Application of the CCQI methodology for assessing the quality of carbon credits

This document presents results from the application of version 3.0 of a methodology, developed by Oeko-Institut, World Wildlife Fund (WWF-US) and Environmental Defense Fund (EDF), for assessing the quality of carbon credits. The methodology is applied by Oeko-Institut with support by Carbon Limits, Greenhouse Gas Management Institute (GHGMI), INFRAS, Stockholm Environment Institute, and individual carbon market experts. This document evaluates one specific criterion or sub-criterion with respect to a specific carbon crediting program, project type, quantification methodology and/or host country, as specified in the below table. Please note that the CCQI website Site terms and Privacy Policy apply with respect to any use of the information provided in this document. Further information on the project and the methodology can be found here: www.carboncreditquality.org

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Sub-criterion:	**1.1.3: Financial attractiveness**
Project Type	**Hydropower (dam and run-of-river)**
Date of final assessment:	**12 September 2023**
Score:	**Large Hydropower: 2** **Small Hydropower: 2.68**

Assessment

Relevant scoring methodology provisions

The methodology assesses the financial attractiveness of the individual project or project type to estimate the likelihood that economic actors would normally not pursue the respective mitigation activity in a given market and policy environment without carbon market revenues. The assessment considers three indicators that are important for determining financial attractiveness: The financial attractiveness without carbon credit revenues, the change in financial attractiveness due to carbon credit revenues, and the financial attractiveness with carbon credit revenues. Following the approach of the methodology the following steps are applied to derive the score:

Step 1: Decide whether to apply the methodology to an individual project or at the level of a project type. If the methodology is applied at the level of a project type, clearly define the project type and the geographical scope for the assessment (e.g. global, region, country). Project types may be further differentiated into sub-categories, e.g. considering the project size (e.g. classes of wind turbine sizes), the type of project technology (e.g. on-shore or off-shore wind power), or other project features.

Step 2: Collect the relevant data. Where the methodology is applied to an individual project, data provided by the project may be used, as long as this data can be reasonably verified. Where the methodology is applied at the level of the project type, different data sources could be used, including literature information or a sample of individual projects for which the necessary data is available. To the extent possible, the sample should represent different investment conditions and locations within the geographical scope.

Step 3: Define the carbon credit price used in the calculation of the change in financial attractiveness due to carbon credit revenues. The methodology recommends using the current prices of the relevant markets the project is developed for. Assumptions made by the project proponent on expected carbon prices may be used if they are plausible. In absence of further information, the methodology recommends using a consistent proxy for all projects.

Step 4: Identify for each project the respective value for:

a. The equity IRR without carbon credit revenues (IRR);

b. The change in equity IRR due to carbon credit revenues (ΔIRR); and

c. The equity IRR with carbon credit revenues, calculated as the sum of equity IRR without carbon credit revenues and the change in equity IRR due to carbon credit revenues (IRR+ΔIRR).

Step 5: Identify for the project the relevant project category in the CDM Methodological Tool for Investment Analysis (CDM TOOL 27) according to the following table:

Step 6: Retrieve for each project the country-level expected return on equity (ROE) in the CDM methodological tool for investment analysis for the respective group identified in step 5 (The respective table can be found on page 12 of version 08.00 of CDM TOOL 27).

Table 1 Project categories under the CDM Methodological Tool for Investment Analysis

Group	Categories
1	Energy Industries; Energy Distribution; Energy Demand; Waste handling and disposal
2	Manufacturing industries; Chemical Industries; Construction; Transport; Mining/Mineral production; Metal production; Fugitive Emissions from fuels; Fugitive Emissions from production and consumption of halocarbon, and Sulphur hexafluoride; Solvent use; Carbon capture and storage of CO_2 in geological formations
3	Afforestation and reforestation; Agriculture

Source: CDM Methodological Tool for Investment Analysis (TOOL27)

Step 7: Determine for each project the three indicators, by putting the IRR, the ΔIRR, and the sum of IRR and ΔIRR in relation to the expected return on equity (ROE).

Step 8: If the methodology is applied to a project type, calculate the average values for Indicator 1.1.3.1, Indicator 1.1.3.2, and Indicator 1.1.3.3 for the sample of projects.

Step 9: Apply the scoring approach in the methodology to determine the score for indicator 1.1.3.1.

Step 10: Apply the scoring approach in the methodology to determine the score for indicator 1.1.3.2.

Step 11: Apply the scoring approach in the methodology to determine the score for indicator 1.1.3.3.

Step 12: Apply the scoring approach in the methodology to determine the overall score for sub-criterion 1.1.3.

If a project or project type does not have revenues or cost savings other than carbon market revenues, an IRR cannot be calculated. As these projects fully rely on carbon market revenues, they are clearly not financially viable without carbon market revenues and are therefore assigned a score of 5.

