Computational Learning Framework for Carbon Emissions Predictions Incorporating a RReliefF Driven Features Selection and an Iterative Neural Network Architecture Improvement

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ABSTRACT

Computational Learning Framework for Carbon Emissions Predictions Incorporating a RReliefF Driven Features Selection and an Iterative Neural Network Architecture Improvement

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Concordia University, 2020

Environmental protection is being progressively considered as paramount condition for the planet's continued habitability. After the Kyoto Protocol signature in 1997, governments, industry stakeholders and academia began to work on the development of effective and efficient environmentally driven policies and economic mechanisms, and the proper design of such parameters is critically dependent on carbon emissions projections. In such scenario, inaccurate carbon emissions predictions may be one of the root factors leading to the overall ineffectiveness of the European Union environmental regulatory framework.

Therefore, the present thesis introduces a novel computational learning framework for carbon emissions prediction incorporating a RReliefF driven features selection and an iterative neural network architecture improvement. Our learning framework algorithmic architecture iteratively chains the features selection process and the backpropagation artificial neural network (NN/BP) architecture design based on the data assessment accomplished by the RReliefF algorithm. Thus a better features set - NN/BP architecture combination is obtained for each specific prediction target.

The implemented framework was trained and validated with real world data obtained from the European Union (Eurostats), the International Energy Agency, the Organization for Economic Co-operation and Development, and the World Bank. The validation dataset comprised 26 potential predictors covering the period 1990 - 2014. Additionally, a case study was conducted with a new dataset comprising data obtained from the World Resources Institute's Climate Data Explorer (CAIT), and the World Bank database. The case study dataset comprises 24 potential predictors covering the period 1970 - 2014.

The learning framework also features an Explainable Artificial Intelligence (XAI) module that provides explanations of the predictions in terms of global features impact and local features weights. The global model explanations are computed by means of partial dependence functions,

while local model explanations are computed by means of the interpretable model-agnostic explanations (LIME) algorithm.

The framework evaluation against current mainstream machine learning models, and its benchmarking comparing to recent published researches on carbon emissions prediction indicates that our research contribution is relevant and capable of supporting the improvement of environmental policies. The learning framework outcomes are also expected to provide some ground for future researches targeting carbon emissions causality analysis, as well as potential improvements on both ANNs and XAI techniques.

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I dedicate this academic journey to my family; to my brothers for the constant motivation and support, to my wife and sons for the continued care, understanding and support; and to mom and dad, wherever you are, for watching over me, always, no matter what...Love you all!

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1 INTRODUCTION

Environmental protection is being progressively considered as paramount condition for the planet's continued habitability. In the 21st century reality, development and sustainability can no longer be treated independently, and all environment protection initiatives shall be supported. The United Nations (UN) Conference on Environment and Development Rio Eco92 - Earth Summit, held by Rio de Janeiro in 1992, can be considered the first global attempt towards a blueprint for sustainable development. Since then, a series of important events fostered the progressive construction of an effective climate change avoidance regulatory framework.

After the Kyoto Protocol signature in 1997, governments, industry stakeholders and academia began to work on the development of effective and efficient environmentally driven policies and economic mechanisms. In such context, the European Union (EU) current efforts in support to sustainable development and climate change avoidance comprises three main challenges, i.e. GHG emissions reduction, consistent increment on energy production from renewables (Renewable Energy Directive - RED), and increase in energy efficiency (Energy Efficiency Directive - EED).

Within the EU environment protection framework, the European Union Emissions Trading System (EU-ETS) was launched in 2005, and it currently covers approximately 45% of EU28 (EU27) polluting emissions. The EU-ETS implementation observed a staggered approach, and 2020 is the last year of the third phase, as presented below.

