JOURNAL OF CULTURAL ANALYSIS AND SOCIAL CHANGE

Journal of Cultural Analysis and Social Change,
2026, 11(1), 3036-3046
ISSN: 2589-1316

Does Sustainability Awareness Influence Cryptocurrency Preferences? A Study on the Relationship Between Sustainable Development Goals and the Demand for Green vs. Traditional Cryptocurrencies

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Citation: Juan, A. P. D., Melero, I. M., Gómez-Martínez, R. and Medrano-García, M. L. (2026). Does Sustainability Awareness Influence Cryptocurrency Preferences? A Study on the Relationship Between Sustainable Development Goals and the Demand for Green vs. Traditional Cryptocurrencies, *Journal of Cultural Analysis and Social Change*, 11(1), 3036-3046. https://doi.org/10.64753/jcasc.v11i1.4629

Published: March 04, 2026

ABSTRACT

This study investigates the relationship between public attention to the Sustainable Development Goals (SDGs) and cryptocurrency demand, specifically for Bitcoin (BTC) and Cardano (ADA). Given the environmental concerns associated with Proof-of-Work (PoW) and the sustainability benefits of Proof-of-Stake (PoS), we hypothesize that increased SDG attention leads to higher demand for green cryptocurrencies like Cardano and lower demand for non-green cryptocurrencies like Bitcoin. Using Ordinary Least Squares (OLS) regression and supervised machine learning algorithms, we analyze weekly cryptocurrency returns and Google Trends data from 2020 to 2025. The findings suggest that SDG attention has a statistically significant but weak negative impact on Bitcoin returns, while no significant effect is observed for Cardano. Machine learning models fail to predict cryptocurrency demand effectively. These results indicate that sustainability awareness alone is not a primary driver of cryptocurrency investment behavior.

Keywords: Sustainable Development Goals, Cryptocurrencies, Bitcoin, Cardano, Machine Learning.

INTRODUCTION

The Sustainable Development Goals (SDGs) set forth by the United Nations in 2015 have become a crucial aspect of global discussions on sustainability. As investors and businesses increasingly consider environmental, social, and governance (ESG) factors, understanding their impact on financial markets is essential. Cryptocurrencies, as a relatively new asset class, have sparked debates regarding their sustainability, particularly due to differences in energy consumption between Proof-of-Work (PoW) and Proof-of-Stake (PoS) protocols.

Bitcoin (BTC), which relies on PoW, has been criticized for its high energy consumption, while Cardano (ADA), which uses PoS, is often seen as a greener alternative. This study explores the relationship between SDG attention and the demand for these cryptocurrencies by analyzing how public interest in sustainability—measured through Google Trends data—affects their market performance.

By employing Ordinary Least Squares (OLS) regression models and supervised machine learning algorithms, this research seeks to determine whether heightened attention to SDGs influences cryptocurrency demand. The findings contribute to the ongoing discourse on sustainability and investment behavior in digital assets, offering insights into the role of public awareness in shaping financial markets.

THEORETICAL FRAMEWORK

Sustainable Development Goals (SDGs) have gained increasing global attention as policymakers, businesses, and investors seek to align economic activities with sustainability objectives (UN, 2015). The impact of SDG awareness on financial markets, particularly in the context of cryptocurrencies, is an emerging area of research. This study investigates whether public interest in SDGs influences the demand for green and non-green cryptocurrencies, specifically Cardano (ADA) and Bitcoin (BTC).

Cryptocurrencies operate under different consensus mechanisms, which determine their environmental impact. Bitcoin, the most prominent cryptocurrency, relies on the Proof-of-Work (PoW) protocol, which requires significant computational power and energy consumption (Narayanan et al., 2016). Recent studies indicate that the Bitcoin network's annual electricity consumption is comparable to that of entire countries; for example, it is estimated that in 2024 Bitcoin used around 146,82 TWh and will emit 74.39 MTCO2, figures comparable to the energy consumption and emissions of countries such as Pakistan and Kenya. (Ruiz et al, 2024), carrying a substantial carbon footprint comparable as Denmark carbon Footpring (Aguilar et al, 2019).

In contrast, Cardano uses the Proof-of-Stake (PoS) protocol, which significantly reduces energy consumption and is considered more environmentally friendly (Kiayias et al., 2017). Given these differences, it is hypothesized that increased attention to SDGs may lead to a preference for green cryptocurrencies over non-green ones.

