Analysis of carbon markets contribution to meeting climate goals

TEAM 74

Alexander Pinzón Fernandez
Mateo Orozco Jimenez
Iván Herney Hernández León
Luis David Villareal
Esteban Salamanca
Laura Paola Goyeneche Gomez
Katherin Parra

Correlation One / MinTIC of Colombia

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INTRODUCTION

Business Problem

The PNUMA (Programa de Las Naciones Unidas para el Medio Ambiente) looks forward to increase confidence in carbon markets from a data analysis perspective considering the growing uncertainty regarding transparency in the generation of carbon credits.

There is a high diversity of projects and programmes that search to achieve voluntary greenhouse gasses-GHG emissions reductions objectives through the implementation of GHG mitigation actions in various sectors of the economy, from the forestry sector to public transportation. This diversity of actors and methodologies used bring uncertainty to the companies that buy them, the civil society and the authorities.

The carbon markets have been developed in a mainly voluntary way (goals for reducing and offsetting emissions from companies that voluntarily decide to buy carbon credits for corporate social responsibility and to demonstrate some type of commitment to offsetting their emissions), which means that carbon markets are not standardized and those are very different from each other and it is difficult to account for their robustness.

Business Impact

The impact of this analysis is to know if the generation of carbon credits in the voluntary market has effectively contributed to changing the emission trajectories in the countries that host the projects and if the differentiation of the projects could explain the quality or robustness of the projects. The questions we will solve with this analysis are as follow:

- In which sectors do carbon credits have a greater, lesser or no impact?
- Is there a relationship between the issuance of carbon credits and greenhouse gas emissions?
- In which regions, sectors or countries it is possible to see a better understanding of the impact?

In order to answer the questions posed above, we began with a cleaning of the data and thus performed the EDA (Exploratory Data Analysis). Through the graphs that were obtained from the EDA, it was possible to observe the trend of each of the projects, in addition to visualizing the emission of greenhouse gasses by country, the total carbon bonds issued by country, among others.

Additionally, both databases were merged in order to find a correlation between them (carbon credits generated VS CO2 emitted by country) in a given period of time. This gave us an overview of the problem and the current global situation, therefore we proceeded to build the predictive models using an LFTM network in order to predict the total CO2 to 2050 and obtain the amount of CO2 reduced (or increased) by year determined by the number of credits issued or retired the previous year, not only for the years available in the dataset but for the future.

1. PROJECT DESCRIPTION

1.1 Business Solution

Our solution is essentially an interactive dashboard in which stakeholders can visualize information about the impact of carbon dioxide emissions compared with the bonus market and the behavior depending on the industry sector and in a determined time. We based this on information obtained from BerkeleyUniversity and the World Bank, entities interested in the Climate change analysis.

1.2 Solution Scope

Our main solution is to predict the behavior of the carbon dioxide emissions taking into account the impact of carbon credits in each country. Depending on the results of our mathematical models to predict this behavior, we will provide advice to implement different actions to improve the emissions in the countries.

2. DATASET DESCRIPTION

This section describes the technical summary of each dataset used for this project:

2.1 Berkeley Dataset

Berkeley Carbon Trading Project's Voluntary Registry Offsets Database contains all carbon offset projects listed globally by four major voluntary offset project registries: American Carbon Registry (ACR), Climate Action Reserve (CAR), Gold Standard, and Verra (VCS). These four registries generate almost all the world's voluntary market offsets. (Taken from https://gspp.berkeley.edu/faculty-and-impact/centers/cepp/projects/berkeley-carbon-trading-project/offsets-database)

Column	Description
Project ID	The identification number given by the registries

Project Name	Name of the project on the registry.
ARB Project	Yes = all projects listed on ARB's Issuance & Retirements table or listed as 'proposed' or 'active' ARB projects by the registries. No = all other projects.
Voluntary Status	The status of the project on the voluntary market as designated by the registry.
Scope	Each project falls under a scope according to https://gspp.berkeley.edu/assets/uploads/page/Offsets-Database-ScopesTypes-v4.pdf
Type	Each project is categorized by a type according to https://gspp.berkeley.edu/assets/uploads/page/Offsets-Database-ScopesTypes-v4.pdf
Reduction / Removal	Each project type is categorized as Reductions, Permanent removals, Impermanent removals, or Mixed.
Methodology / Protocol	Defines the eligibility, emissions calculations, and monitoring requirements for specific project types.
Region	Region where the project takes place.
Country	The country where the project takes place.
State	The state or province where the project takes place.
Project	Site Location More details on the location of the project.
Project Developer	The person or organization responsible for developing the offset project. This is often the facility owner, project owner, or offset consultant.
Total Credits Issued	The total number of credits issued by the registry from the start of the project.
Total Credits Retired	The total number of credits retired or cancelled from the start of the project.
Total Credits Remaining	The difference between credits issued and credits retired.
First Year of Project	The first year when credited reductions/removals occurred, marked by the end of the first reporting period.

Credits Issued by Vintage Year (reductions/removals occurring in 1996 - 2021)	Credits issued by year when reductions/removals occurred, often called the vintage year, taken as the year of the end of the reporting period.
Credits Retired in 1996 – 2021	Lists credits retired/canceled by the retirement year.
Credits Retired in Year Unknown	Lists credits retired with no retirement date.
Credits remaining by vintage 1996 – 2021	Lists credits remaining and available in each issued vintage year.
Project Owner	The organization, company, or individual who owns the offset project.
Offset Project Operator	The organization, company, or individual which operates the offset project.
Authorized Project Designee	The organization, company, or individual that has first right of refusal for credits issued.
Verifier	Each registry requires a certified third party to verify that the project complies with the requirements of the protocol and that the claimed reductions are monitored and reported as per the requirements of the protocol.
Estimated Annual Emissions Reductions	Some registries note the emissions reductions that the developer expects to produce annually as submitted in early project documents.
PERs (Credits Issued in Future Years)	Lists credits which are ex-ante, which are credits issued before the carbon emission reductions are realized. Reforestation and afforestation projects, for example, may sell credits for expected future tree growth.
Registry / ARB	For filtering and sorting purposes, ARB projects (including all projects listed on ARB's Issuance & Retirements table or listed as 'proposed' or 'active' ARB projects by the registries) are listed in this column as “ARB” rather than by the registry that initially issued the credits.

ARB Project Detail	Some of the projects from the ACR, CAR, and Verra registries are also registered as compliance offsets under the California Air Resources Board's (ARB's) offset program and can be used by California emitters to comply with the state's cap-and-trade requirements. These projects use ARB-approved protocols. Yes Listed as a compliance offset project in ARB's offset project table Yes - Early Action Listed as an early action project in ARB's offset project table Proposed Listed as a proposed or active ARB offset project by the registry but not yet listed in ARB's own project table Terminated Listed as a terminated ARB project by the registry Inactive Listed as an inactive ARB project by the registry
Project Listed	The date that the project was listed on the registry, declaring the project's intention to generate carbon offset credits with a final version of the project design document.
Project Registered	The date that the project was registered as a registry offset project.
ARB ID	The California Air Resources Board assigned each of its projects with its own ID number.
CCB / Certifications	Verra's Climate, Community & Biodiversity (CCB) Standards independently verify carbon offsets for other co-benefits related to conserving biodiversity and supporting local communities. Their ongoing status and current compliance to CCB is notated as follows- Validated, Verified, Under Validation, & Under Verification. Other registries also can list other certifications.
Project Type	The registry's designation of type/sector as downloaded from the registry website.
Registry Documents	Link to the registry site where you can download project documents.
Project Website	External project website.
Credits Issued in 1996 – 2021	Credits issued by issuance year.

Notes from Registry	Notes from the registry.
Notes from Berkeley Carbon Trading Project	Unique attributes, findings, and context discovered during our data processing.
Date added to database	The database version and release date when the project was added.

2.2 World Bank Dataset

This dataset contains the total Greenhouse gasses emitted by country, since 1970 to 2018. It also contains some countries summarized as regions. (Taken from https://data.worldbank.org/indicator/EN.ATM.CO2E.PC)

Table "Data" (wide format)

1. Country Name (String)
2. Country Code (String)
3. Indicator Name (Category, only one)
4. Indicator Code (Category, only one)
5. Date (columns)

Table "Metadata – Countries" (long format)

1. Country Name (String)
2. Country Code (String)
3. Region (String)
4. Income_Group (Category)

Table "Metadata – Indicators (long format)

1. INDICATOR_CODE (String)
2. INDICATOR_NAME (String)
3. SOURCE_NOTE (String)

3. SOLUTION ARCHITECTURE

The app is uploaded to Azure, so it that way it can be accessible for all stakeholders. It was developed in Dash (for python) and many libraries were added to achieve the goals for this project.

https://carbon-market-analysis.azurewebsites.net

3.1. Tools Used

- Dash
- Python
- Azure
- Google Collaborative
- GitHub

4. RESULTS

This process has three steps: Structuring, Cleaning and Enriching and it will be explained as follows:

4.1 Datasets structuring

The datasets mentioned before, were first structured one by one. It means that we only took into account the tables that were important for our project. For example, in Berkeley's dataset, we took only the first table "projects", since the other tables only had information description about what was stated in that first table.

