An Approach to Green Financial Credit Risks Modeling

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Abstract

This research is focused on developing the general strategy and systemic approach to credit risks evaluation, including green indicators in the scoring model. The mathematical problem statement of the task has been made. The main idea of our research was to find the scoring model which allows giving the credits to those companies which modify their business, production, and economic-based with the aim to decrease the pollution, gas emission, carbon oil, and other environmental influences on the world and climate change. It was shown that evaluation only the financial indicators was not such effective and precise as expected but adding the green indicators gave us a more precise and accurate model. Different machine learning methods were tested and the best scoring model which includes both financial and green indicators was built. The hypothesis of the importance and need of including green indicators in the model was approved and further developed.

Keywords

Green Indicators, Systemic approach, Scoring Models, Green Credits, Sustainable Development, Green Deal.

1. Introduction

Climate change has recently become a major issue for society. This is a global concern as it can be seen with the occurrence of the word “climate change” in Google books and requests. It became more than 8 times more relevant and cites nowadays in comparison to the period of 1985th. Climate change is a crucial challenge for society, even shown by the increase of policies and actions taken by governments nowadays. In particular, the Paris agreement [1] demonstrates the will of barely all countries of the world to take climate change as a serious issue and to find solutions in the near future. Whether it is the climate change itself or the fight against it, it has huge consequences on the companies’ social and environmental behavior as well as on the financial sphere. Green finance is indeed a major challenge today and businesses need to adapt their strategies to maintain growth. An essential tool for companies’ development is credit. So the task of implementing a green force for the companies who make production and business in each country is quite important. In the global mean the country should stimulate their business and citizens to decrease the number of policies each day. For this reason, it is proposed special types of green credits for businesses and individuals, where is evaluated how new projects and improvements or rebuilding of existing businesses will decrease the policies and negative environmental influence on green metrics. Special agencies are focused on approach development for the evaluation of this influence but there is no still proper approach to this.

2. Problem statement

The main idea of this article is to develop an approach for business credits, aimed to obtain more sustainable development indicators. It is focused on the companies’ credit risk and tries to establish a means to forecast the credit probability of companies default based on given financial, but also green indicators. Thus, the problem statement could be presented as follows: how to build a scoring model

XXI International Scientific and Practical Conference "Information Technologies and Security" (ITS-2021), December 9, 2021, Kyiv, Ukraine
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which gives the possibility to financial entities to assess a credit risk according to environmental measures?

Research work will be divided into two major parts. The first one supports and demonstrates the hypothesis that companies' green health has indeed a significant impact on the associated credit risk. For that, datasets containing average data about loans, environmental taxes, and greenhouse gas emissions of companies in the USA were used. The classifying model was created in order to determine credit risk categories. Thereafter, the second part aims to establish a reliable model to assess companies' credit ratings from the financial and environmental features of these companies.

3. Literature review

The risks related to climate change include transition risks (such as changing technology, business models, and consumer demands from the transition to a low-carbon economy), water-related risks (such as water pollution, water scarcity, and flooding), resource-related risks (including stranded assets and scarcity of certain minerals), and natural capital-related risks (such as ecosystem degradation, deforestation, air pollution, extreme weather events, and soil nutrient loss) [2]. The fundamental problem with assessing climate risk is trying to map the physical risks onto their fiscal and economic indicators. It is difficult to quantify physical risks: climate risk, in general, is not quantifiable at all. So agencies go through a process of trying to granulate those risks in a way that they can integrate them into the financial measures that they use. Here we must talk about the levels of physical risk and how they actually translate into financial and economic risks.

For example, HSBC published a report in 2018 that ranks 67 countries for their vulnerability to climate change [3]. It considers four pillars that are detailed in the figure below: physical impacts, transition risks, sensitivity to extreme events, and potential to respond to climate risks. This report aims to predict whether some countries will face important environmental risks. It shows the more vulnerable countries are India, Pakistan, and the Philippines. But it is also important for investors because it gives them new keys to understand the evolution of different countries.

To limit the environmental impacts, governments, and international organizations issue recommendations and take action. The main international goal is the Paris agreement [1], which was signed in 2015 by 195 delegations and aims to limit global warming to well below 2, preferably to 1.5 degrees Celsius in 2100, compared to pre-industrial levels. But this kind of policy also has consequences on companies' and investors' businesses.