- EU-ETS phase 1 (2005-2007) - the absence of reliable data on actual emissions and consequent wrong estimations led to allowances surplus:
  - Allocated allowances: 6370 MtCO2-eq;
  - CO2 emissions: 6215 MtCO2.
- EU-ETS phase 2 (2008-2012):
  - Allocated allowances: 11373 MtCO2-eq;
  - Carbon emissions: 9613 MtCO2.
- EU-ETS phase 3 (2013-2020):
  - Allowances surplus in 2017: 1.6 billion.

The observed evolution of the EU trading system indicates it sustained and substantial structural supply-demand imbalance that kept distorting the market and compromising the scheme effectiveness as an emissions reduction driver (Crespo and Wang, 2020).

Moreover, notwithstanding the systematic and continued EU28 efforts and policies addressing the reduction of carbon emissions, the EU member States' projections converge to an EU-wide total GHG emissions reduction of at most 32%, which falls short of the 40% target for 2030. EU-ETS specific projections indicate that the stationary installations could reach a 10% reduction on emissions between 2020-2030, which is insufficient for the accomplishment of the 2030 reduction target of 43% compared to 2005 levels (International Energy Agency, 2020).

Thus, inaccurate carbon emissions predictions may be one of the root factors leading to the overall ineffectiveness of the EU28 (EU27) environmental regulatory framework. Therefore the achievement of the European Union ambitious targets will require additional policies resulting from new holistic and creative approaches targeting carbon emissions predictions.

In such scenario, and considering the findings related to the EU-ETS experience, our contribution explored the following research opportunities: a) market based climate change avoidance policies efficiency could be relevantly improved by a better accuracy on carbon emissions trends prediction; b) there is a crucial need for more accurate carbon emissions predictions better supporting each climate change avoidance initiative (i.e. EU-ETS, EED, RED) by considering the particularities of industry / economy sectors under their coverage; and c) machine Learning methods and techniques have the potential capacity to grasp such particularities from economic and energy consumption indicators, what might lead to more realistic carbon emissions forecasts.

1.1 Research Objectives

The present document records the research leading to the development of the Computational Learning Framework for Carbon Emissions Predictions Incorporating a RReliefF Driven Features Selection and an Iterative Neural Network Architecture Improvement. The design of such iterative learning framework fulfills the following research objectives: a) improve overall carbon emissions forecast accuracy by the ad hoc definition of the predictors set and of the neural network architecture according to specific economy/industry sectors, in the context of the European Union; b) provide explanations on the impacts of the selected features on the carbon emissions predictions, in order to effectively support the design and implementation of environmental initiatives and policies.

The developed framework incorporates the state-of the-art RReliefF (Robnik-Šikonja and Kononenko, 2003) algorithm for the assessment and selection of the most relevant environmental related predictors set. Such algorithm was innovatively engineered with a backpropagation neural network, aiming at the conformation of a forecast framework able to improve its architecture according to the selected predicting features. The framework evaluation against current mainstream machine learning models, and its benchmarking comparing to recent published researches on carbon emissions prediction indicates that our research contribution is relevant and capable of supporting the improvement of environmental policies effectiveness.

Moreover, in order to better support the design of more effective CO2 related environmental policies, the designed prediction framework incorporates a module featuring an Explainable Artificial Intelligence (XAI) approach. In such module we implemented partial dependence functions for global model explanations (Friedman, 2001), and the local interpretable model-agnostic explanations (LIME) algorithm (Ribeiro et al., 2016), for local model explanations. The two techniques combined accomplished the explanation of the learning framework predictions.

1.2 Research Contribution

Within our research we designed and implemented a computational learning framework for carbon emissions predictions incorporating a RReliefF driven features selection method, and an iterative neural network architecture improvement.

The Relief family of algorithms (Kira and Rendell,1992; Robnik-Šikonja and Kononenko, 2003) incorporates the ability to probabilistically qualify non-linear features' correlations in a dataset. Such features assessment is accomplished by a non-parametric and non-myopic technique that runs in low order polynomial time.

The RReliefF algorithm outcomes are attributes weights that feature a probabilistic interpretation, i.e. the weights are proportional to the difference between two conditional probabilities: the probability of the attribute's value being different conditioned on the given nearest hit, and on the nearest given miss.