The relationship between cryptocurrencies and sustainability encompasses both challenges and opportunities. Current evidence indicates that environmental concerns represent one of the biggest challenges to the long-term legitimacy of cryptocurrencies (Mora, 2021)

However, there is also an evolution within the crypto ecosystem to address these issues: from fundamental technological changes (such as PoS adoption) to greater transparency and voluntary self-regulation (e.g., "Crypto Climate Accord" type initiatives). Academically, this topic is gaining traction, with research exploring whether public sustainable awareness influences demand for different cryptoassets. For example, initial studies have tested whether interest in the SDGs translates into preference for green cryptocurrencies (such as Cardano) over traditional ones (Bitcoin), although findings so far suggest that sustainability alone is not yet a primary driver of cryptocurrency investment behavior

As global climate awareness and ESG regulations increase, sustainability can be expected to move from a theoretical debate to a tangible factor in cryptocurrency valuation and adoption.(Aroa, 2025)

Investor sentiment and market behavior have been widely studied in financial literature, particularly regarding how public attention influences asset prices. The efficient market hypothesis (Fama, 1970) suggests that asset prices fully reflect available information, while behavioral finance theories argue that investor sentiment and public attention can create price inefficiencies (Shiller, 2003). Prior studies have shown that Google Trends data can serve as a proxy for investor interest and public sentiment towards financial assets (Preis et al., 2013).

The use of Google Trends data as an indicator of SDG attention follows previous research demonstrating its effectiveness in capturing shifts in public interest and investor behavior (Vlastakis & Markellos, 2012). Additionally, the integration of machine learning approaches provides a more nuanced understanding of potential nonlinear relationships and predictive patterns within financial markets (Bianchi et al., 2022).

By combining these methodologies, this study contributes to the growing body of literature exploring the intersection of sustainability awareness and financial markets, particularly in the cryptocurrency sector. The findings will provide insights into whether sustainability considerations influence investment decisions in the digital asset space.

METHODOLOGY AND DATA

To test the hypotheses, we employed two complementary analytical approaches: Ordinary Least Squares (OLS) regression and supervised machine learning classification algorithms.

Methodology

The Hypotheses of This study are:

- **H1**: Greater attention to the SDGs leads to increased demand for green cryptocurrencies (Cardano).
- **H2**: Greater attention to the SDGs leads to decreased demand for non-green cryptocurrencies (Bitcoin).

For both hypotheses, we validate **H0** (the null hypothesis) if:

1. The **beta coefficient** in the OLS model is statistically significant and aligns with the hypothesized direction.

2. The machine learning models demonstrate predictive capability, as measured by **ROC AUC** and **PRC AUC** scores greater than **0.6**.

We constructed two OLS models to examine the relationship between SDG attention and cryptocurrency returns:

1. **Model 1**: SDG attention as the independent variable and **Cardano (ADA)** returns as the dependent variable.

   $R\_ADA_t = a + b\ V\_SDG_t + u_t$

   Where:
   - R_ADA_t: Is the weekly return of ADA Cardano quotation
   - R_SDG_t: Is the variation of the attention of ODS goals measured as Google Trends searches

2. **Model 2**: SDG attention as the independent variable and **Bitcoin (BTC)** returns as the dependent variable.

   $R\_BTC_t = a + b\ V\_SDG_t + u_t$

   Where:
   - R_BTC_t: Is the weekly return of Bitcoin quotation
   - R_SDG_t: Is the variation of the attention of ODS goals measured as Google Trends searches

The beta coefficients from these models were used to assess the strength and direction of the relationship.

On the other hand, we employed supervised machine learning algorithms to predict cryptocurrency demand trends based on SDG attention. The steps included:

1. Google Trends data for the five SDG-related terms were used as input features.
2. Binary classification targets were created based on whether weekly returns for ADA or BTC were above or below their respective median values.
3. We tested using the following classification algorithms: Random Forest, Decision Trees and Bayes Network.
4. Model performance was assessed using **ROC AUC** (Receiver Operating Characteristic Area Under Curve) and **PRC AUC** (Precision-Recall Curve Area Under Curve). A score above **0,6** was considered indicative of predictive capability.

The use of 10-fold cross-validation ensures that the evaluation of machine learning models is robust and generalizable.

Data Collection

The study relies on two primary datasets:

1. **Cryptocurrency Returns**: Weekly returns of **Cardano (ADA)** as a representative of green cryptocurrencies that uses POS protocol, and **Bitcoin (BTC)** as a representative of traditional, non-green cryptocurrencies, based on POW protocol. The data spans fro**m January 19, 2020, to January 19, 2025** (T = 262 weeks) and was sourced from Investing.com.
2. **Google Trends Data**: Weekly search interest data from **Google Trends** for the same period, capturing global attention toward the theme **Sustainable Development Goals (SDGs)**.