In fact, the previous documentation gives information about climate change and risk-related from an environmental point of view. Yet, what is interesting for this research work is to understand how climate change shapes business trends, in particular for companies and the financial sphere. A report published in The Economist [4] makes the link between environmental change forecasts and their impact on finance. According to the report, the world's current stock of manageable assets is estimated to be US$143trn [4] and the resulting expected losses to these assets due to global warming are valued at US$4.2trn. This is the average expected loss, but the value-at-risk calculation includes a wide range of probabilities, and the tail risks are far more serious. Warming of 5°C in 2100 could result in US$7trn in losses – more than the total market capitalization of the London Stock Exchange - while 6°C of warming could lead to a present value loss of US$13.8trn of manageable financial assets, roughly 10% of the global total.

Several organizations have specialized in studying the impact of the green transition on financial risks. The PACTA tool (Paris Agreement Capital Transition Assessment) (2DII s.d.) [1], developed by 2° Investing Initiative (2DII) with backing from UN Principles for Responsible Investment, enables users to measure the alignment of financial portfolios with climate scenarios as well as to analyze specific companies. The independent financial think tank Carbon Tracker (Carbon-Tracker-Initiative s.d.) carries out an in-depth analysis on the impact of the energy transition on capital markets and the potential investment in high-cost, carbon-intensive fossil fuels. It issued reports giving advice about how to minimize the financial risk. In particular, the major oil companies should consider a 2°C scenario with big policies taken by the government in the 2020s. This is also what the big actors PRI (Principle of Responsible Investment), Vivid Economics, and ETA (Energy Transition Advisors) advocate. They created the Inevitable Policy Response (IPR) project which provides forecast policy scenarios about future environmental restrictions. As today's policies seem to fail international objectives, IPR expects that forceful policy will be taken around 2025 [5]. The later these policies are implemented, the more important and disruptive risks will be.

All the presented studies are based on scenarios. It is needed to forecast several scenarios regarding global temperatures, global carbon emissions, national and international policies, etc. Thus, the prediction model is able to assess the assets' value at risk. Several scenarios are given by climate institutions. What is important to assess the financial risk of a portfolio, is to assess the portfolio alignment with the possible scenarios of climate change, given by different institutions.

In addition to the models based on international possible scenarios, we can find articles assessing the consistency of economies with green measures. Article [6] described a method used to assess the development of green finance in China. On the contrary of assessing risk, it builds an index that measures the level of development of green finance and applies it to China. The assessment was based only on green credit because it represents 95% of green finance volume in China and because data were available. The obtained results are the index values each year from 2011 to 2019 for China. The paper also presents the means to forecast the index evolution in the next year thanks to the classical Gray model. Nevertheless, the article assesses only green credits but, even only in the financial sphere, there are other factors that affect green finance, such as green bonds, green funds, and green insurance, etc.

Authors of [7] offered a complete guide about scoring models and scorecards for the evaluation of the credits. The idea of a scorecard is to transform the probabilities of a client paying the loan (creditworthiness of an individual) into a number that could be easily interpreted, guiding business decisions. Although scorecards are not new, they changed a lot with the appearance of the new Big Data/AI scenario, especially after the 2008 Financial Crisis. The idea of scoring models and scoring cards was used in this research as a way to calculate the green indicators' influence on the credit return probability.

Whether for companies or individuals, financial institutions have always needed to know the reliability of borrowers before deciding to grant credit or not. The modern US history of consumer credit scoring began in 1956 when Fair, Isaac, and Company (known now as FICO) was created with the goal of developing a standardized and impartial credit scoring system [8]. Today, a vast majority of financial entities use the FICO score introduced in 1989. It is a number between 300 and 850 determined by the following factors (by descending level of importance) [9]: payment history, amounts owed, length of credit history, types of credit used, and recent credit inquiries. Such factors are registered by the "big three of credit bureaus": Experian, TransUnion, and Equifax [9].

Concerning business credit scoring, which is the topic of this research work, there is not many widely applied method as the FICO score. But lenders usually use data provided by private information brokers, the major one is The Dun & Bradstreet Corporation, which offers a wide range of products and services for risk and finance, operations and supply, and sales and marketing. It is indeed more efficient to share information between lender actors as shown [10] in cross-country macro-level tests which prove that information exchanges add value. Besides, an analysis based on the specific payment information contained in firm-level reports [11] concludes that exchange-generated information is valuable in assessing borrower quality. Moreover, private information exchanges are able to solve, at least to a considerable extent, the menu of problems that might otherwise devalue the information they collect, including credibility problems, data coverage problems, and data bias problems.