The dataset taken from the World Bank was not re-structured from the start but it was later re-structured after doing the data cleaning.

4.2 Datasets cleaning

As well as the dataset structuring, the cleaning of both datasets was done separately, this helped us to understand each dataset more and give us a general view of the behavior of the carbon dioxide emissions and the carbon credits market.

For Berkeley's dataset, it was checked first if there was not any missing data related to carbon dioxide emissions, also if there was consistency of the data.

For the World Bank's dataset, the columns related to years which were full of null values were discarded and dropped, since this will not have any impact in the analysis.

Berkeley's data per country and year was grouped, because the World Bank data has the same granularity. This way, it'd be comparable between them. Also, it was critical to check for unit integrity between datasets.

4.3 Datasets enriching

After cleaning the data, it was important to enrich it, mainly because it was needed to add additional data to do further processing. To enrich the data, the following was done:

- To obtain the country names we can use the same package to import another dataset with the information from every country, including the relation country - country code.

- From the country_attibutes dataset, some codes belong to an aggregate region (North America, Africa Eastern and Southern, etc). Then we need to eliminate this regions and only keep the countries

- Now we make a join between the CO_2 emissions and the country codes (Right join to eliminate the regions in the CO_2 emissions.

- After handling the missing values we transform the data from a wide format to a long format.

- One carbon credit is equal to one metric ton of carbon dioxide then we need to convert the variable CO2_emitted (Kt) to tonnes

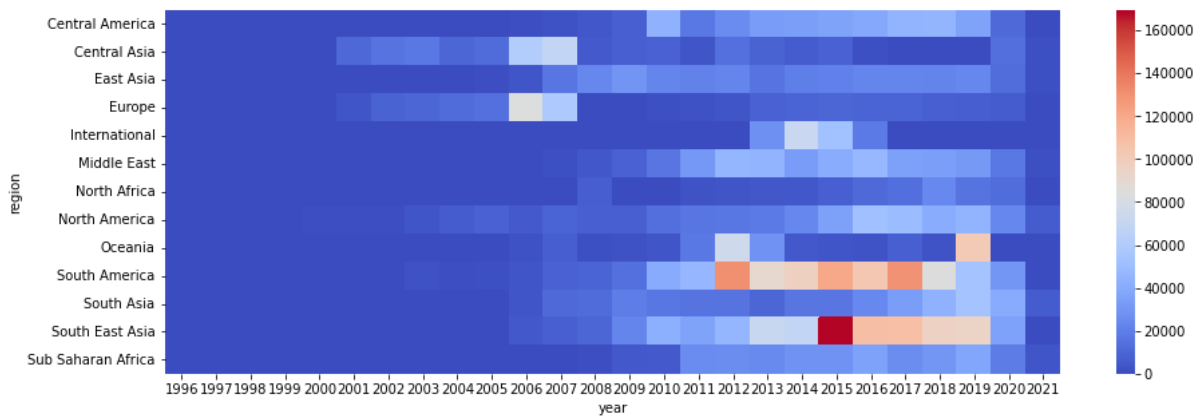
4.4 Exploratory Data Analysis

The description of the EDA implemented and the results achieved will find as follows:

The main data to analyze for this project are the carbon dioxide emissions in relationship with the carbon credit market. In order to see the behavior of the emissions by country, plotting and getting statistics for this was the main goal. By this, it is easier to comprehend how it is working, if it has improved or not, and later on, choose the best model to predict how it will be in the incoming years.

Some of the visualizations of interest and that will be provided by the EDA are the following:

4.4.1. Behavior of carbon emissions over time in differents regions

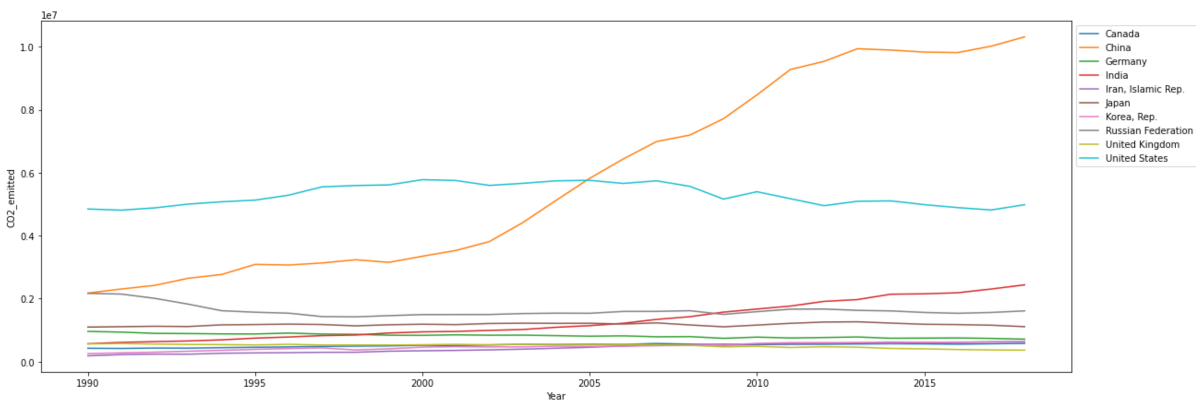


During the exploratory analysis of the data, we found that there were countries that registered no CO2 emissions for some years, this doesn't necessarily mean that they did not emit any, but that at the time no data was provided, and it impacted those first approaches into the data.

Through a heatmap, it was easier to spot the regions that emitted more CO2, however, we found many outliers in the data regarding the emissions by region (outliers that we took into account later on since they represent CO2 emitted by certain countries).

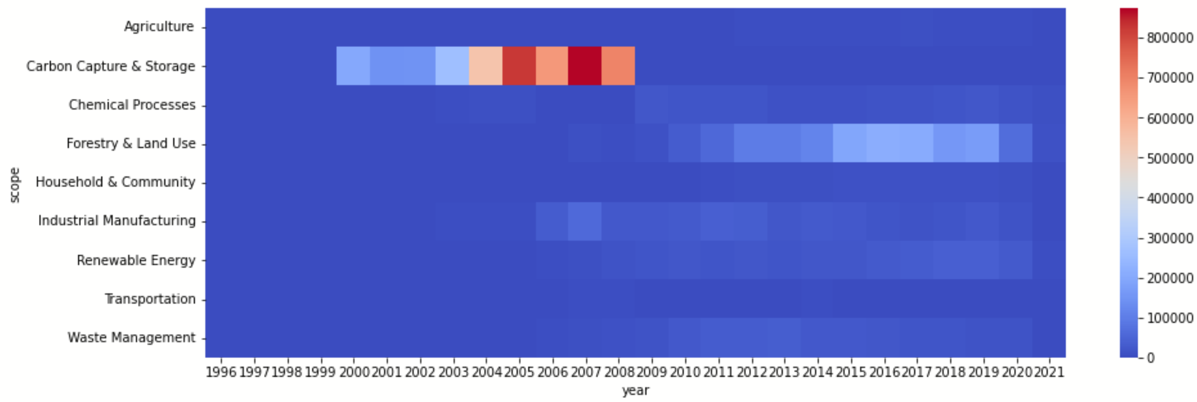
Nevertheless, it is important to see the representation of the data by country since carbon credits are emitted by country.

4.4.2. Behavior of carbon emissions: top 10 countries with more CO2 emitted by year.



It was also found that China and the United States are the countries that emit the most carbon dioxide. Throughout the years, these countries in particular, have turned down their participation in different agreements, so the result of this graph does match the reality.

4.4.3 Behavior of carbon markets by years and segments



This plot is showing the carbon credits issued by scope (sectors of the economy).