The following search terms were used:

- "Sustainable Development Goals"
- "2030 Agenda"
- "Quality Education"
- "Gender Equality"
- "Climate Change"

These terms were selected to proxy public interest in the SDGs, as they represent key themes within the 2030 Agenda.

RESULTS

Although the full output of the regressions and models trained are collected in the annex, the main results to highlight from the regressions and estimated models are:

1. Ordinary Least Squares (OLS) Regression Results

Model 1: Bitcoin (BTC) Returns (Figure 1)

- **Dependent Variable**: Weekly returns of Bitcoin (R_BTC).
- **Independent Variable**: Attention to SDGs (V_ODS).
- **Key Findings**:
    - The coefficient for **V_ODS** is **-0.00172716** and is statistically significant at the **1% level** (p-value = 0.0075). This indicates that increased attention to SDGs is associated with a slight decrease in Bitcoin returns.
    - The model has a low **R-squared value of 0.027**, suggesting that SDG attention explains only a small portion of the variance in Bitcoin returns.
    - The **F-statistic** is significant (p-value = 0.007486), indicating that the model is statistically valid.

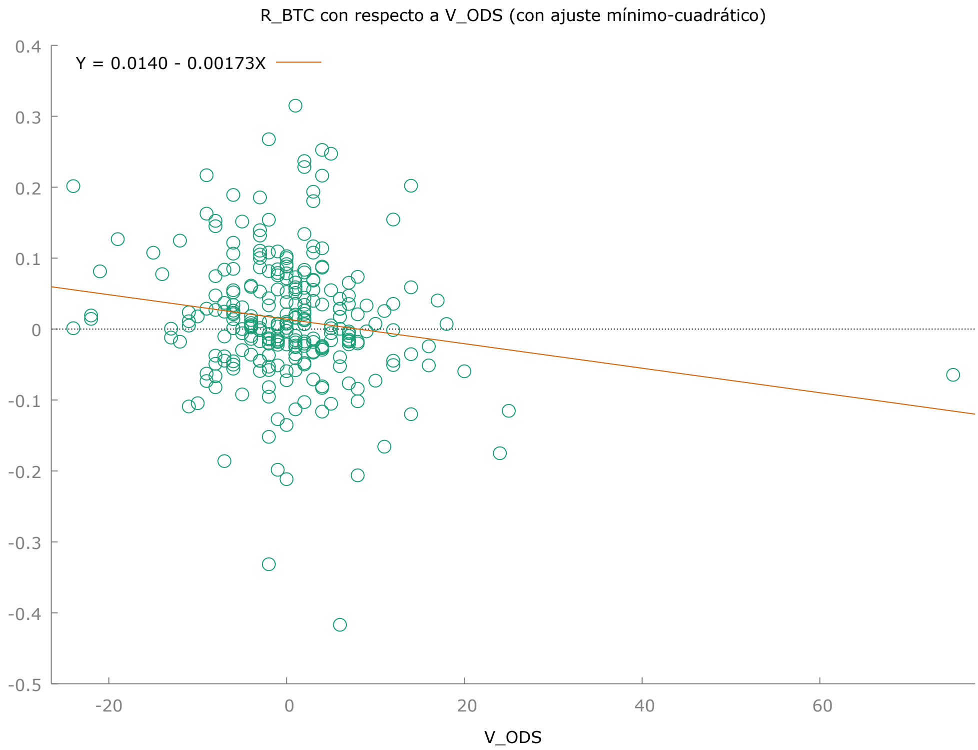

FIGURE 1. Model 1 regression
Source: Authors' own research

Model 2: Cardano (ADA) Returns (Figure 2)

- **Dependent Variable**: Weekly returns of Cardano (R_ADA).
- **Independent Variable**: Attention to SDGs (V_ODS).
- **Key Findings**:
    - The coefficient for **V_ODS** is **-0.00170779**, but it is **not statistically significant** (p-value = 0.1133). This suggests that attention to SDGs does not significantly influence Cardano returns.
    - The model has an even lower **R-squared value of 0.0096**, indicating that SDG attention explains very little of the variance in Cardano returns.
    - The **F-statistic** is not significant (p-value = 0.113271), suggesting that the model lacks explanatory power.