The specific case of micro-credit is also interesting in the business credit scoring field. In fact, small businesses is quite an important part of the economy, for example in the USA it represents half of all private sector employment and nonfarm gross domestic product (SBA s.d.). Small business credit scoring (SBCS) is a lending technology used by many financial institutions since the 1990s to evaluate applicants for credits under $250,000. It is mainly used to evaluate opaque small businesses by using hard information such as consumer data on the owner obtained from consumer credit bureaus, data on the business collected by the financial institution, and in some cases, information on the firm from commercial credit bureaus. This quite recent technology allowed the development of small business loans because the scoring extends to opaque and risky borrowers, low-income areas, and lending over greater distances; it also increases loan maturity [12].

Finally, another widely used way to establish creditworthiness is a credit rating. The credit rating represents analysis and evaluation by some well-known credit rating agencies of the qualitative and quantitative data for the prospective debtor. This data includes not only the information provided by the prospective debtor but also (what is more importantly) other non-public information obtained by the credit rating agency's analysts. Rating agencies provide opinions about the quality of bonds issued by corporations. The most used scale (in particular used by Standard & Poor's (S&P)) is formed with letter grades: AAA, AA, A, BBB, BB, etc., with pluses and minuses as well [13]. Credit agencies do not attach a hard number of default probabilities to each grade, yet some organizations led studies to link credit rating with a probability of default. For example, Moody’s Investor Services used data from 1970 to 2005 [14] to establish the average cumulative default rates per letter of rating agencies (Fig. 1).

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
Aaa	0.00	0.00	0.00	0.03	0.11	0.18	0.27	0.36	0.45	0.56	0.66	0.78	0.90	0.97	1.04	1.12	1.22	1.25	1.25	1.25
Aa	0.01	0.02	0.05	0.12	0.19	0.29	0.38	0.46	0.51	0.58	0.65	0.76	0.92	1.06	1.16	1.29	1.44	1.58	1.74	1.91
A	0.02	0.10	0.24	0.37	0.51	0.67	0.83	1.01	1.22	1.42	1.63	1.82	2.02	2.21	2.49	2.81	3.17	3.53	3.88	4.20
Baa	0.18	0.53	0.98	1.52	2.06	2.60	3.13	3.65	4.23	4.89	5.50	6.17	6.85	7.56	8.24	8.84	9.41	9.97	10.44	10.91
Ba	1.23	3.31	5.75	8.26	10.57	12.65	14.48	16.28	18.05	19.86	21.62	23.41	25.15	26.82	28.29	29.78	31.14	32.17	33.15	33.97
B	5.65	12.35	18.65	24.09	29.06	33.50	37.47	40.71	43.59	46.12	47.56	48.77	49.65	50.51	51.26	51.77	51.96	52.12	52.12	52.12
Caa-C	21.12	33.53	43.47	51.01	56.52	61.05	64.58	68.50	71.98	74.72	75.16	75.16	75.16	75.16	75.16	75.16	75.16	75.16	75.16	75.16

Sample Period: 1970-2005, monthly cohort spacing

Figure 1: Average Cumulative Default Rates by Whole Letter Rating, Withdrawal-Adjusted [14]

All these ways to assess business credit scoring consider only companies’ financial indexes. Yet, very recent studies are beginning to raise the question of whether environmental and more generally ESG companies’ behaviors have to be considered to improve credit risk scoring.

4. Green finance modelling and forecasting

4.1. Searching for the link between enterprise credit risks and environmental behavior of the company

It should be emphasized again that based on the literature review that companies’ environmental behavior has a real impact on the probability of default of the same companies’ credit. Yet, each article provides its conclusion based on a particular database, so it is essential to check whether there is indeed a link between credit risk and environmental behavior with the data available here. That is why in this part we will use datasets showing average data with an environmental and financial indicator in order to determine companies’ credit risk category.