Information sources considered

1 CDM Project Search. Data accessed on 17 February 2023 https://cdm.unfccc.int/Projects/projsearch.html

2 World Development Indicators – Lending interest rate (Indicator: FR.INR.LEND). Data accessed on 19 January 2022. https://databank.worldbank.org/source/world-development-indicators

3 Tax Foundation – Corporate Tax Rates around the World, 2021. Data accessed on 19 January 2022. https://taxfoundation.org/publications/corporate-tax-rates-around-the-world/

4 CDM TOOL27 Methodological tool: Investment analysis – Version 08.0 https://cdm.unfccc.int/methodologies/PAmethodologies/tools/am-tool-27-v8.pdf

5 IGES CDM Project Database, Version 13.1. Data accessed on 24 May 2022. https://www.iges.or.jp/en/pub/iges-cdm-project-database/en

6 World Bank. Inflation, GDP deflator: linked series (annual %). Data accessed on 6 July 2022. https://data.worldbank.org/indicator/NY.GDP.DEFL.KD.ZG.AD

7 Haya (2009) Measuring emissions against an alternative Future: Fundamental flaws in the structure of the Kyoto Protocol's Clean Development Mechanism. Working Paper. University of California, Berkley. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=1562065

8 Haya & Parekh (2011) Hydropower in the CDM: Examining additionality and criteria for sustainability. Working Paper. The Energy and Resources Group. University of California, Berkeley. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2120862

9 Cames et al. (2016) How additional is the Clean Development Mechanism?. Oeko-Institut. https://climate.ec.europa.eu/system/files/2017-04/clean_dev_mechanism_en.pdf

10 Bogner & Schneider (2011) Is the CDM Changing Investment Trends in Developing Countries or Crediting Business-as-Usual? A Case Study on the Power Sector in China. https://www.researchgate.net/publication/286141379

11 IEA (2021) Hydropower special market report - Analysis and forecast to 2030. https://www.iea.org/reports/hydropower-special-market-report

12 Sun et al (2019) Development and present situation of hydropower in China. https://iwaponline.com/wp/article/21/3/565/65977/Development-and-present-situation-of-hydropower-in

13 Carbon Market Watch (2012) Hydro power projects in the CDM – Policy Brief. https://carbonmarketwatch.org/wp-content/uploads/2009/07/120228_Hydro-Power-Brief_LR_WEB.pdf

14 Fearnside (2013) Credit for climate mitigation by Amazonian dams: loopholes and impacts illustrated by Brazil's Jirau Hydroelectric Project. Carbon Management, 4:6, p. 681-696. https://www.tandfonline.com/doi/pdf/10.4155/cmt.13.57?needAccess=true&role=button

15 Van Eynde et al. (2013) Case-studies of Vietnamese Hydropower CDM Projects: Shortcomings and Barriers. In: The Governance of Climate Relations between Europe and Asia: Evidence from China and Vietnam as Key Emerging Economies. https://www.academia.edu/5179429/Case_studies_of_Vietnamese_Hydropower_CDM_Projects_Shortcomings_and_Barriers

Assessment outcome

The project type is assigned a score of 2 for large-scale hydropower (i.e., projects with an electric power generation capacity larger than 15 MW) and 2.68 for small-scale hydropower (i.e., projects with an electric power generation capacity up to 15 MW).

Justification of assessment

Project type

The assessment is applied at the level of the project type. The project type ‘hydropower’ can be split into the subtypes ‘Run-of-River’ and ‘Dam’. These are defined as follows:

Dams:

“Installation of a new hydro power plant by building a new dam or the installation of additional power generation capacity at an existing reservoir. The electricity is fed into a national or regional electricity grid. This project type does not include pumped-storage hydropower. The project type reduces emissions by displacing more greenhouse gas intensive electricity generation.”

Run-of-River:

“Installation of a new hydro power plant with no or minimal storage. The plant harvests energy from flowing water, such as rivers or streams. The electricity is fed into a national or regional electricity grid. The project type reduces emissions by displacing more greenhouse gas intensive electricity generation.”

Information sources considered in the analysis

To assess financial attractiveness of this project type, we evaluate information from two sources: 1) investment analysis data from projects registered under carbon crediting programs and 2) relevant literature.

Basing the assessment on data from projects that were submitted under carbon crediting programs might be subject to a selection bias, as it is likely that projects that are economically viable without carbon credits do not apply for registration. However, a key element of the analysis is assessing the extent to which carbon credits improve the financial attractiveness and contribute to clearing the benchmark for the specific project type. This information is only available in data from projects registered under carbon crediting programs. We therefore still consider this source of information for conducting the assessment, noting that the results may include a bias towards higher likelihood of additionality.

To mitigate possible biases of the data analysis, we consider the context of the investment decision for this project typ. Hence, in a second step, we also consult relevant literature.

Analysis of data from registered projects

Selection of the data for analysis

As the CDM project database contains the most comprehensive financial analysis data available among carbon credit programs, only data from CDM projects is considered. Other carbon crediting programs currently do not require the disclosure of information on financial attractiveness. Therefore, only few projects from other programs include relevant information.