Within the learning framework, prediction candidates (features) are ranked based on the weights computed by RReliefF, and iteratively used to jointly define the best features set as well as the best neural network architecture, in terms of prediction accuracy.

The designed framework is composed by four modules, i.e.: 1) The Features Engineering Module (FEM); 2) the Model Generation Module (MGM), 3) the Model Evaluation Module (MEM), and 4) the Predictions Explanation Module (PEM), which will be described in session 4. The Features Engineering Module and the Model Generation Module iteratively interdependent design comprises the core innovative contribution of our research.

The learning framework features and corresponding taxonomy of our research approach is introduced below.

- Theory / Domain: Computational Learning Theory / Statistical Learning Theory.
- Learning Approach: Machine Learning.
- Machine Learning (ML) Method: Supervised Learning;
  - ML Algorithm: ANN - BP.
- Data Processing:
  - Features Engineering Method: RReliefF-BFE;
  - Search Method: Backward Feature Elimination (BFE);
  - Feature ‘Quality’ Assessment Algorithm: RReliefF;
  - Ad hoc feature selection defined per economy/industry sector.
- Explainable AI Approaches / Methods:
  - Global Explanation: marginal effects analysis / partial dependence functions - partial dependence plots;
  - Local Explanation: perturbation approach / Local Interpretable Model-agnostic Explanations - LIME.

To the best of our knowledge, our proposed learning framework is the first to implement an iterative Neural Network architecture improvement supported by a Backward Feature Elimination search method driven by the RReliefF algorithm. The framework iteratively learns (NN/BP architecture, features subset) on *ad hoc* basis, i.e. specifically for each economy / industry sector.

2 BACKGROUND AND RELATED WORK

2.1 European Union Emissions Trading System Effectiveness Analysis

According to the recent European Environment Agency (EEA) Indicator Assessment on GHG emission trends and projections (European Environment Agency, 2018a), total EU GHG emissions reductions, excluding those ones deriving from land use, land use change and forestry (LULUCF), reached 22.4% and 21.9% bellow 1990 levels in 2016 and 2017 respectively.

The 2017 reduction is equivalent to 15.3% bellow 2005 levels, while GHG emissions from sectors covered by the EU-ETS in the same year were 26.4% below 2005 levels, when considering scheme scope adjustment of approximately 331 MtCO2 for 2005. The EU GDP though grew by approximately 53% between 1990 and 2016. The European Union emission intensity with reference to the EU GDP decreased by almost 50% between 1990 and 2014 (European Commission, 2015a). Figure 1 presents both emissions and emissions intensity of the economy trends between 2005 and 2017. When considering 2005 as reference, emissions intensity in 2017 is approximately 30% lower.