4.2. Development of an approach for green credit loan returns evaluation

As there is no appropriate approach, allowing us to implement and include green factors in parallel with financial factors, we need to propose a special system approach and define the main stages and models, which are required to make it possible. This approach could be modified in the future and incorporate new information, metrics, and mechanisms given from the future developed metrics and mechanisms from the international credit rating companies and governmental tasks. For now, we see such main steps which should be done in this approach:

Step 1. To define the main enterprise’s risks categories and to calculate for each category the probability of the risk. In this step, it is also reasonable to define the limits for acceptable risk.

Step 2. To develop different risk categories classification models based only on the financial indicators for the different companies. To find the best scoring model for forecasting the probability of default for each category.

Step 3. To evaluate the most relevant green indicators and their importance to the projects for a different types of industries. To set up their measures and limits for each sector based on the indicators given by the international ranking agencies and standards.

Step 4. To evaluate green indicators for each company and project and put them in the dataset.

Step 5. To build and find the best forecasting models for the enterprise credit defaults based on their sustainable behavior and available GHG indicators.

Finally, the mathematical problem statement of our task could be made as follows: to find such function f that:

$$
\begin{array}{llll}
f: & F_n & \rightarrow & \{Minimal, Low, Moderate\} \\
 & (f_1,...,f_n) & \mapsto & f(f_1,...f_n)
\end{array},
$$

where F_n is the set where the n features $(f_1,...f_n)$, financial and environmental indicators take their appropriate values.

4.3. Modeling of the financial and green indicators by different machine learning methods

The conducted and presented here research consists of machine-learning methods, so the work is always supported by databases. In this first part, three datasets are used: the first one is issued from the FRED (Federal Reserve Bank of Saint Louis) and is about the average loan value for all non-financial companies taking credit from a commercial bank in the US and their classification into 3 default risk categories: minimal, low, and average (FRED 2021). Data are available quarterly for 20 years (from 1997 to 2017) for each category so there are 243 observations is presented in Figure 2.

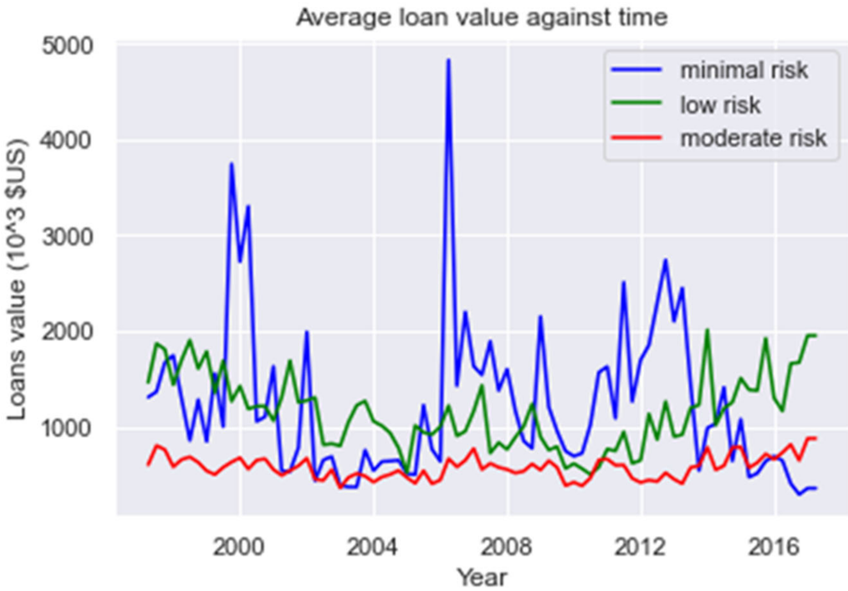

Figure 2: Visualization of the average loan value dataset

The two following datasets give average data about greenhouse gas (GHG) emissions and environmental taxes related to non-financial companies in the USA. Both datasets are sorted by business sectors and come from Organization for economic cooperation and development (OECD 2021). The GHG emissions are calculated in tons of CO2 equivalent and the taxes are evaluated in US Dollars. We take here only data from 1997 to 2017 to be consistent with the financial dataset but we have a division into different sectors and units so there are 3921 observations for the GHG emissions and 1479 for environmental taxes.

The following figure 3 sums up what kind of data we have inside the two datasets.

For the GHG dataset as well as environmental tax one, the values presented are the average of the total value for all non-financial companies in the USA, scaled down the individual company level. We can see on each picture the available data divided also by business sector. For the next stages, it would be useful to monitor and score companies due to their business sector also and for each sector to develop the main indicators and measures for them to evaluate their sustainable development before giving them credits for improving their business.