In the CDM database, hydropower projects are listed under the project type "hydro" with the sub-types “run-of-river”, “new dam”, “existing dam”, “run-of-river + new dam” and “higher efficiency power”. The latter four were summarized under “dam” for this analysis. As of December 2022, the database contains 2229 entries with active reference numbers for the project type “hydro”.

The CDM website (Source 1) allows downloading a “Database for PA and POAs”[1] (henceforth referred to as the CDM database) in Microsoft Excel format. This database contains comprehensive information on all aspects of individual projects, such as the project name, project status, location, key financial information, etc. Next to this database, detailed documentation for each project is available on the CDM website (Source 1). This includes the project design document (PDD) which is often complemented by excel sheets containing the financial analysis for the project.

The analysis for this project type is based on all projects for which all necessary information is available. Projects were not included in the analysis if any of the following parameters was not available:

- IRR without carbon credits (information required for calculating indicator 1.1.3.1 and 1.1.3.3.)
- IRR with carbon credits (information required for calculating indicator 1.1.3.2)
- IRR benchmark (information required for all three indicators)

Out of the 2229 projects, 1583 have complete data (see Table 2). These projects are considered in the further analysis. Table 1 also shows the distribution between the two sub-types as well as between large-scale projects (i.e., projects with an electric power generation capacity larger than 15 MW) and small-scale projects (i.e., projects with an electric power generation capacity up to 15 MW).

Table 2 **Number of hydropower projects with available data, split by project sub-type and project size**

	Run-of-river	Dam	Sum
Small-scale	577	129	704
Large-scale	547	332	879
Sum	1124	459	1583

Source: CDM project database, own compilation

The projects have a regional focus, which can be seen in Table 3. Over 80% of projects are implemented in the region “Eastern Asia”, all but 10 of them in China.

[1] PA = Project Activities; PoA = Programme of Activities

Table 3 **Number and share of analysed projects by region**

	Number	% of all projects
Regions		
Eastern Africa	2	0.13%
Middle Africa	1	0.06%
Central America	14	0.88%
South America	89	5.62%
Eastern Asia	1288	81.36%
South-Eastern Asia	105	6.63%
Southern Asia	79	4.99%
Southern Europe	4	0.25%
Melanesia	1	0.06%
Sum	1583	

Source: Own calculation

Determination of the relevant indicators and scores

The methodology uses the following three indicator values to assess financial attractiveness:

1.1.3.1 The internal rate of return (IRR) without carbon credit revenues, in relation to the relevant IRR benchmark

1.1.3.2 The change in IRR due to carbon credit revenues, in relation to the relevant IRR benchmark

1.1.3.3 The IRR with carbon credit revenues, calculated as the sum of IRR without carbon credit revenues and the change in IRR due to carbon credit revenues, in relation to the relevant IRR benchmark

For each of the 1583 projects with complete data available in the CDM database, the values for these three indicators and the associated scorings are calculated, using the respective scoring formulas outlined in the methodology. Finally, average scores are determined for each indicator. These are calculated for all projects as well as for different sub-groups of projects, differentiating by project size (small-scale / large-scale) and project subtype (run-of-river / dam).

Table 4 provides the scoring results.

Table 4 **Scoring results for sub-criterion 1.1.3 for the project type hydropower**

1.1.3.1.	1.1.3.2.	1.1.3.3.	Score 1.1.3
3.04	3.58	3.96	**2.62**

Source: Own calculation

The overall score for sub-criterion 1.1.3 is 2.62, based on data from registered projects for the project type hydropower on a global level.

Table 5 contains the scoring results differentiated by project type and project size. The results show that the differences in scorings between large-scale and small-scale projects and between dam and run-of-river projects are relatively small. T-tests are conducted to determine whether these differences are statistically significant. T-tests take the distribution of the data into account, to determine whether the difference between two groups is statistically significant or whether it is coincidental. These tests are conducted for each of the indicator values and the overall score (see Annex I, Table 8 and Table 9).

Table 5 **Scoring results for the project type hydropower, differentiated by project sub-type and project size**

Project sub-type

	1.1.3.1.	1.1.3.2.	1.1.3.3.	Score 1.1.3.
Dam	3.04	3.54	3.93	**2.55**
Run-of-River	3.04	3.60	3.97	**2.60**

Project size

	1.1.3.1.	1.1.3.2.	1.1.3.3.	Score 1.1.3.
Small-scale	3.08	3.67	4.01	**2.68**
Large-scale	3.00	3.51	3.92	**2.50**

Source: Own calculation

The t-tests show that the difference between dam and run-of-river projects for any of the indicator values or the overall score is not significant. In contrast, the t-test is significant for the difference between the scoring of the different project sizes. This means that there is very low likelihood (less than 5%) that the difference we observe is coincidental. With regard to the project size, the t-test is significant for indicator 1.1.3.1., indicating that small-scale projects are less economically attractive without carbon credits than large ones. It is important to note that t-tests take into account the distribution of the data, not just the mean. Therefore, a bigger difference in mean does not necessarily mean a significant result.

