

A.4 Key Outputs and Visualizations

This repository contains outputs including processed datasets, graphs, and visualizations showcasing data trends and results. It also includes AI Auditor output logs validating UN SDG claims.

A.5 License

The repository is licensed under the **MIT License** and is freely accessible for research purposes.

Appendix B: Academic Publications

Published Work

1. Quantifying the Social Impact of Carbon Projects and Generative AI Tool for United Nations Sustainable Development Goals Claims Verification

- **Publication Venue:** Springer Nature Book – *"Digital Transformation and Sustainability: Methods and Applications"*
- **Expected Publication Date:** 31st December 2024
- **Abstract:**
This chapter presents frameworks and AI-driven methodologies to integrate and verify United Nations Sustainable Development Goals (UN SDG) claims in carbon credit projects. It highlights the development of evaluation techniques and AI-based auditing tools to ensure transparency, accountability, and socio-economic impact assessment, promoting sustainable development.