Concerning the financial dataset, the credit risk is classified into three categories by the FRED by comparison with the credit rating letters usually given by credit agencies (like S&P) as minimal (A- or more), low (BBB+ to B-) or moderate risk (CCC or less).

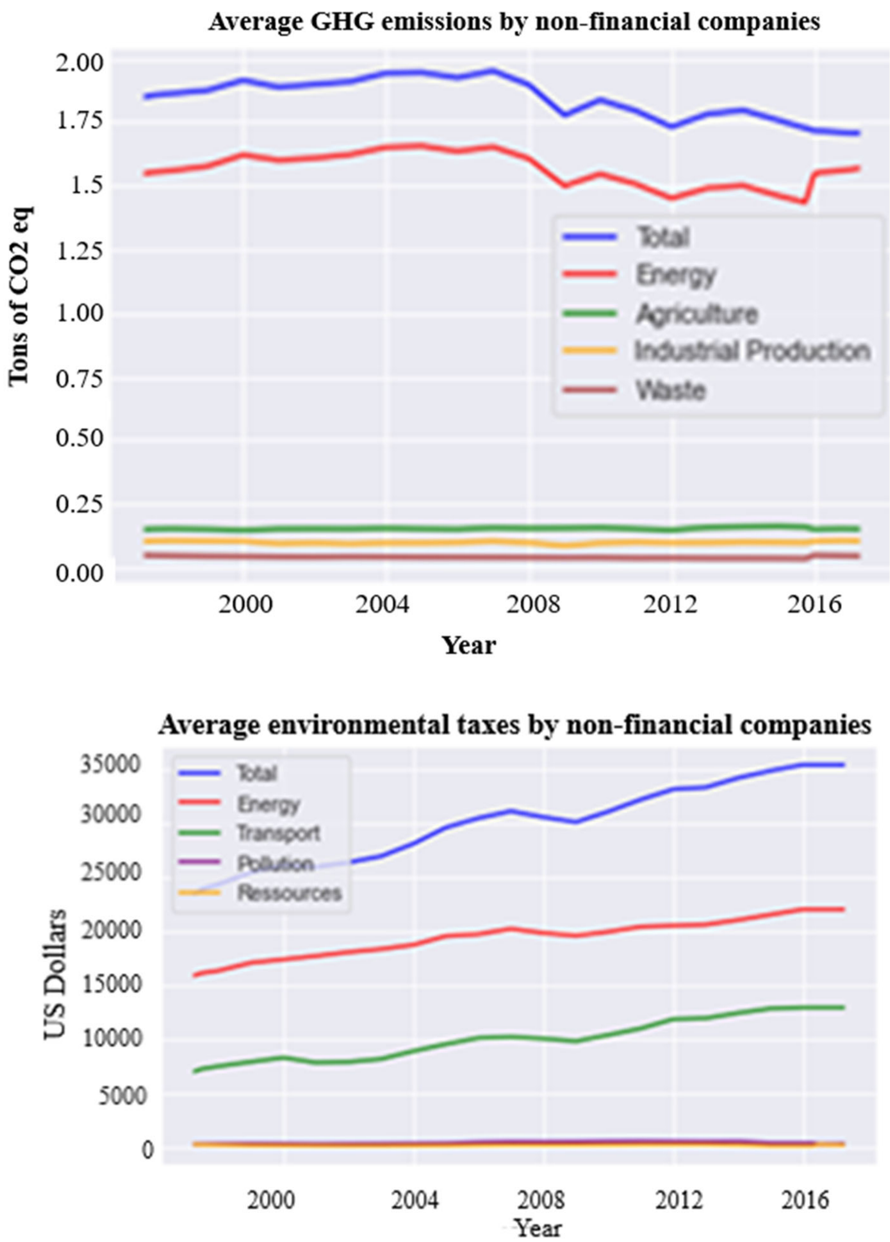

Figure 3: Visualization of the environmental datasets (GHG and taxes)

The next step was to assess ranges for the probability of default of each risk category:

$$P = \begin{cases} \text{Minimal:} & 0 \le P < 0.014 \\ \text{Low:} & 0.014 \le P < 0.232 \\ \text{Moderate:} & 0.232 \le P \le 0.569 \end{cases}.$$

Here we need to admit that the highest range for the moderate risk is less than 1 because in this case, it means that it represented the companies' behavior of each category due to existed dataset. It means the quantity or partition of the defaulted company in each category.