Sensitivity analysis with regard to assumptions on carbon credit prices and financial benchmarks

The results in Table 5 fully rely on the assumptions that project developers have made for key input parameters. These assumptions are reflective of the specific circumstances in which each project takes place (e.g., the country, the debt-equity ratio, the project start date, the length of the crediting period) as well as the individual expectations of each project developer (e.g., in relation to future carbon credit prices). Our assessment of the data in the CDM database shows, however, that for projects for which similar circumstances apply, assumptions for input values sometimes differ substantially. For example, project developers' assumptions on carbon credit prices sometimes vary for the same project type and the same registration year.

To assess how this might affect the results, we conduct a sensitivity analysis for key input parameters. The objective is to test if applying harmonized values for projects that share similar circumstances would affect the results in a statistically significant way.

The following two input parameters are considered for the sensitivity analysis:

1) the financial benchmark; and

2) the carbon credit price.

For each parameter we derive an adjusted value, hereinafter referred to as "adjusted benchmark" and "adjusted carbon price". To conduct the sensitivity analysis, we substitute the benchmark and carbon price used by the project developers in their PDDs by these adjusted values and then recalculate the three indicators for financial attractiveness.

Implementing the sensitivity analysis for all projects is not feasible within the scope of this assessment. The limiting factor is the time that would be required to review for all 1583 projects whether they provide financial data in a format that is suitable for substituting the original data with the adjusted value for the carbon price. Therefore, the sensitivity analysis is conducted for a sample of projects.

For this purpose, stratified random sampling is used, taking into account the two sub-types of the project type (run-of-river/dam) and the different project sizes (small-scale/large-scale). For a detailed description of the sample drawing process see Annex II. The total sample size was 93 projects.

For each of these 93 projects it is assessed whether an Excel file is provided by the project developers and whether the file has sufficiently detailed information to recalculate the IRR with our adjusted carbon price and/or adjusted benchmark (see next steps). It is found that this information is available for 32 out of the 93 projects. This sample of projects is used for further analysis. The sample structure can be seen in Table 6.

Table 6 Sample structure of hydropower projects used in the sensitivity analysis

	Run-of-river	Dam	Sum
Small-scale	13	3	16
Large-scale	8	8	16
Sum	21	11	32

Source: Own calculation

Adjusted benchmark

In this scenario, we derive an "adjusted benchmark" for each project. We derive the adjusted benchmark from independent third-party information on typical financial benchmarks for the relevant country and industry.

For each of the 32 projects, the three indicators (1.1.3.1, 1.1.3.2 and 1.1.3.3) are recalculated using the adjusted benchmark instead of the original benchmark used in the PDD. To do so, we review the financial information in each PDD to identify the applicable type of benchmark for each project. There are two types of IRR that project developers can use in their financial analysis: Equity IRR (which is considers the financing structure of the project) and project IRR (which does not consider the financing structure). Depending on the type of IRR, the benchmarks differ: To be financially viable, the equity IRR has to surpass the return on equity (ROE). For the project IRR, the IRR has to surpass the weighted average cost of capital (WACC).

Most PDDs specify whether they use an equity IRR or project IRR to assess the financial attractiveness of the project. Where PDDs do not provide this information, we assume that a project IRR has been used.

We derive the applicable adjusted benchmark for each project in the following ways:

- For the ROE we use data provided in the CDM methodological tool for investment analysis (CDM TOOL27), as recommended in Step 6 of the CCQI methodology. The tool provides country-specific values for the expected return on equity (ROE) for three broad sectors (see Table 1 in TOOL27). As part of the 'Energy Industry', hydropower belongs to group 1. We take the benchmark from the year of the project's start date.
- The values provided in the CDM TOOL27 only apply to projects that use an equity IRR in their financial analysis. For those projects using a project IRR, the WACC was calculated using the approach described in Annex III.

As CDM TOOL27 provides values in real terms, parameters that are available in nominal values were adjusted using the 20-year median of inflation from the World Bank time series "inflation GDP deflator: linked series (Source 6). Many projects do not specify whether they conducted their financial analysis in nominal or in real terms. For calculating the adjusted benchmark, it we assume that these projects used nominal terms for their financial data.

Adjusted carbon price

In this scenario, we re-calculate the indicators 1.1.3.2 and 1.1.3.3 based on a uniform carbon price. The carbon price is an important input factor when calculating the contribution that carbon credit revenues can make for a project to clear the financial benchmark. If the carbon price used is higher or lower than what can reasonably be expected, this might skew financial calculations of a project. Hence, to assess the implications of different assumptions in carbon prices on the indicator scores, we choose a uniform carbon price of EUR 10 per ton/CO_2e across all projects to recalculate the indicators.