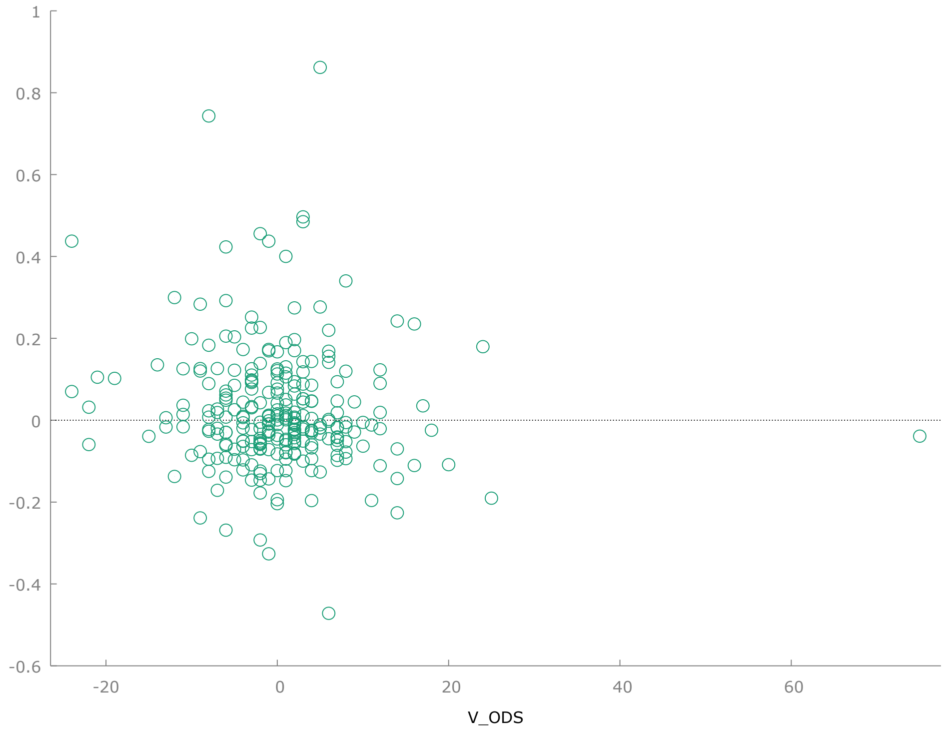

FIGURE 2. Model 2 regression
Source: Authors' own research

2. Machine Learning Classification Results

Random Forest Models

- **Bitcoin (BTC) Classification**:
  - **Correctly Classified Instances**: **25.95%**.
  - **ROC Area**: **0.498** (close to random chance).
  - **PRC Area**: **0.269**.
  - The model performs poorly, with no predictive capability for Bitcoin demand based on SDG attention.
- **Cardano (ADA) Classification**:
  - **Correctly Classified Instances**: **27.86%**.
  - **ROC Area**: **0.520** (slightly better than random chance).
  - **PRC Area**: **0.310**.
  - The model also performs poorly, with no meaningful predictive capability for Cardano demand based on SDG attention.

J48 Decision Tree Models

- **Bitcoin (BTC) Classification**:
  - **Correctly Classified Instances**: **26.72%**.
  - **ROC Area**: **0.495**.
  - **PRC Area**: **0.262**.
  - The model fails to predict Bitcoin demand effectively.
- **Cardano (ADA) Classification**:
  - **Correctly Classified Instances**: **27.10%**.
  - **ROC Area**: **0.501**.
  - **PRC Area**: **0.270**.
  - The model also fails to predict Cardano demand effectively.

Bayesian Network Models

- **Bitcoin (BTC) Classification**:
  - **Correctly Classified Instances**: **29.01%**.
  - **ROC Area**: **0.479**.

  - **PRC Area**: **0.248**.
  - The model performs no better than random chance.
- **Cardano (ADA) Classification**:
  - **Correctly Classified Instances**: **31.30%**.
  - **ROC Area**: **0.480**.
  - **PRC Area**: **0.256**.
  - The model also performs no better than random chance.

Hypothesis Validation

Based on these results, the study hypotheses must be validated in the following way:

H1: Greater attention to SDGs leads to increased demand for green cryptocurrencies (Cardano): **Not supported**.

Neither the OLS model nor the machine learning models show a significant relationship between SDG attention and Cardano demand. The **beta coefficient** in the OLS model is not significant, and the machine learning models lack predictive capability (ROC and PRC areas ≤ 0.6).

H2: Greater attention to SDGs leads to decreased demand for non-green cryptocurrencies (Bitcoin). **Partially supported**.

The OLS model for Bitcoin shows a statistically significant negative relationship between SDG attention and Bitcoin returns. However, the machine learning models fail to predict Bitcoin demand effectively, suggesting that SDG attention alone is not a strong predictor.