5. MODEL SELECTION

Regarding the business question "Is there a relationship between the issuance of carbon credits and greenhouse gas emissions?" we could relate the total credits (issued and retired) by country with the total CO2 emitted by the country each year. As a result, we have a time series from 1996 until 2018 with these variables.

	country	year	credits_issued	credits_retired	registry_issued_credits	credits_remaining	CO2_emitted
0	Argentina	1996	0	0	0	0	126560000.0
1	Argentina	1997	0	0	0	0	127320000.0
2	Argentina	1998	0	0	0	0	133170000.0

With the previous dataset, we could create a categorization model (possibly a machine learning regression model) to obtain the amount of CO2 reduced (or increased) by year determined by the number of credits issued or retired the previous year, not only for the years available in the dataset but for the future.

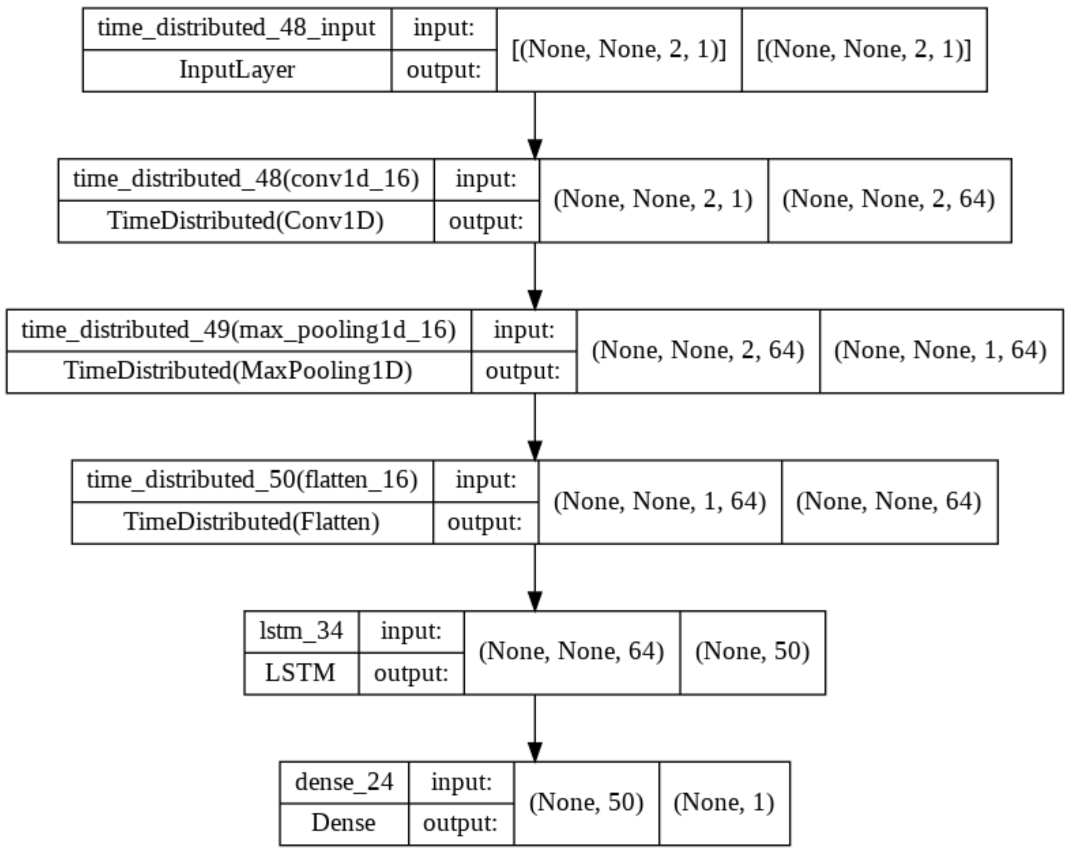
We start creating a projection model for the variables involved:

5.1 Projection CO2_emitted: Option 1 CNN LSTM

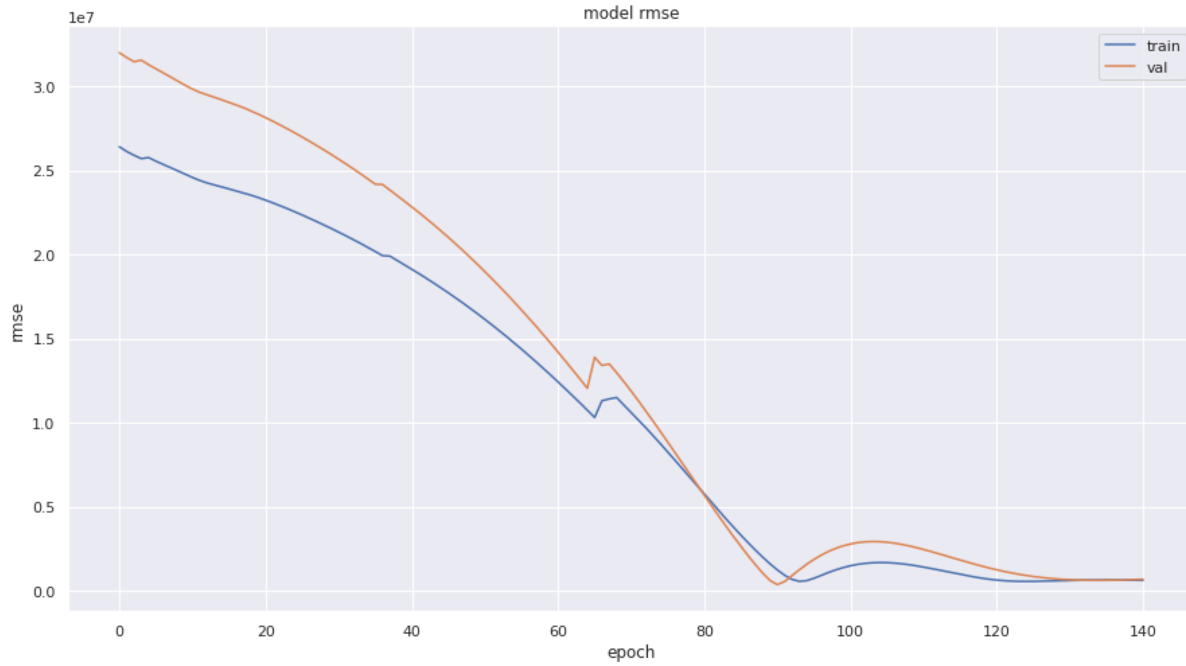
The first proposed model is a Convolutional Neural Network combined with a Long Short Term Memory model to predict the total CO2 emitted yearly.

Why the combination of a CNN with an LSTM? The LSTM is very useful with the seq2seq kind of data (as text or time series) and the CNN adds a component of feature extraction (mostly used for image data).

Following is the network structure:

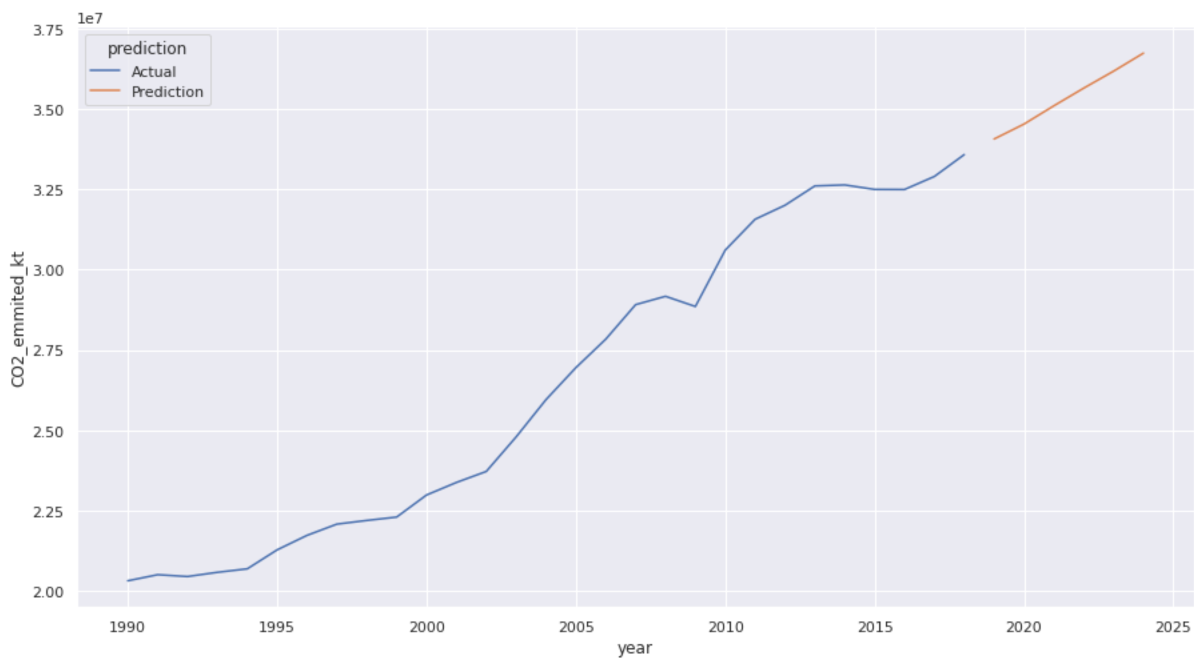


We train the model with a sequence of 4 periods, a subsequence of 2 periods, and 1 feature (CO_2 emitted), we use the Keras sequential model adding each layer. The parameters used were the Adam optimizer, the MSE loss function, the RMSE metric to compare with other models, and a validation split of 10% (Due to the reduced amount of data available).