Results of the sensitivity analysis

Table 7 shows the results of the sensitivity analysis. It shows the scores for our sample of 32 projects for four different scenarios:

- Original data: here we calculate the indicators and scores using the original data provided by project developers.

- Adjusted benchmark and adjusted carbon price: here we calculate the indicators and scores by adjusting both the benchmark and the carbon price.
- Adjusted carbon price: here we calculate the indicators and scores by adjusting the carbon price but using the original data for the benchmark.
- Adjusted benchmark: here we calculate the indicators and scores by adjusting the benchmark but using the original data for the carbon price.

Table 7 Scoring for hydropower in different scenarios

Original data				Adjusted benchmark and adjusted carbon price			
1.1.3.1	1.1.3.2	1.1.3.3	**Score 1.1.3.**	1.1.3.1	1.1.3.2	1.1.3.3	**Score 1.1.3.**
2.91	3.45	3.99	**2.46**	1.85	4.07	4.75	**2.23**

Adjusted carbon price				Adjusted benchmark			
1.1.3.1	1.1.3.2	1.1.3.3	**Score 1.1.3.**	1.1.3.1	1.1.3.2	1.1.3.3	**Score 1.1.3.**
2.91	3.66	4.17	**2.62**	1.85	3.88	4.68	**2.10**

Source: Own calculation

T-tests show that the difference in mean was significant between the scenario with the original data and each of the scenarios with an adjusted benchmark and/or adjusted carbon price (see Annex I, Table 12 to Table 15).

The scoring in the scenario with the adjusted carbon price was higher. This can be explained by the fact that project developers, on average, assumed a lower carbon price (8.57 Euros) than our adjusted carbon price (10 Euros) in the sample.

The scoring with the adjusted benchmark is lower than with the original data. This can be explained by the fact that project developers' assumptions about the benchmark were on average higher (11.2%) compared with the scenario with adjusted benchmarks (8.6%). In fact, 50% of projects in the sample would have passed the adjusted benchmark without carbon credit revenues in the adjusted benchmark scenario. The difference in the scorings between the scenario with the original data and with the adjusted benchmark is substantially larger for hydropower (0.52) than for most other project types assessed by the CCQI (landfill gas utilization 0.12, industrial biodigesters 0.09, recovery of associated gas from oil fields -0.48, solar photovoltaic power 0.06, wind power (onshore) 0.04).

Analysis of relevant literature

As the sensitivity analysis illustrates, the analysis of financial attractiveness is based on several assumptions, which can influence the results. It therefore only gives an indication of the financial attractiveness of this project type with and without carbon credit revenues. Hence, we consulted relevant literature to further analyze the likelihood of additionality for this project type.

Literature shows that factors other than financial attractiveness are likely to influence the investment decisions for large-scale hydropower plants. An analysis by the International Energy Agency points out that the expansion of hydropower since the 1970 was mainly driven by public sector investment in large-scale hydropower plants, as part of economic development and irrigation policies. This is illustrated by the fact that in spite of nearly 70% of plants being owned by the private sector, the public sector owns 70% of installed capacity. The larger a hydropower plant, the more likely it is to be developed or sponsored by governmental institutions (Source 11).

This means that large-scale hydropower plants are often part of a governmental planning process. For these governmental decision-making processes, other factors other than financial viability play an important role, such as energy security, irrigation or the achieving of renewable energy targets. Thus, it is unlikely that carbon credits play a large role in the decision to invest in large-scale hydropower plants (Source 8 and 9).

This is evident through analysis of the situation of hydropower projects in China, India, Brazil and Vietnam, the four countries with the highest share of analyzed CDM projects (China 80.1%, Vietnam 5,2%, India 4.4%, Brazil 2.2%, Source 1).

In China, medium and large-scale hydropower plants are developed by state institutions or other state-owned actors, such as local governments, the Ministry of Water Resources, regional watershed communities, the National Development and Reform Commission and the state-owned power cooperations (Source 10). Furthermore, China's five-year plan determines the location of certain large-scale hydropower dams well as prescribing specific targets for the size of the capacity additions (Source 12 and 13).

In the case of India, a planning commission, composed of governmental and private actors, identifies potential large hydropower sites and determines central factors around the plant developments. They also take into account a variety of factors, such as energy security, displacement, grid stability and irrigation. These processes are also aligned with a five-year planning cycle (Sources 8 and 13).

In Brazil governments also play a central role in the development of large-scale hydropower plants. Fearnside (2013) points out that the expansion of hydropower is largely driven by governmental plans and policies, motivated by a desire for energy independence and promoting industrialization. He argues that the Brazilian government's support for hydropower plants was triggered by the Bolivian government's decision to take over Petrobrás facilities in Bolivia, endangering Brazil's gas supply (Source 14).

In Vietnam, an analysis found that governmental decision-making is crucial for the development of hydropower plants in the carbon market, as Vietnam's power development plans detail where and how large-scale hydropower project should be developed. About half the plants included in the plan were at the same time developed as CDM projects. The authors conclude that it is highly unlikely that they would not have been built without the CER revenues (Source 15).