DISCUSSION, CONCLUSION, AND IMPLICATIONS

The results indicate that attention to SDGs, as measured by Google Trends, does not significantly influence the demand for green cryptocurrencies like Cardano. This contradicts the initial hypothesis that increased sustainability awareness would drive demand for environmentally friendly cryptocurrencies. For Bitcoin, the OLS model suggests a slight negative relationship between SDG attention and returns, but this finding is not robustly supported by the machine learning models. Nevertheless, the poor performance of the machine learning models (ROC and PRC areas close to 0.5) indicates that SDG attention is not a reliable predictor of cryptocurrency demand, whether for green or non-green cryptocurrencies.

There are some limitations that we should highlight:

- The study relies on **Google Trends data** as a proxy for SDG attention, which may not fully capture public interest or investor behavior.
- Cryptocurrency returns are influenced by numerous factors beyond SDG attention, such as market trends, regulatory changes, and macroeconomic conditions, which were not controlled for in this analysis.
- The temporal scope of five years may not be sufficient to capture long-term trends in sustainability awareness and cryptocurrency demand.

The results of this study have several important implications for different actors in the crypto and financial ecosystem:

For regulators: The lack of a strong impact of sustainability on cryptocurrency demand suggests that if governments and regulatory bodies seek to promote greener crypto assets, they will need to implement concrete policies, such as incentives for adopting proof-of-stake networks or taxes on proof-of-work mining. Examples include the proposed DAME tax in the U.S. and the MiCA regulation in the EU, which aims to increase transparency regarding the environmental impact of crypto assets.

For institutional investors: As major financial institutions are increasingly subject to ESG standards, their role could be crucial in the transition toward more sustainable cryptocurrencies. Investment funds and asset managers that integrate environmental criteria into their portfolios can drive the adoption of energy-efficient blockchain networks.

For cryptocurrency projects: Developers of new blockchains can leverage these findings to focus their strategies on sustainability—not only from a technical perspective (such as adopting proof-of-stake) but also in terms of communication and transparency to attract both retail and institutional investors.

For the general public and retail investors: Financial education on the relationship between cryptocurrencies and sustainability is essential. Although sustainability is not currently a key factor in investment decisions, the increasing scrutiny of cryptocurrencies from an environmental standpoint could change this situation in the future. As global conclusion the findings suggest that investors in the cryptocurrency market do not significantly factor in sustainability concerns, as reflected by SDG attention, when making investment decisions. This implies that other factors, such as profitability, volatility, and technological advancements, may play a more critical role in driving cryptocurrency demand. Further research is needed to explore additional variables and refine the models to better understand the relationship between sustainability awareness and cryptocurrency markets.

Conflicts of Interest: The authors declare that they have no known competing financial or non-financial interests that could have appeared to influence the work reported in this paper.

Funding: No funding was received for this work.

REFERENCES

Bianchi, D., Büchner, M., & Tamoni, A. (2022). Bond risk premia with machine learning. Review of Financial Studies, 35(3), 1220-1255.

Ruiz, A. M., & Choperena, (2024) O. E. F. Impacto Ambiental y Soluciones Sostenibles en la Minería de Bitcoin: Un Análisis Dialéctico.

Aguilar, R., & Jiménez, E. (2019). Vulnerabilidades del Bitcoin

Mora, H., Morales-Morales, M. R., Pujol-López, F. A., & Mollá-Sirvent, R. (2021). Social cryptocurrencies as model for enhancing sustainable development. Kybernetes, 50(10), 2883-2916.

Arora, R., Kapoor, M., Singh, N., & Yaqub, M. Z. (2025). Green cryptocurrency and business strategies: Framework and insights from a stewardship literature review. Business Strategy and the Environment.

Fama, E. F. (1970). Efficient capital markets: A review of theory and empirical work. Journal of Finance, 25(2), 383-417.

Kiayias, A., Russell, A., David, B., & Oliynykov, R. (2017). Ouroboros: A provably secure proof-of-stake blockchain protocol. Annual International Cryptology Conference, 357-388.

Narayanan, A., Bonneau, J., Felten, E., Miller, A., & Goldfeder, S. (2016). Bitcoin and cryptocurrency technologies: A comprehensive introduction. Princeton University Press.

Preis, T., Moat, H. S., & Stanley, H. E. (2013). Quantifying trading behavior in financial markets using Google Trends. Scientific Reports, 3, 1684.

Shiller, R. J. (2003). From efficient markets theory to behavioral finance. Journal of Economic Perspectives, 17(1), 83-104.