The main idea of credit scoring for companies is to find or build an appropriate classification model which can forecast future defaults based on some financial and credit indicators and variables. While we postulated that we focus on green credits it also means that we also need to evaluate the perspective, modernization, and business part of green measures also. So the objective is to create classifying forecasting models with financial data and environmental data (GHG and taxes) also. Then based on both models we can decide if it is reasonable to add green indicators and if these features are useful to predict the credit risk category.

Now that the credit risks associated with the FRED dataset are well defined, we can work through the three datasets in order to find whether there is an actual link between the companies' environmental behavior and the probability of default of their credits.

In total, we received 29 features that can be used to forecast the credit risk category. After the financial one which is the loan value, there are 12 features that can be used about GHG emissions and 16 about environmental taxes.

We used different classical classifiers implemented on the scikit-learn python library: gradient boosting, random forest, k-nearest neighbors, logistic regression, neural network. Nevertheless, even with the method GridsearchCV that enables the tune of the model's parameters and to check the results with cross-validation, the accuracies of the classification were not good. Taking all the 29 features made the models more complex. Table 1 is the sum-up of the four best models trained on a training set of 200 observations and tested on a testing set of 43 observations. The last column contains the confusion matrix, where each row of the matrix represents the instances in an actual class (low, minimal, and moderate credit risk) while each column represents the instances in a predicted class.

Table 1
Sum up of the best classifying models with 29 features

Model	Best parameters	Score	Confusion matrix
K-nn	K=13	58%	$\begin{bmatrix} 7 & 6 & 2 \\ 2 & 7 & 3 \\ 1 & 4 & 11 \end{bmatrix}$
SVM	Kernel='rbf' C=1000 Gamma=1e-07	52%	$\begin{bmatrix} 4 & 1 & 1 \\ 8 & 7 & 2 \\ 4 & 4 & 12 \end{bmatrix}$
Random Forest	N_estimators=100 class_weight: {Minimal:4, Low:3, Moderate:2}	56%	$\begin{bmatrix} 7 & 3 & 5 \\ 4 & 10 & 2 \\ 1 & 0 & 11 \end{bmatrix}$
Gradient Boosting	Learning rate=0.1 N_estimators=100 Max_depth=5	61%	$\begin{bmatrix} 6 & 5 & 0 \\ 2 & 10 & 1 \\ 6 & 2 & 11 \end{bmatrix}$

Received results cannot approve our idea of the necessity to use the green indicators it just approved that the quality of the credit models is not really high. So these perspective methods are not really useful for the limited datasets. But these methods (for example, gradient boosting) can help us to determine the most important features and variables from all available green and environmental indicators and what GHG factors should be monitored. Thus we decided the method developed especially for the situation of limitation data.

The Group Method of Data Handling (GMDH) is a method invented by Ukrainian scientist Prof. O.G. Ivakhnenko in 1968 which aims at solving of the classical AI problems - identification, short-term and long-term forecasting of random processes, and pattern recognition in complex systems [17]. Within the GMDH, the "Pointing Finger" clustering algorithm can be implemented for classification and works very good with small datasets in theory.

Firstly we tried the GMDH classifier with only financial features as input, the results of accuracy are presented in Table 2 and the ROC curve is shown in Figure 4. At the next stage, we implemented this algorithm and fit it on the dataset with all 29 features.

Table 2
Performances of GMDH for the dataset with only financial features

		Training sample		
Risk level	Precision	Recall	F1-score	Support
Low	0.46	0.57	0.51	54
Minimal	0.49	0.51	0.50	65
Moderate	0.95	0.77	0.85	81
accuracy		0.63		200
Confusion matrix		$\begin{bmatrix} 31 & 22 & 1 \\ 30 & 33 & 2 \\ 6 & 13 & 62 \end{bmatrix}$		
		Test sample		
Risk level	Precision	Recall	F1-score	Support
Low	0.67	0.67	0.67	15
Minimal	0.46	0.67	0.55	9
Moderate	0.93	0.74	0.82	19
accuracy		0.70		43
Confusion matrix		$\begin{bmatrix} 10 & 4 & 1 \\ 3 & 6 & 0 \\ 2 & 3 & 14 \end{bmatrix}$		