The situation of small-scale hydropower plants is not directly comparable. Small-scale hydropower plants are far more likely to be privately developed and owned (Source 11). Additionally, Borges and Schneider (2011) found that in China, the development of small-scale hydropower plants is less centrally organized and faces more substantial barriers than large-scale hydropower plants in spite of the governmental support, particularly those under 20 MW.

Researchers have also studied the accuracy and verifiability of the investment analysis for renewable energy projects under the CDM (Haya and Parekh 2011). They have pointed out that the investment analysis for hydropower projects might involve more uncertainty than for other types of renewable energy projects, e.g., wind energy in India. They explain that in India, wind investors and project developers record key cost items in legal agreements before the start of construction. This makes it more difficult to choose different assumptions when submitting the project to a carbon crediting program. For hydropower, Haya and Parekh argue that capital cost is much more uncertain, and assumptions represent only a best estimate that is often revised over time. This would make these projects more vulnerable to strategic adjustments to initial assumptions (such as the financial benchmark) to show that a project is less viable than it is (Source 8).

Conclusion

Based on the analysis of data from registered projects, the project type hydropower would score 2.62 in the sub-criterion 1.1.3 (see Table 4 above). However, literature shows that for the main host countries, the circumstances of large-scale hydropower are exceptional. As they are part of long-term central planning processes, other factors such as energy security, environmental concerns or irrigation policy play a central role. It is unlikely that carbon credit revenues substantially influence these decisions.

Thus, our overall assessment is that there is a low likelihood that carbon credits increase the attractiveness of large-scale hydropower projects, as financial viability is not a central concern in the decision-making process for these plants. Because of this, an expert judgement was applied, **scoring large hydropower plants with a 2.**

As this line of argument does not necessarily apply to small-scale hydropower plants, those were scored based on the data on financial attractiveness analysis from registered projects. This corresponds to **a score of 2.68** (see Table 5).

Annex I – T-test results

Table 8 T-Tests for project types (indicator values)

	Dam	Run-of-river
Mean	0.75	0.76
Variance	0.10	0.16
Observations	459	1123
Hypothesized Mean Difference	0.00	
df	1070	
t Stat	-0.39	
P(T<=t) two-tail	0.70	
t Critical two-tail	1.96	

	Dam	Run-of-river
Mean	0.37	0.37
Variance	0.34	0.09
Observations	459	1123
Hypothesized Mean Difference	0.00	
df	558	
t Stat	0.00	
P(T<=t) two-tail	1.00	
t Critical two-tail	1.96	

	Dam	Run-of-river
Mean	1.12	1.13
Variance	0.25	0.22
Observations	459	1123
Hypothesized Mean Difference	0.00	
df	795	
t Stat	-0.27	
P(T<=t) two-tail	0.79	
t Critical two-tail	1.96	

Source: Own calculation. Note: The t-tests compares the values for the indicators, i.e., the values that are used to later derive the scores.

Table 9 T-Test for project types (scores 1.1.3.)

	Dam	Run-of-river
Mean	2.55	2.60
Variance	0.65	0.64
Observations	459	1123
Hypothesized Mean Difference	0.00	
df	841	
t Stat	-1.14	
P(T<=t) two-tail	0.25	
t Critical two-tail	1.96	

Source: Own calculation.

Table 10 T-Test for project sizes (indicator values)

Indicator value 1.1.3.1.	Large-scale	Small-scale
Mean	0.78	0.73
Variance	0.25	0.01
Observations	879	704
Hypothesized Mean Difference	0.00	
df	988	
t Stat	2.47	
P(T<=t) two-tail	0.01	
t Critical two-tail	1.96	

Indicator value 1.1.3.2.	Large-scale	Small-scale
Mean	0.35	0.39
Variance	0.27	0.03
Observations	879	704
Hypothesized Mean Difference	0.00	
df	1091	
t Stat	-1.95	
P(T<=t) two-tail	0.05	
t Critical two-tail	1.96	

Indicator value 1.1.3.3.	Large-scale	Small-scale
Mean	1.13	1.12
Variance	0.39	0.03
Observations	879	704
Hypothesized Mean Difference	0.00	
df	1036	
t Stat	0.31	
P(T<=t) two-tail	0.76	
t Critical two-tail	1.96	

Source: Own calculation. Note: The t-tests compares the values for the indicators, i.e., the values that are used to later derive the scores.

Table 11 T-Test for project sizes (score 1.1.3.)

	Dam	Run-of-river
Mean	2.55	2.60
Variance	0.65	0.64
Observations	459	1123
Hypothesized Mean Difference	0.00	
df	841	
t Stat	-1.14	
P(T<=t) one-tail	0.13	
t Critical one-tail	1.65	
P(T<=t) two-tail	0.25	
t Critical two-tail	1.96	

Source: Own calculation.

Table 12 T-test for different scenarios (indicator value 1.1.3.1.)