United Nations (UN). (2015). Transforming our world: The 2030 agenda for sustainable development. Retrieved from https://sdgs.un.org/publications/transforming-our-world-2030-agenda-sustainable-development

Vlastakis, N., & Markellos, R. N. (2012). Information demand and stock market volatility. Journal of Banking & Finance, 36(6), 1808-1821.

ANNEX

```
Modelo 1: MCO  usando las observaciones 2020-01-19:2025-01-19 (T = 262)
Variable dependiente: R_BTC

             coeficiente   Desv. típica   Estadístico t   valor p
  ---------------------------------------------------------------
  const        0.0139595    0.00551465        2.531       0.0120  **
  V_ODS      −0.00172716   0.000640751       −2.696       0.0075  ***

Media de la vble. dep.  0.013623   D.T. de la vble. dep.   0.090304
Suma de cuad. residuos  2.070561   D.T. de la regresión    0.089240
R-cuadrado              0.027186   R-cuadrado corregido    0.023444
F(1  260)               7.265872   Valor p (de F)          0.007486
Log-verosimilitud       262.3469   Criterio de Akaike     −520.6938
Criterio de Schwarz    −513.5571   Crit. de Hannan-Quinn  −517.8254
rho                     0.042062   Durbin-Watson           1.914599
```

```
Modelo 2: MCO, usando las observaciones 2020-01-19:2025-01-19 (T = 262)
Variable dependiente: R_ADA
```



```
            coeficiente   Desv. típica   Estadístico t   valor p
  --------------------------------------------------------------
  const       0.0223832    0.00924985        2.420       0.0162  **
  V_ODS      −0.00170779   0.00107475       −1.589       0.1133

Media de la vble. dep.  0.022051   D.T. de la vble. dep.   0.150120
Suma de cuad. residuos  5.825348   D.T. de la regresión    0.149684
R-cuadrado              0.009618   R-cuadrado corregido    0.005809
F(1, 260)               2.524981   Valor p (de F)          0.113271
Log-verosimilitud       126.8406   Criterio de Akaike     −249.6811
Criterio de Schwarz    −242.5444   Crit. de Hannan-Quinn  −246.8127
rho                     0.190646   Durbin-Watson           1.616778
```

```
=== Run information ===

Scheme:       weka.classifiers.trees.RandomForest -P 100 -I 100 -num-slots 1 -K 0 -M 1.0 -V 0.001 -S 1

Relation:                GreenCripto_1-weka.filters.unsupervised.attribute.Remove-R1-weka.filters.unsupervised.attribute.Remove-R1-2-
weka.filters.unsupervised.attribute.Remove-R3-10-weka.filters.unsupervised.attribute.Remove-R2

Instances:    262
Attributes:   7
              R_BTC_D
              V_SDG_Tema
              V_SDG
              V_A2030
              V_QA_Ed
              V_Gender_Eq
              V_Climate_Ch
Test mode:    10-fold cross-validation

=== Stratified cross-validation ===
=== Summary ===

Correctly Classified Instances          68               25.9542 %

Incorrectly Classified Instances       194               74.0458 %

Kappa statistic                         -0.0058
Mean absolute error                      0.3708
Root mean squared error                  0.4534
Relative absolute error                 99.8164 %
Root relative squared error            105.1984 %
Total Number of Instances              262

=== Detailed Accuracy By Class ===

                 TP Rate  FP Rate  Precision  Recall   F-Measure  MCC      ROC Area  PRC Area  Class

0         128    0  130    0  176      0          128    0  148      -0         003   0   587     0 225     BAJA+
0         276    0  387    0  226      0          276    0  249      -0         105   0   396     0 261     SUBE+
0         347    0  289    0  313      0          347    0  329      0          056    0  569     0 309     BAJA
0         239    0  200    0  291      0          239    0  262      0          042    0  477     0 268     SUBE
Weighted Avg.    0  260    0  266    0  257      0          260    0  256      -0          005   0   498     0 269

=== Confusion Matrix ===

  a  b  c  d   <-- classified as
  6 25 10  6 |  a = BAJA+
 11 21 25 19 |  b = SUBE+
  8 25 25 14 |  c = BAJA
  9 22 20 16 |  d = SUBE
```

```
=== Run information ===

Scheme:       weka.classifiers.trees.J48 -C 0.25 -M 2

Relation:                GreenCripto_1-weka.filters.unsupervised.attribute.Remove-R1-weka.filters.unsupervised.attribute.Remove-R1-2-
weka.filters.unsupervised.attribute.Remove-R3-10-weka.filters.unsupervised.attribute.Remove-R2

Instances:    262
Attributes:   7
              R_BTC_D