We use an early stop call to avoid overfitting the model with a result of 140 epochs to train, with an RSME of 629.204,38.

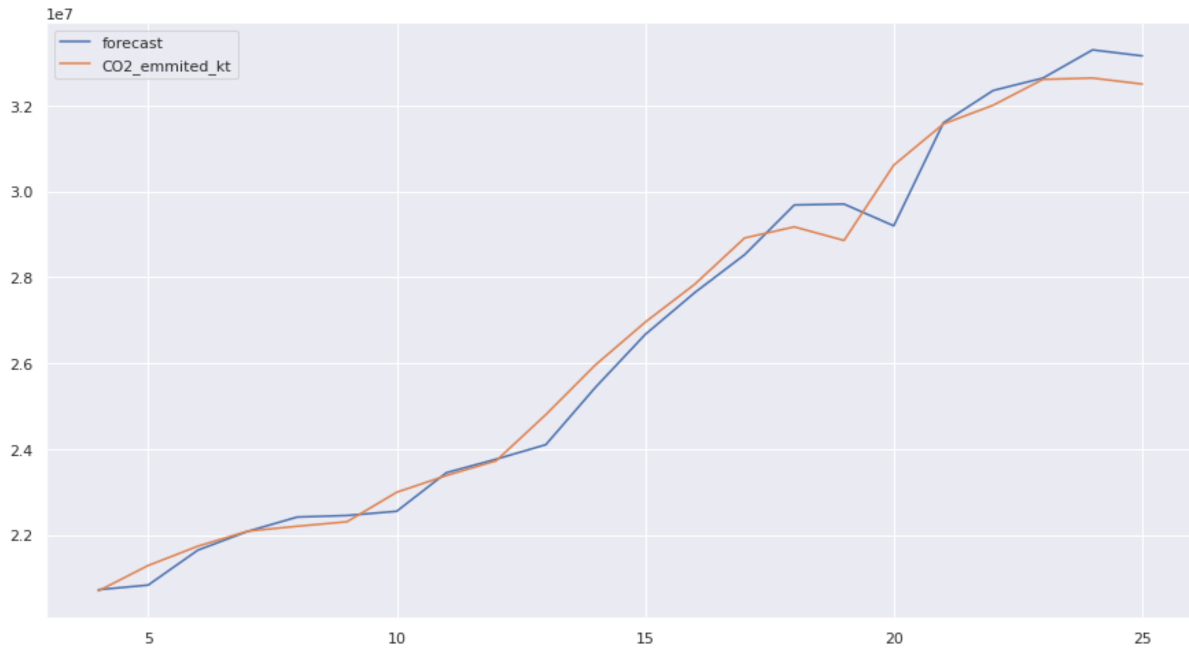
We keep the model and proceed to make a forecast for the next periods:



5.2 Projection CO2_emitted: Option 2 ARIMA (1, 1, 1)

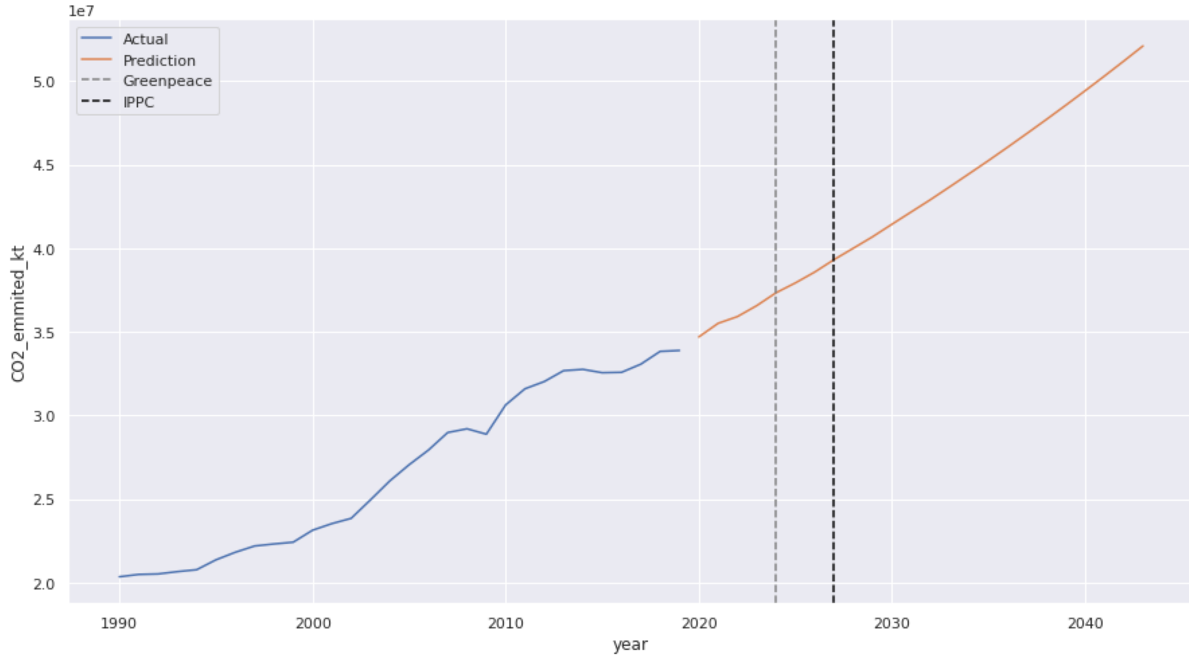
We built an ARIMA model to compare the results. The best model splitting the data with a test set of 10% is an ARIMA (1,1,1). The RMSE is 323.180,94 (beating the CNN LSTM model), and the general results are the following:

Model review, projecting emissions for the 25 period available.

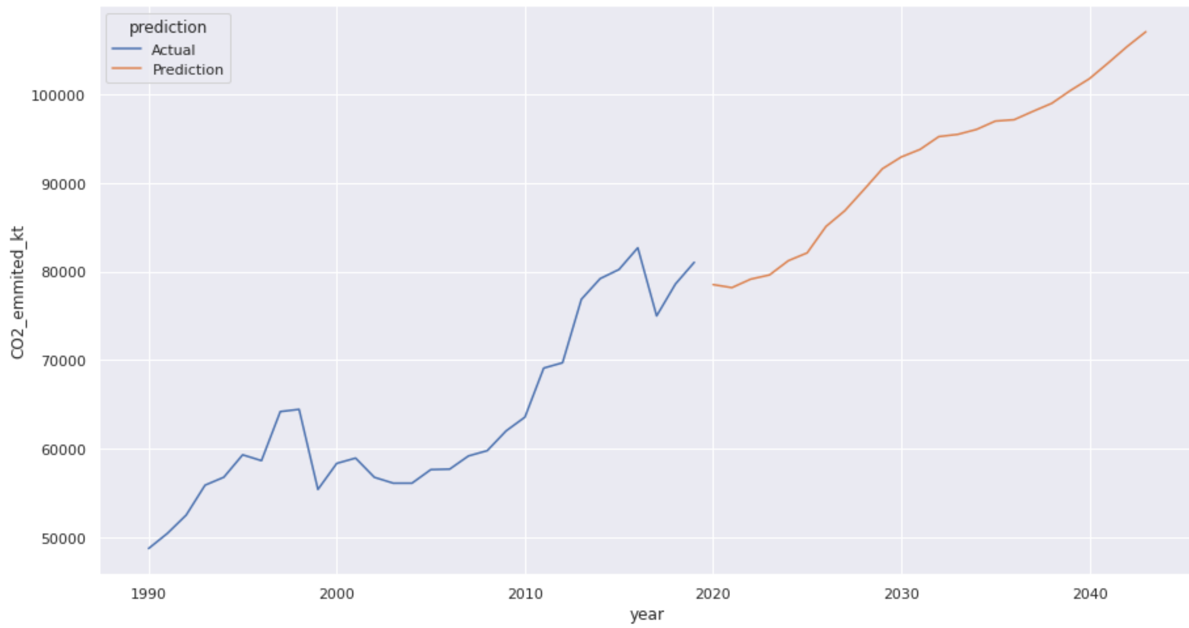


After comparing both models ARIMA (1,1,1) with a RMSE of 323180.93 and the neural network with a RMSE of 629.204,38. Although the Arima model had a better score, we prefer to work with the CNN - LSTM.