	No adjustments	Adjusted benchmark
Mean	0.76	1.01
Variance	0.01	0.07
Observations	32	32
Pearson Correlation	0.75	
Hypothesized Mean Difference	0.00	
df	31	
t Stat	-7.53	
P(T<=t) two-tail	0.00	
t Critical two-tail	2.04	

Source: Own calculation. Note: The t-tests compares the values for the indicators, i.e., the values that are used to later derive the scores.

Table 13 T-test for different scenarios (indicator value 1.1.3.2.)

	No adj.	Adj. benchmark
Mean	0.34	0.44
Variance	0.02	0.03
Observations	32	32
Pearson Correlation	0.92	
Hypothesized Mean Difference	0.00	
df	31	
t Stat	-7.74	
P(T<=t) two-tail	0.00	
t Critical two-tail	2.04	

	No adj.	Adj. price
Mean	0.34	0.39
Variance	0.02	0.03
Observations	32	32
Pearson Correlation	0.95	
Hypothesized Mean Difference	0.00	
df	31	
t Stat	-5.14	
P(T<=t) two-tail	0.00	
t Critical two-tail	2.04	

	No adj.	Adj. benchmark & price
Mean	0.34	0.50
Variance	0.02	0.05
Observations	32	32
Pearson Correlation	0.87	
Hypothesized Mean Difference	0.00	
df	31	
t Stat	-8.12	
P(T<=t) two-tail	0.00	
t Critical two-tail	2.04	

Source: Own calculation. Note: The t-tests compares the values for the indicators, i.e.,. the values that are used to later derive the scores.

Table 14 T-test for different scenarios (indicator value 1.1.3.3.)

	No adj.	Adj. benchmark
Mean	1.10	1.45
Variance	0.01	0.07
Observations	32	32
Pearson Correlation	0.43	
Hypothesized Mean Difference	0.00	
df	31	
t Stat	-8.30	
P(T<=t) two-tail	0.00	
t Critical two-tail	2.04	

	No adj.	Adj. price
Mean	1.10	1.15
Variance	0.01	0.02
Observations	32	32
Pearson Correlation	0.93	
Hypothesized Mean Difference	0.00	
df	31	
t Stat	-5.14	
P(T<=t) two-tail	0.00	
t Critical two-tail	2.04	

	No adj.	Adj. benchmark & price
Mean	1.10	1.51
Variance	0.01	0.08
Observations	32	32
Pearson Correlation	0.45	
Hypothesized Mean Difference	0.00	
df	31	
t Stat	-9.05	
P(T<=t) two-tail	0.00	
t Critical two-tail	2.04	

Source: Own calculation. Note: The t-tests compares the values for the indicators, i.e., the values that are used to later derive the scores.

Table 15 T-tests for different scenarios (scores 1.1.3.)

	No adj.	Adj. benchmark
Mean	2.46	2.10
Variance	0.89	0.84
Observations	32	32
Pearson Correlation	0.92	
Hypothesized Mean Difference	0.00	
df	31	
t Stat	5.33	
P(T<=t) two-tail	0.00	
t Critical two-tail	2.04	

	No adj.	Adj. price
Mean	2.46	2.62
Variance	0.89	0.94
Observations	32	32
Pearson Correlation	0.98	
Hypothesized Mean Difference	0.00	
df	31	
t Stat	-5.15	
P(T<=t) two-tail	0.00	
t Critical two-tail	2.04	

	No adj.	Adj. benchmark & price
Mean	2.46	2.23
Variance	0.89	0.84
Observations	32	32
Pearson Correlation	0.88	
Hypothesized Mean Difference	0.00	
df	31	
t Stat	2.82	
P(T<=t) two-tail	0.01	
t Critical two-tail	2.04	

Source: Own calculation.

Annex II -Sample drawing

Stratified random sampling is a sampling technique that is suitable when the studied population consist of varying sub-populations. It allows for a proportional representation of the individual sub-groups in the total sample. The population is first divided into smaller subgroups, or strata, based on common characteristics of the individuals, and then the required number of elements from each stratum is randomly selected to form the final sample. The stratum size, i.e., the number of sample elements per stratum represents the weight of the stratum in the total population. The population of total projects was divided into four strata, based on project size and project type (see Table 2).