              V_SDG_Tema
              V_SDG
              V_A2030
              V_QA_Ed
              V_Gender_Eq
              V_Climate_Ch
Test mode:    10-fold cross-validation

=== Stratified cross-validation ===
=== Summary ===

Correctly Classified Instances          70               26.7176 %
Incorrectly Classified Instances       192               73.2824 %
Kappa statistic                          0.01
Mean absolute error                      0.37
Root mean squared error                  0.5428
Relative absolute error                 99.6032 %
Root relative squared error            125.9446 %
Total Number of Instances              262

=== Detailed Accuracy By Class ===

                 TP Rate  FP Rate  Precision  Recall   F-Measure  MCC      ROC Area  PRC Area  Class
```

```
0         128    0  172    0  140      0          128    0  133      -0         046   0   475      0 171     BAJA+
0         276    0  328    0  256      0          276    0  266      -0         051   0   431      0 262     SUBE+
0         375    0  279    0  338      0          375    0  355      0          093    0  566      0 314     BAJA
0         239    0  210    0  281      0          239    0  258      0          030    0  505      0 272     SUBE
Weighted Avg.    0  267    0  256    0  264      0          267    0  265      0          010    0  495      0 262

=== Confusion Matrix ===

  a  b  c  d   <-- classified as
  6 19 14  8 |  a = BAJA+
 17 21 22 16 |  b = SUBE+
  9 19 27 17 |  c = BAJA
 11 23 17 16 |  d = SUBE
```

```
=== Run information ===

Scheme:              weka.classifiers.bayes.BayesNet  -D  -Q  weka.classifiers.bayes.net.search.local.K2  --  -P  1  -S  BAYES  -E
weka.classifiers.bayes.net.estimate.SimpleEstimator -- -A 0.5

Relation:               GreenCripto_1-weka.filters.unsupervised.attribute.Remove-R1-weka.filters.unsupervised.attribute.Remove-R1-2-
weka.filters.unsupervised.attribute.Remove-R3-10-weka.filters.unsupervised.attribute.Remove-R2

Instances:    262
Attributes:   7
              R_BTC_D
              V_SDG_Tema
              V_SDG
              V_A2030
              V_QA_Ed
              V_Gender_Eq
              V_Climate_Ch
Test mode:    10-fold cross-validation

=== Stratified cross-validation ===
=== Summary ===

Correctly Classified Instances          76               29.0076 %
Incorrectly Classified Instances       186               70.9924 %
Kappa statistic                          0
Mean absolute error                      0.3715
Root mean squared error                  0.431
Relative absolute error                 99.9921 %
Root relative squared error            100.0001 %
Total Number of Instances              262

=== Detailed Accuracy By Class ===

                 TP Rate  FP Rate  Precision  Recall   F-Measure  MCC      ROC Area  PRC Area  Class

0         000    0  000    ?          0 000    ?          ?        0  472     0 169     BAJA+
1         000    1  000    0  290      1          000    0  450      ?         0 474     0 277     SUBE+
0         000    0  000    ?          0 000    ?          ?        0  489     0 270     BAJA
0         000    0  000    ?          0 000    ?          ?        0  478     0 246     SUBE
Weighted Avg.    0  290    0  290    ?          0 290    ?          ?        0  479     0 248

=== Confusion Matrix ===

  a  b  c  d   <-- classified as
  0 47  0  0 |  a = BAJA+
  0 76  0  0 |  b = SUBE+
  0 72  0  0 |  c = BAJA
  0 67  0  0 |  d = SUBE
```

```
=== Run information ===

Scheme:       weka.classifiers.trees.RandomForest -P 100 -I 100 -num-slots 1 -K 0 -M 1.0 -V 0.001 -S 1

Relation:               GreenCripto_1-weka.filters.unsupervised.attribute.Remove-R1-weka.filters.unsupervised.attribute.Remove-R1-2-
weka.filters.unsupervised.attribute.Remove-R3-10-weka.filters.unsupervised.attribute.Remove-R1

Instances:    262
Attributes:   7
              R_ADA_D
              V_SDG_Tema
              V_SDG
              V_A2030
              V_QA_Ed
              V_Gender_Eq
              V_Climate_Ch
Test mode:    10-fold cross-validation

=== Detailed Accuracy By Class ===

                 TP Rate  FP Rate  Precision  Recall   F-Measure  MCC      ROC Area  PRC Area  Class

0         241    0  221    0  237      0          241    0  239      0          021    0  518      0 269     BAJA
0         366    0  383    0  303      0          366    0  331      -0         017   0   503      0 350     SUBE+