Following are the projections for the global and Colombia CO2 emissions. We had to train another CNN - LSTM using the same structure but changing the sequence length (Time sequence = 9, subsequence = 3) to improve the performance over the Colombian time series.



Global emissions



Colombia emissions

We also add an interesting analysis using the projection regarding the CO_2 Budget there is available in the world since 2014. According to Greenpeace and the WFF there is only 350 billion tons available, but the Word Resources Institute and the IPCC are more optimistic with 485 billion tons available. We add the years when both budgets will be reached, the first one will be reached in 2024 and the second one in 2027, if we use the projections given by the model.

Now we have the projections for the CO_2 emitted, we can explore a model that could give us the possibility to predict the CO_2 change if we change another known variable.

5.3 Classification model (CO_2 Reduction in the next period vs Fossil fuel energy consumption (% of total))

We started with the exploratory data analysis to identify if the carbon credits issued each year is a good variable to predict the change in global CO_2 emissions, but we found out that there is no correlation between both variables, that means we had to look for another variable that we could use for this purpose.

Using the same World Bank API we find the variable Fossil fuel energy consumption (% of total), which was joined with CO_2 emissions data, then the percentage of change is calculated.

	year	CO2_emmited_kt	fossil_percentage	change_CO2_percentage	change_fossil_percentage
2	1992	20457550.0	80.082441	-0.002733	-0.002218
3	1993	20588180.0	79.983132	0.006385	-0.000993
4	1994	20696360.0	79.792983	0.005254	-0.001901
5	1995	21287210.0	79.817372	0.028548	0.000244
6	1996	21737560.0	79.834188	0.021156	0.000168
7	1997	22087310.0	79.977068	0.016090	0.001429
8	1998	22201450.0	79.759761	0.005168	-0.002173
9	1999	22306080.0	79.727224	0.004713	-0.000325
10	2000	22992490.0	79.783849	0.030772	0.000566
11	2001	23382530.0	80.038307	0.016964	0.002545
12	2002	23725130.0	80.057041	0.014652	0.000187
13	2003	24799710.0	80.553523	0.045293	0.004965
14	2004	25959200.0	80.651539	0.046754	0.000980
15	2005	26953170.0	80.724477	0.038290	0.000729

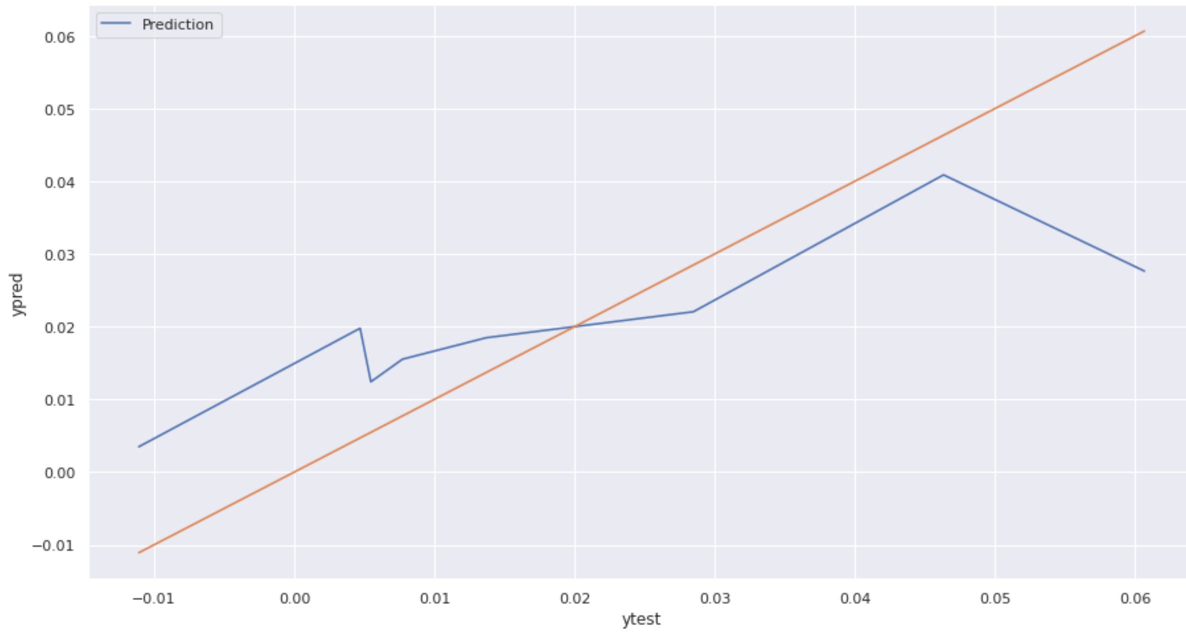
Then the existing correlations are evaluated, finding a correlation of 0.66. Then we proceed to train the model and make the predictions.

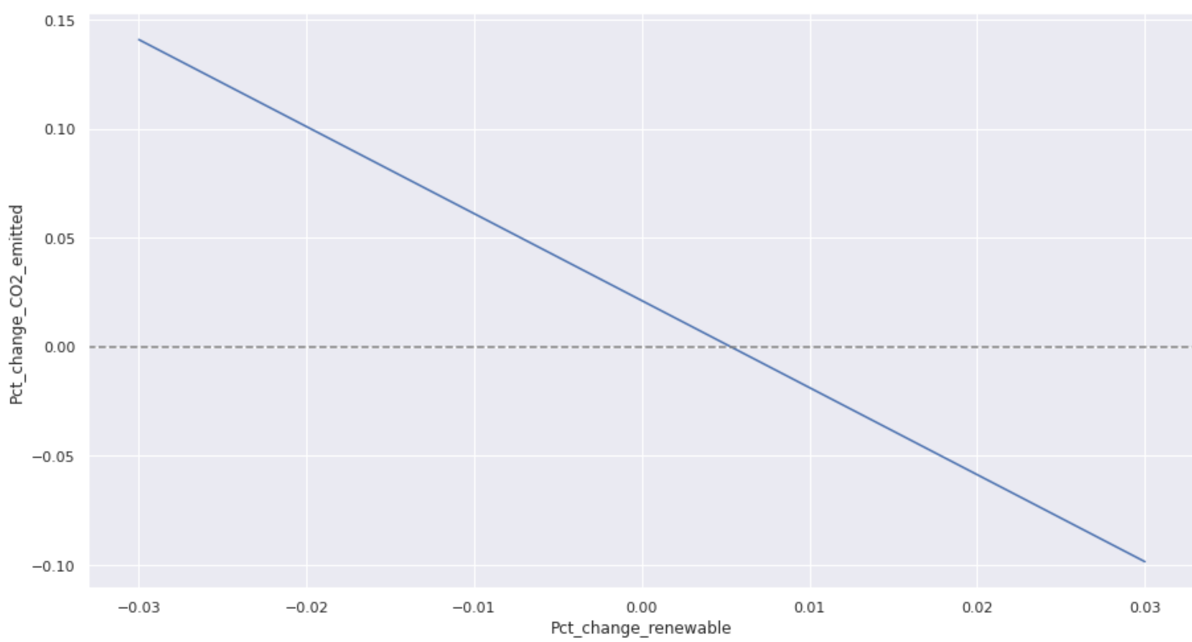
	CO2_emmited_kt	fossil_percentage	change_CO2_percentage	change_fossil_percentage
CO2_emmited_kt	1.000000	0.751742	0.114788	-0.165088
fossil_percentage	0.751742	1.000000	0.364191	0.367848
change_CO2_percentage	0.114788	0.364191	1.000000	0.666134
change_fossil_percentage	-0.165088	0.367848	0.666134	1.000000

The model was trained using the Scikit learn library, using specifically the SVR model (linear kernel). The data was splitted in a training and test sets of 70% and 30% respectively. Then, applying the methods of gridsearch and cross validation (5 folds) over a param grid the model was trained, finding the following best parameters: {'C': 1001, 'epsilon': 0.007, 'gamma': 0.7001}.