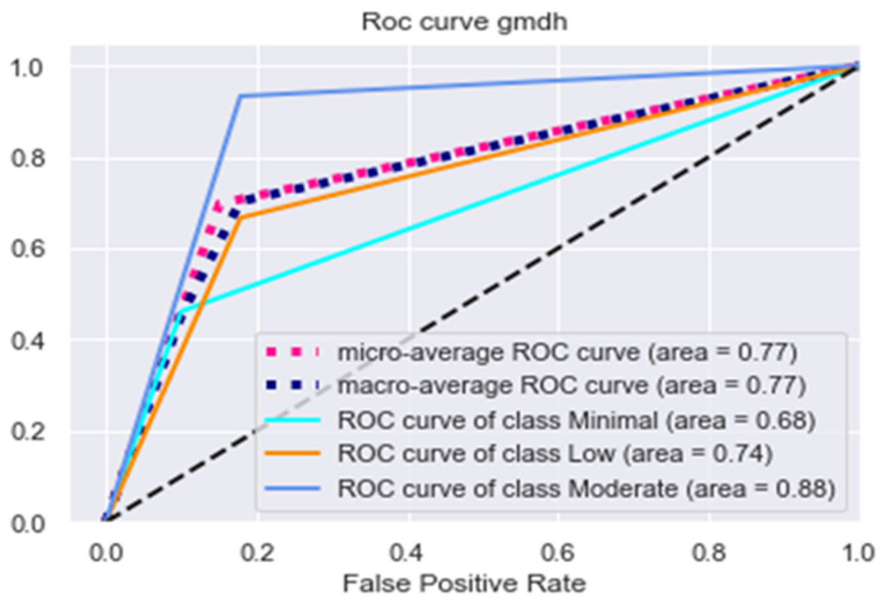

Figure 4: ROC-curve for GMDH for the dataset with only financial features

Obtained results are shown for both training and test datasets in Table 3 and the accuracy ROC-metric is shown in Figure 5. As we can see from earlier results the choice of the GMDH algorithm was really correct and as was expected it works better than other methods because of its idea and development features, especially to a really small dataset.

Table 3
Performances of GMDH for the dataset with all financial and green features

Training sample				
Risk level	Precision	Recall	F1-score	Support
Low	0.96	0.91	0.93	70
Minimal	0.82	0.91	0.86	58
Moderate	0.94	0.89	0.91	72
accuracy		0.91		200
Confusion matrix		$\begin{bmatrix} 64 & 5 & 1 \\ 2 & 53 & 3 \\ 1 & 7 & 64 \end{bmatrix}$		
Test sample				
Risk level	Precision	Recall	F1-score	Support
Low	0.85	0.92	0.88	12
Minimal	0.83	1.00	0.91	15
Moderate	1.00	0.75	0.86	16
accuracy		0.88		43
Confusion matrix		$\begin{bmatrix} 11 & 1 & 0 \\ 0 & 15 & 0 \\ 2 & 2 & 12 \end{bmatrix}$		

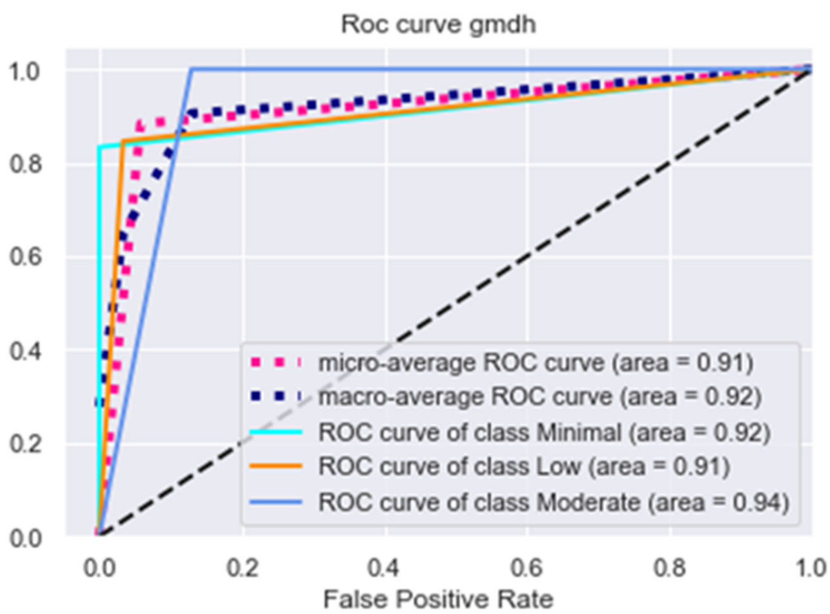

Figure 5: ROC-curve for GMDH for the whole dataset with all financial features and green indicators