0         321    0  283    0  325      0          321    0  323      0          038    0  521      0 352     BAJA+
0         091    0  106    0  148      0          091    0  113      -0         018   0   552      0 217     SUBE
Weighted Avg.    0  279    0  271    0  269      0          279    0  272      0          008    0  520      0 310

=== Confusion Matrix ===

  a  b  c  d   <-- classified as
 14 20 15  9 |  a = BAJA
 18 30 26  8 |  b = SUBE+
 16 31 25  6 |  c = BAJA+
 11 18 11  4 |  d = SUBE
```



```
=== Run information ===

Scheme:       weka.classifiers.trees.J48 -C 0.25 -M 2
Relation:                GreenCripto_1-weka.filters.unsupervised.attribute.Remove-R1-weka.filters.unsupervised.attribute.Remove-R1-2-
weka.filters.unsupervised.attribute.Remove-R3-10-weka.filters.unsupervised.attribute.Remove-R1

Instances:    262
Attributes:   7
              R_ADA_D
              V_SDG_Tema
              V_SDG
              V_A2030
              V_QA_Ed
              V_Gender_Eq
              V_Climate_Ch
Test mode:    10-fold cross-validation

=== Stratified cross-validation ===
=== Summary ===

Correctly Classified Instances          71               27.0992 %

Incorrectly Classified Instances       191               72.9008 %

Kappa statistic                          0.0039
Mean absolute error                      0.3667
Root mean squared error                  0.541
Relative absolute error                 99.5738 %
Root relative squared error            126.0753 %
Total Number of Instances              262

=== Detailed Accuracy By Class ===

                 TP Rate  FP Rate  Precision  Recall   F-Measure  MCC      ROC Area  PRC Area  Class

0         207    0  230    0  203      0          207    0  205      -0         023    0   479     0 212     BAJA
0         354    0  356    0  312      0          354    0  331      -0         002    0   507     0 318     SUBE+
0         308    0  272    0  324      0          308    0  316      0          037     0  516     0 324     BAJA+
0         136    0  138    0  167      0          136    0  150      -0         001    0   495     0 163     SUBE
Weighted Avg.    0  271    0  266    0  267      0          271    0  268      0          005     0  501     0 270

=== Confusion Matrix ===

  a  b  c  d   <-- classified as
 12 22 20  4 |  a = BAJA
 18 29 19 16 |  b = SUBE+
 20 24 24 10 |  c = BAJA+
  9 18 11  6 |  d = SUBE
```

```
=== Run information ===

Scheme:              weka.classifiers.bayes.BayesNet  -D  -Q  weka.classifiers.bayes.net.search.local.K2  --  -P  1  -S  BAYES  -E
weka.classifiers.bayes.net.estimate.SimpleEstimator -- -A 0.5

Relation:                GreenCripto_1-weka.filters.unsupervised.attribute.Remove-R1-weka.filters.unsupervised.attribute.Remove-R1-2-
weka.filters.unsupervised.attribute.Remove-R3-10-weka.filters.unsupervised.attribute.Remove-R1

Instances:    262
Attributes:   7
              R_ADA_D
              V_SDG_Tema
              V_SDG
              V_A2030
              V_QA_Ed
              V_Gender_Eq
              V_Climate_Ch
Test mode:    10-fold cross-validation

=== Stratified cross-validation ===
=== Summary ===

Correctly Classified Instances          82               31.2977 %

Incorrectly Classified Instances       180               68.7023 %

Kappa statistic                          0
Mean absolute error                      0.3682
Root mean squared error                  0.4291
Relative absolute error                 99.9846 %
Root relative squared error            100      %
Total Number of Instances              262

=== Detailed Accuracy By Class ===

                 TP Rate  FP Rate  Precision  Recall   F-Measure  MCC      ROC Area  PRC Area  Class

0         000    0  000    ?          0 000    ?          ?        0  480     0 214     BAJA
1         000    1  000    0  313      1          000    0  477      ?        0 481     0 305     SUBE+
0         000    0  000    ?          0 000    ?          ?        0  483     0 290     BAJA+
0         000    0  000    ?          0 000    ?          ?        0  469     0 159     SUBE
Weighted Avg.    0  313    0  313    ?          0 313    ?          ?        0  480     0 256

=== Confusion Matrix ===

  a  b  c  d   <-- classified as
  0 58  0  0 |  a = BAJA
  0 82  0  0 |  b = SUBE+
  0 78  0  0 |  c = BAJA+
  0 44  0  0 |  d = SUBE
```