The scoring method was negative mean squared error, with a score of -0.000179. We also calculate the MSE: 0.000179 and the RMSE: 0.0134.

If we plot the test data versus the data predicted, we obtain the following result (the red line is the identity line):

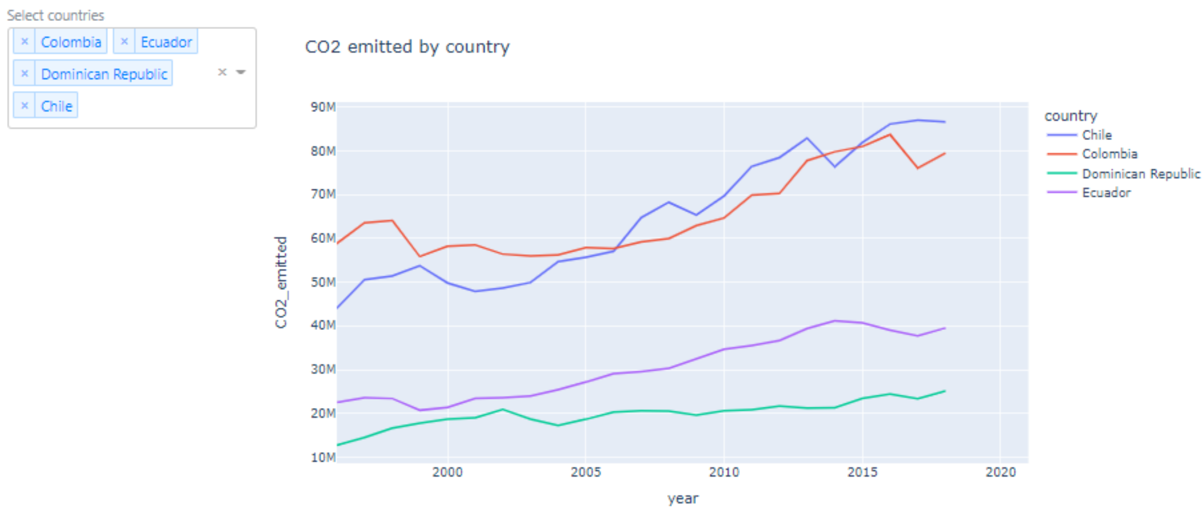




FUNCTIONAL DASHBOARD

Request Interface

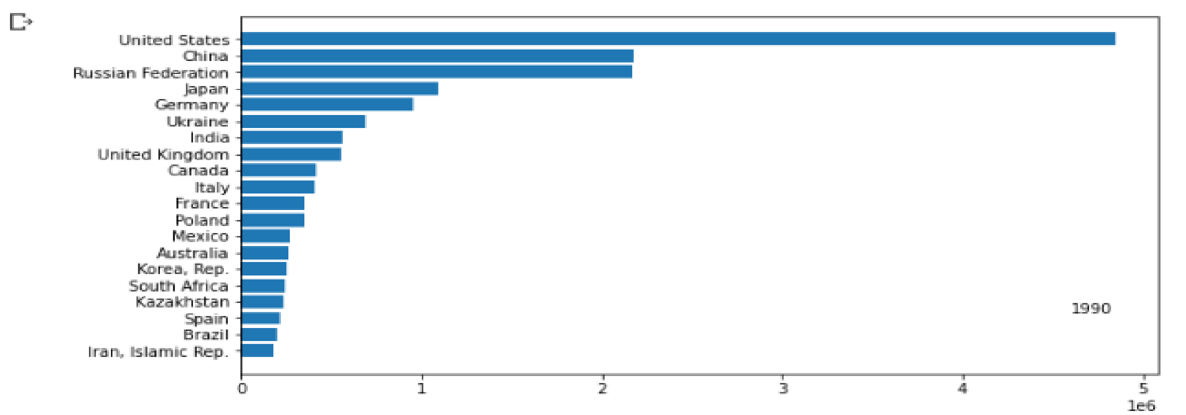
Analyzing CO2 emitted: In this section the user can select the country to be analyzed and to see the trend of the last decades regarding the CO2 emitted:



Analyzing Carbon Market Data: In this section the user can interact with the different variables, only select the categories for the axis X and the numerical variables in the second input of the form.

The construction of interactive graphics that will be added to the application as part of a pedagogical component begins, making several deployments in the behavior at a global and regional level against carbon credits, population and economic data are included at this stage of development brought from the world bank database.

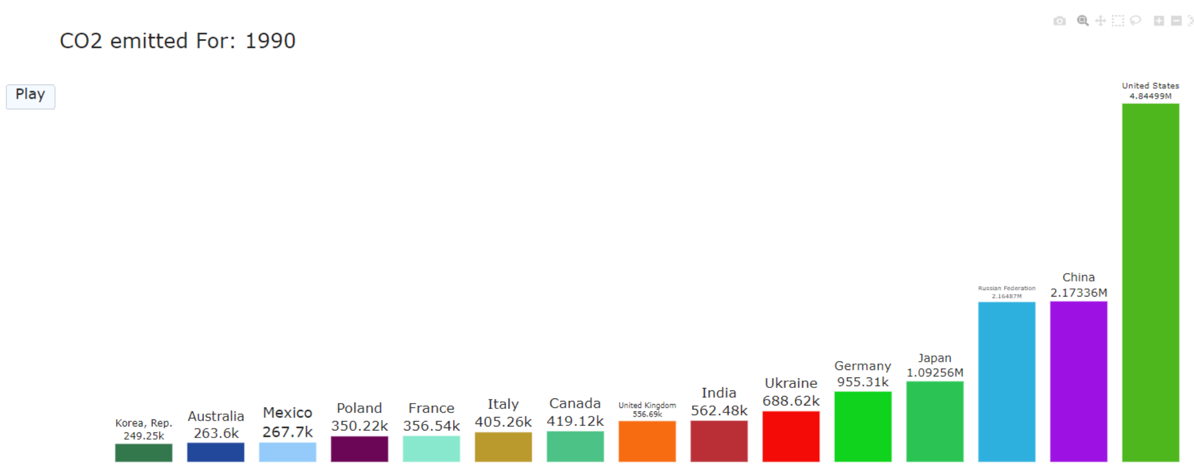
CO2 emitted



An animation is created with the behavior of emissions by country in the last 20 years, obtaining the following result.

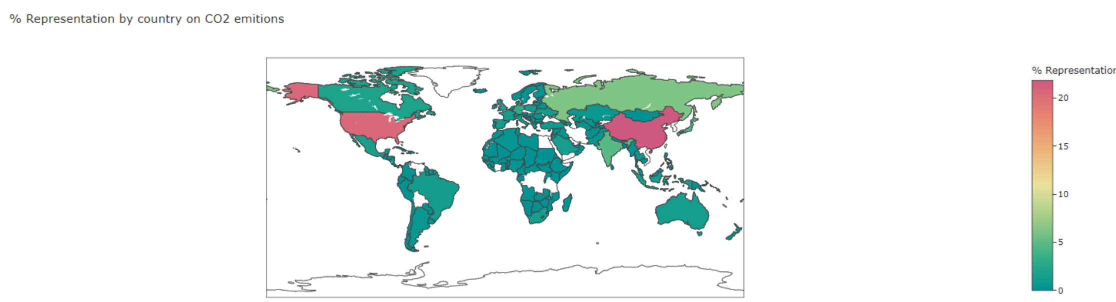
Available in: [Animation]

However, incompatibility was evidenced when deploying in dash, making it necessary to migrate the simulation in an environment compatible with the tool to be used.