Thanks to this clustering method, it is possible to classify all loans into one of the three risk categories, given the environmental data about taxes and greenhouse gas emissions and the loan value, with 88% accuracy. Furthermore, the second implementation of the algorithm shows worse results when only financial features, that is to say, the loan value, are given as input. So this preliminary modeling approved our hypothesis that the green indicators are important and should be also monitored and included in the scoring model [18, 19].

Eventually, usage of financial and environmental features to classify credit risk category allow us to obtain a better-determined function than usage of financial features only. Thus, there is an effective link between green aspects and credit risks for companies; it is essential to consider environmental aspects when dealing with the credit probability of default. Nevertheless, this conclusion is drawn only from average data and not real companies. In fact, the figures appearing in these datasets are taken from total data from the USA and leveled to a company scale. We need more accurate information to support the statement proven here and to give a real credit scoring model, applicable for the different types and sector companies.

Furthermore, we chose another 3 datasets which had already needed indicators: financial data, environmental behavior, and credit rating. The first two datasets were from the Carbon Disclosure Project. The first dataset contained six financial indicators as revenue. Cost of revenue, operating income, operating expenses, depreciation and amortization, EBIDTA on 368 US and Canadian companies for the years 2018, 2019, and 2020. The second dataset was made based on the green indicators: greenhouse gas emissions and water security for the same companies in the previous dataset. The third dataset was made based on the Standard & Poor's forecast of credit ratings for 592 big US firms.

On the new dataset the task was divided into three sub-stages: establishing a predicting model with only green features, then only financial and finally with both of them using different machine learning methods. The logistic regression was the most accurate model received on each step.

Table 4

Comparison of models accuracy depending on the indicators and variables

Indicators used for the classification model	Accuracy
Green indicators only	35%
Financial indicators only	88%
All features	93%

The results support the statement proven in the first stage: using environmental features allows to predict more accurately (93% against 88%) the companies' credit rating. It also shows that financial indicators are crucial because using only green indicators gives a classifier worse than randomization. Moreover, when all features are used to predict credit rating, we notice that they are all approximately equally important.

5. Conclusions

The research presents an important step in the forecasting of companies' credit risk related to environmental and financial aspects. In conducted research, we can make sum up here that indeed it is a link between a company's credit risk and ratings and its green and environmental-oriented behavior. In the first stage, working on average data of all non-financial US companies allowed to prove the statement. Nevertheless, on the failed attempts to build a proper dataset on own hands, it is clear that in the future banks should gather all needed information from the companies before evaluating their credit scores. Moreover, new interests and efforts of all international projects are focused on Green Deal so the importance of evaluating these factors for the companies is already fixed. Probably, based on these indicators, new world credit risks rating agencies with their own ratings and metrics could be made (such as INCRA).

To conclude, the environmental behavior of companies impacts the probability of their credit defaults, and we provided here a model which assesses this probability, given environmental and financial information about the companies. Moreover, a mathematical classifying model was created in order to classify any company of which the features needed are available by credit rating. In the future, we will work on the improvement of the accuracy and precision of the best classification models based on the new requirements and indicators. In this research, it was proposed a global model and a new approach but in our next research, we will focus on developing different scoring models for different business sectors or company sizes and individual green credit needs.

Here the general systematic approach with main stages for evaluating the sustainable development of the projects and companies before receiving them green credits was proposed. Now the whole world is waiting for JP Morgan, Fitch, and other international companies to offer reasonable metrics and explain how to evaluate them. We also understand that it would primarily depend on the general situation and formal world-level documents, but at the next stage it would be the challenge for each country to develop an approach for stimulating companies to decrease their pollution and emissions based on pollution limits, defined by international agencies, and country-specific penalties for not complying with the appropriate standards.

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