The approach to calculate the required sample size was based on the CDM "Guideline: Sampling and surveys for CDM project activities and programmes of activities" (Version 03.1) and is as follows:

1. Step:

Determine an expected (arithmetic) mean and the expected overall variance through available data comparable or literature. As the data for the indicator mean and variance is available for all projects, the values for indicator 1.1.3.1. are taken to calculate the expected mean and overall variance. The calculation uses the following equations:

$$\bar{m} = \frac{(g_a \times m_a) + (g_b \times m_b) + (g_c \times m_c) + \ldots + (g_k \times m_d)}{N}$$

$$SD^2 = \frac{(g_a \times SD_a^2) + (g_b \times SD_b^2) + (g_c \times SD_c^2) + \ldots + (g_k \times SD_k^2)}{N}$$

Where:

g_i = Size of the i^{th} group, where i=a,…,k

$\bar{m}_i$ = Mean of the ith group, where i=a,…,k

SD_i = Standard deviation of the ith group, where i=a,…,k (note that these are all squared- is the group size is actually being multiplied by the group variance)

N = Population total

Applied to the four different strata groups:

$$\bar{m} = \frac{(577 \times 0.73) + (547 \times 0.78) + (127 \times 0.73) + (322 \times 0.76)}{1583}$$

$$SD^2 = \frac{(577 \times 0.01) + (547 \times 0.32) + (127 \times 0.01) + (332 \times 0.13)}{1583}$$

Thereafter, overall variance and overall proportion of projects is calculated as follows:

$V = \frac{SD^2}{\bar{m}^2} = \frac{0.14}{0,57} = 0.25$

2. Step

The total sample size was determined with the following equation:

$$n \geq= \frac{1.96^2 NV}{(N-1) \times 0.2^2 \ + 1.440^2 \ V}$$

Where:

n = Sample size

N = Total number of projects (1583)

V = $\frac{SD^2}{\bar{m}^2} = \frac{overall\ variance}{\bar{m}^2}$

$\bar{p}$ = Overall proportion

1.96 = Represents a confidence level of 95%

0.2 = Represents a precision level of 20%

The proportional allocation of the sample is obtained as follows:

$n = \frac{g_i}{N} \times n \quad where\ i = 1, \ldots k$ and k is the number of projects in the country subregion.

Where:

g_i = Size of the i_{th} group where i=1,…,k

N = Population total

The minimum sample size for large-scale projects required is thus 93 projects. This number is divided according to the number of projects in the individual country subregions, resulting in the following strata sizes. As we do not expect there to be complete data for all projects, we assume a response rate of 25%.

Sample run-of-river/ small: $n_{RoR/s} = \frac{\frac{577}{1583} \times 93}{0.25} = 34$

Sample run-of-river/ large: $n_{RoR/l} = \frac{\frac{547}{1583} \times 93}{0.25} = 33$

Sample dam/small: $n_{D/s} = \frac{\frac{127}{1583} \times 93}{0.25} = 8$

Sample dam/large: $n_{D/l} = \frac{\frac{332}{1583} \times 93}{0.25} = 20$

In the next step, the subsamples are randomly selected from the CDM Database for PAs and PoAs. The projects in the database are divided by project size and project types into separate sheets. The RAND function is used to assign a random number to each project cell, and then the required number of cells is selected. The structure of the CDM database is used for building the initial data sample, as its header exhibits an already comprehensive row of information categories. Additional information categories are added to the database for detailed analysis, such as IRR type, real or nominal terms, equity share of project financing, and underlying CER price.

Annex III Calculation of the WACC

There is no publicly accessible database for WACC across industries and countries. The WACC for an individual firm can be calculated using the following formula:

$$WACC = r_e \times W_e + r_d \times W_d \times (1 - T_c)$$

Where:

r_e = Cost of equity
W_a = Percentage if financing that is equity
r_d = Cost of debt
W_d = Percentage of financing that is debt
T_c = Corporate tax rate

The most accurate way of calculating a WACC benchmark would be to build a peer group of companies active in a particular country and industry related to the project type and calculate the average WACC that applies among that group. This would require very comprehensive data. The second-best option is to calculate the benchmark by using country specific data for the parameters listed in the formula above. This option is used for the assessment.

As the WACC consist of debt and equity, calculating the WACC requires information on the debt-equity ratio. For most projects no information is available in the project design document or other key project documentation. An assumption is therefore made that the percentage is 50 percent for each source of financing. This assumption is guided by the respective guidelines in CDM TOOL 27 that recommends this procedure for cases where information is not available (see paragraph 25 on page 9). Furthermore, the corporate tax rate is applied to the cost of debt, which depends on the country in which the project is implemented.

The required data for each of the parameters were sourced as follows:

1) Cost of equity: Data from the CDM TOOL27 was used. Hydropower within project category 1 of the Methodological Tool for Investment Analysis. For projects with nominal values, the cost of equity was adjusted with the 20-year median of inflation from the World Bank time series “Inflation GDP deflator: linked series” (Source 6).

2) Cost of debt: The “World Development Indicator DataBank” includes a time series on the lending interest rate for meeting short- and medium-term financing needs of the private sector (Source 5). The data description specifies that when reporting these data, countries should use effective and not nominal interest rates. This data is used, taking into account the host country and the start date of the project activity. To account for yearly fluctuations, the 5-year average is used. The lending interest rates used for calculating WACC are also based on effective interest rates.

3) Corporate tax rate: The “Tax Foundation” maintains a time series with the relevant data (Source 3) that is used for the analysis. This data is used, taking into account the host country and the start date of the project activity. To account for yearly fluctuations, the 5-year average is used.