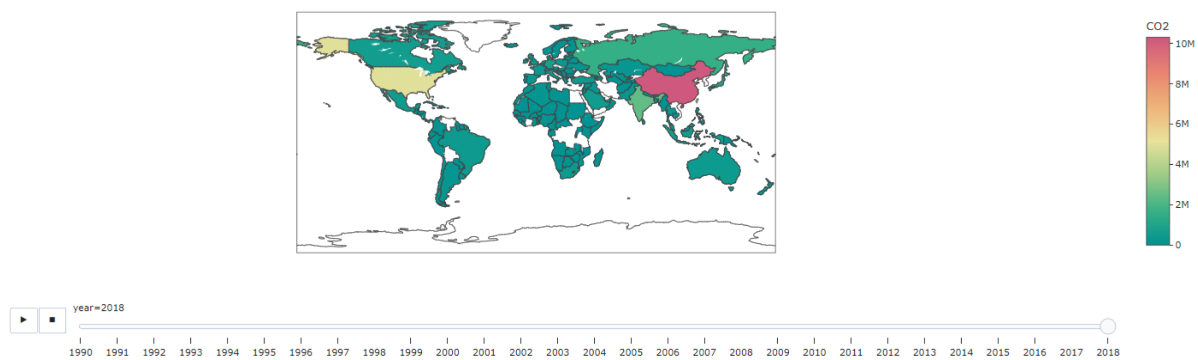


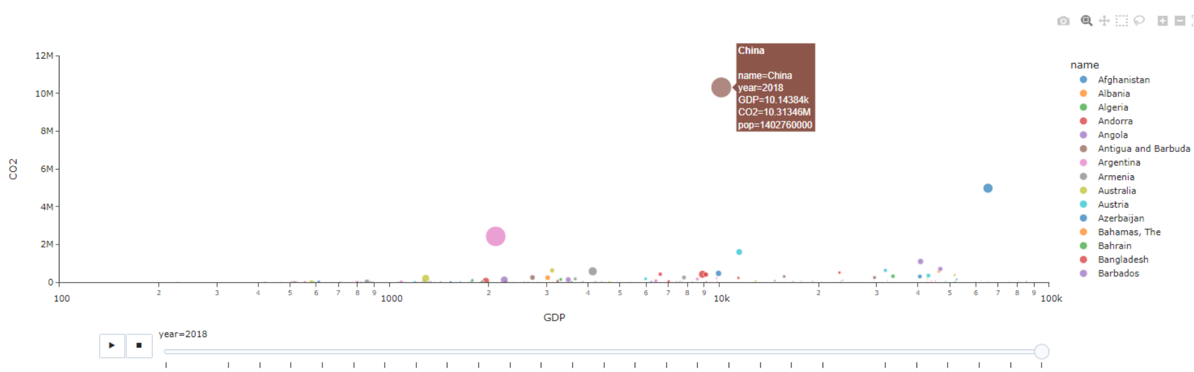
A variable is created to show the percentage of representation of emissions by country and is later displayed.

	index	name	CO2	% Representation	code
0	35	China	169414.16	21.843747	CHN
1	181	United States	158927.74	20.491660	USA
2	140	Russian Federation	48348.20	6.233870	RUS

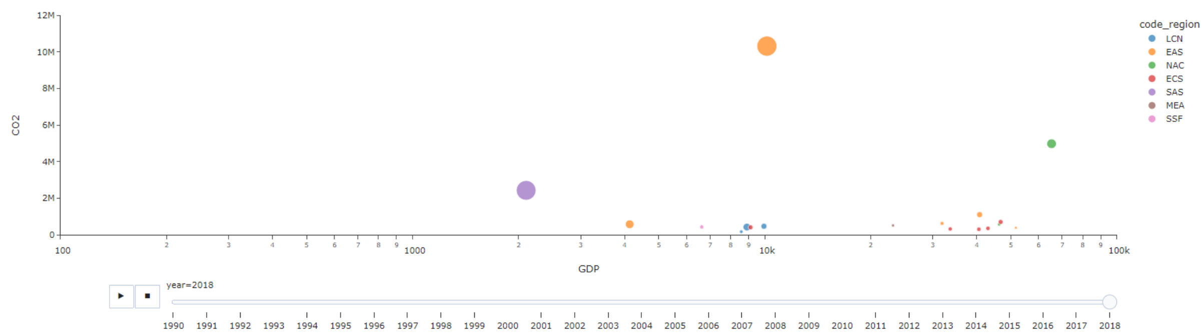


Animation with the behavior of emissions by country

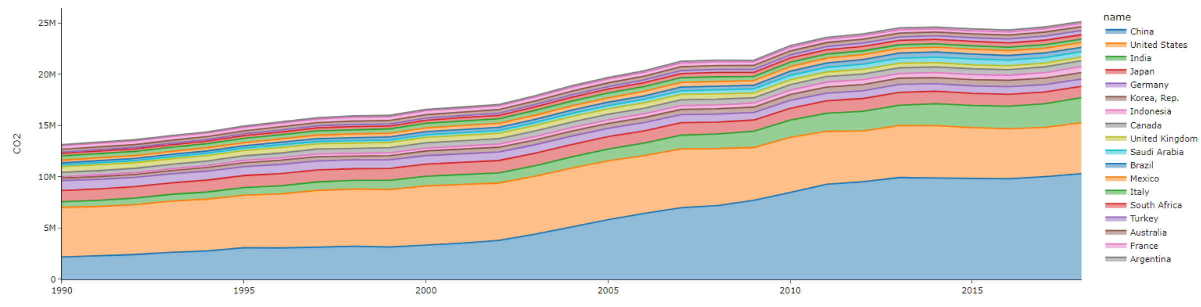




Animation with the behavior of emissions against the GDP (Gross Domestic Product) of the member countries of the G20:



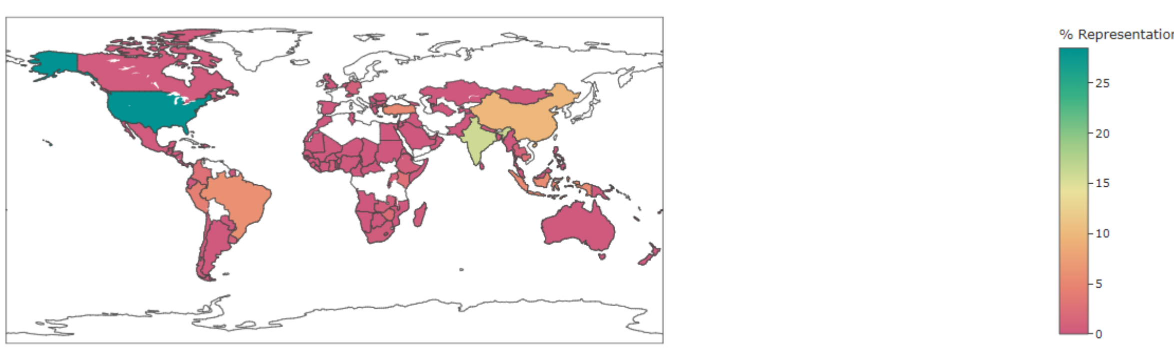
The behavior of this group of countries can be seen in the following graph of areas



Carbon Market

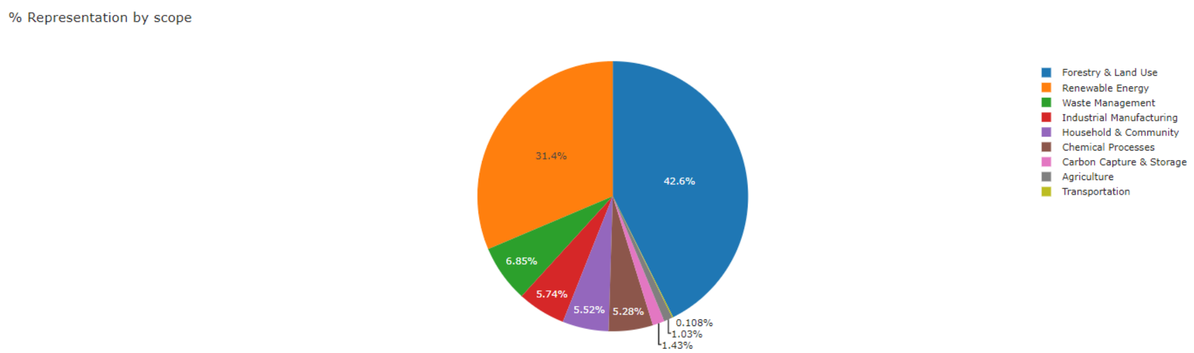
A variable is created to show the percentage of representation in the carbon markets by country and is subsequently displayed:

	country	total_credits	% Representation	code
114	United States	630127.144	28.489768	USA
46	India	351686.525	15.900708	IND
21	China	218245.441	9.867472	CHN
11	Brazil	133413.850	6.032004	BRA
47	Indonesia	118096.626	5.339471	IDN

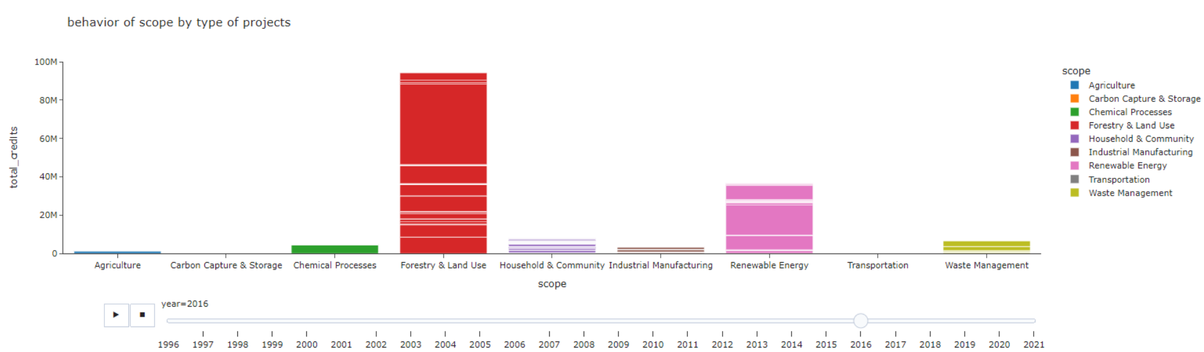


A variable is created to show the percentage of representation in the carbon markets by type of project and is subsequently displayed:

	scope	total_credits	% Representation
3	Forestry & Land Use	943214.998	42.645324
6	Renewable Energy	694399.487	31.395696
8	Waste Management	151563.844	6.852615
5	Industrial Manufacturing	126972.623	5.740779
4	Household & Community	122078.407	5.519498

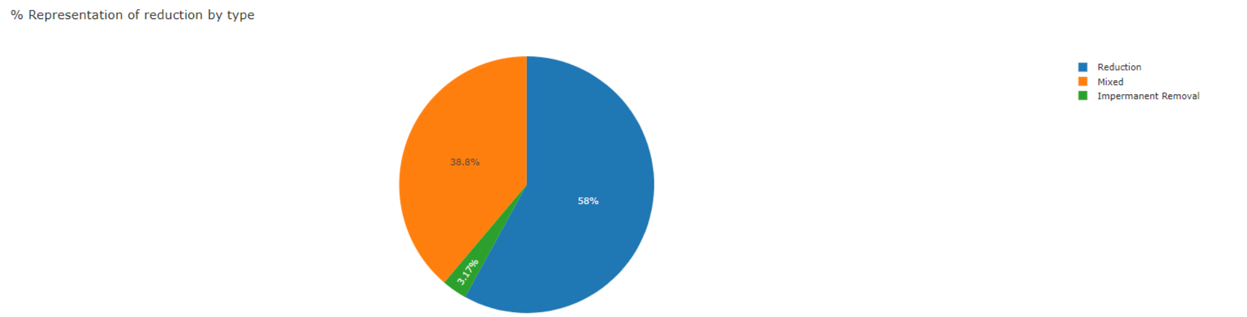


And a simulation of their behavior over time is created:

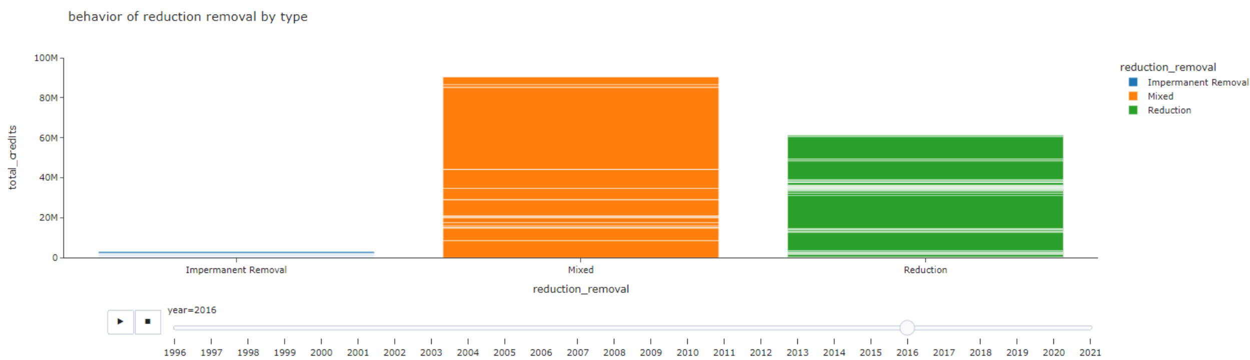


A variable is created to show the percentage of representation in the carbon markets by types of removal and is subsequently displayed:

	reduction_removal	total_credits	% Representation
0	Impermanent Removal	70105213	3.169648
1	Mixed	858194672	38.801323
2	Reduction	1283466631	58.029029



And a simulation of their behavior of reduction removal over time is created:



6. CONCLUSIONS

As a first approach to analysis, an artificial intelligence model based on the prediction of future time series was carried out. When performed in this way, the time series had different behaviors and did not yield a desirable value. For this reason, we decided to pass to the second stage of analysis. This second phase corresponds to the use of carbon credit data and CO2 emissions data, and by considering only these two variables, it is possible to predict that there is no improvement in the behavior of carbon emissions due to the issuance of carbon credits. We conclude that emissions are continuing growing although the credits issuance.

Our analyses show that even if carbon credits mitigate in a certain way the amount of CO2 emitted, this activity does not have a great impact on the improvement of the global GHG emissions trend.

Once it was discovered that the prediction showed a rising trend with no improvement, we proceeded with the third stage of analysis. It corresponds to reviewing the simulations and visualizations again but focusing our attention on the time series, this is another module that seeks to simulate future trends using the existing data of emissions observed (1992 - 2018). In this way, it was possible to understand why these trends could predict the increase of CO2 emissions. In this third stage of analysis, more data were used, including variables like GDP and the population of each country.

By 2001 the uncertainty behind the performance of carbon credits did not allow the more emitting countries to standardize the carbon markets as a regulated instrument to reduce GHG emissions. At that moment the United States was at the top of the list. Later, in 2005, one of the hottest years globally and when climate change began to be a concern on the governments' agenda, carbon credits gained relevance as an international standard. At the same time, China was already beginning its trends of growing economy (according to 2005 GDP) and China became the largest contributor of CO_2 emissions followed by the USA and India.

In addition, the general understanding of carbon credits assumes that their purpose is to remove or eliminate CO_2. Nevertheless in 2005 new GHG mitigation activities were created as a mixed category, including emissions reductions, removals and avoided emissions. This possibility of certifying avoided emissions as a consequence of the reduction of the deforestation rate creates doubts and concerns about the additionality and integrity of the credits resulting from these activities.

In addition to these concerns, the projects with the biggest mitigation potential since 2010 are implementing mitigation activities related to the avoidance of emissions as result of reforestation activities. One of the most complex situations is that these activities are not sufficiently monitored and normally are implemented in countries where technical and technological capacities to monitor ecosystems are very poor. Therefore, the performance, quality and standardization of these activities cannot be guaranteed.

From another point of view a positive trend could be identified in the reduction of GHG emissions of countries that started to implement mitigation projects in the non-conventional energies sector. For example, in the Berkeley database, the data for Ukraine reflects a behavior of quite high emissions but since 2018 (before the pandemic) this behavior begins to decrease. What has Ukraine done differently in this regard since 2018? Looking into the historical data of this country, it was possible to visualize that Ukraine reactivated the generation of energy through nuclear plants and left the energy sources with fossil fuels aside, managing to reduce its CO_2 emissions.

In this phase, what was carried out was an exploration of the countries that had outliers with a downward trend, evaluating their behavior and understanding the action they implemented to reduce emissions. If each country manages to find an outlier to reduce its net CO_2 emissions they could make decisions in line with the global commitments in climate change. Apparently, countries and even carbon credits projects are not focusing their attention in attacking key emissions sources.

7. FUTURE WORK

- The analyses and artificial intelligence models developed by ANALITICO2 could be detailed at the level of specific sectors and mitigation activities according to national circumstances. The consideration of economic variables could inform better climate policies and could provide decision-makers with a better understanding of how carbon markets could be considered as realistic solutions.
- New regulatory instruments can be put in place to incentivize the generation of carbon credits in relevant sectors that could transform GHG emissions trends.
- Voluntary carbon markets are an instrument to motivate the private sector to transform their value chains, nevertheless, they need to move faster to a better carbon intensity performance. The use of carbon credits from nature-based approaches, mainly avoiding emissions, are not offering enough evidence to consider them as the preferent option of compensation.
- Deforestation is a huge problem for countries like Colombia, not only at the climate level but also in biodiversity and food security. Avoiding emissions from projects and programmes trying to reduce deforestation need to prove additionality, performance and environmental integrity of their contribution. Data science instruments should be considered as a source of solutions to strength monitoring capacities in Colombia.

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