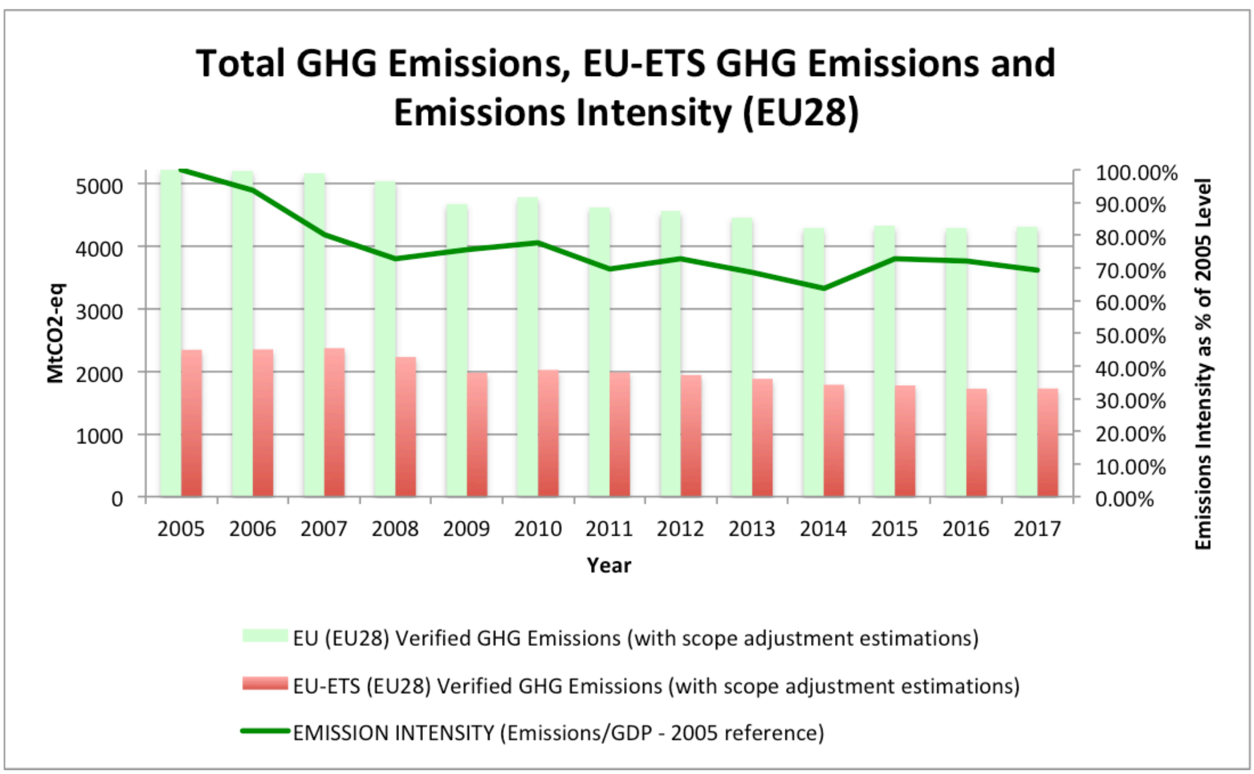

Figure 1 - EU28 historical GHG emissions with scope adjustment and emission intensity. (Crespo and Wang, 2020)

Thus it is possible to imply that the EU continues to successfully decouple GHG emissions and GDP, and it is clear that the emissions intensity of the European economy had a marked decrease that reflected, to some extent, the systematic and consistent greening efforts addressing GHG emissions, as well as energy production and efficiency. However, additional factors contributed for the occurrence of such phenomenon.

The reductions on GHG emissions and emission intensity of economy accomplished since 1990 is attributed to a combination of several factors, e.g. use of renewables, less carbon intensive fuels, improvements in energy efficiency, economy structural changes and economic recession. An increased contribution of services and a lower share of the energy-intensive industries for total GDP, in association with the 2008 economic crises are amongst the most influential reducing factors. According to the World Bank database, the value added by EU industry (as percentage of its GDP, with reference to basic prices) decreased from about 29% in 1990 to 21.98% in 2017, when services and industry respectively contributed with 74% and 25.6% of EU GDP, with reference to purchaser prices (Crespo and Wang, 2020).

Along with the 2008 economic crisis and the structural shift observed in the European economy, the GHG emissions reduction accomplished by the EU are mostly due to contributions provided by the power generation / fuel combustion sector, throughout all European climate change avoidance initiatives. Hereafter then it will be demonstrated that it was particularly true for the EU-ETS.

2.2 EU-ETS GHG Emissions Trends

In 2005 EU-ETS emissions represented approximately 45% of EU verified emissions, while in 2017 such coverage comprised 40% of the total, when its reduction reached 26.4% of 2005 levels, which is already below the 2020 reduction target.

When considering the scheme scope adjustment, the EU-ETS emissions presented an almost continuous decrease trend throughout its phases, as can be observed in figure 2. The scope adjustment was designed to reflect the scheme coverage evolution, as previously described in table 1, and as such, it compensates for the increment in the number of States, installations and gases observed within 2005-2012.

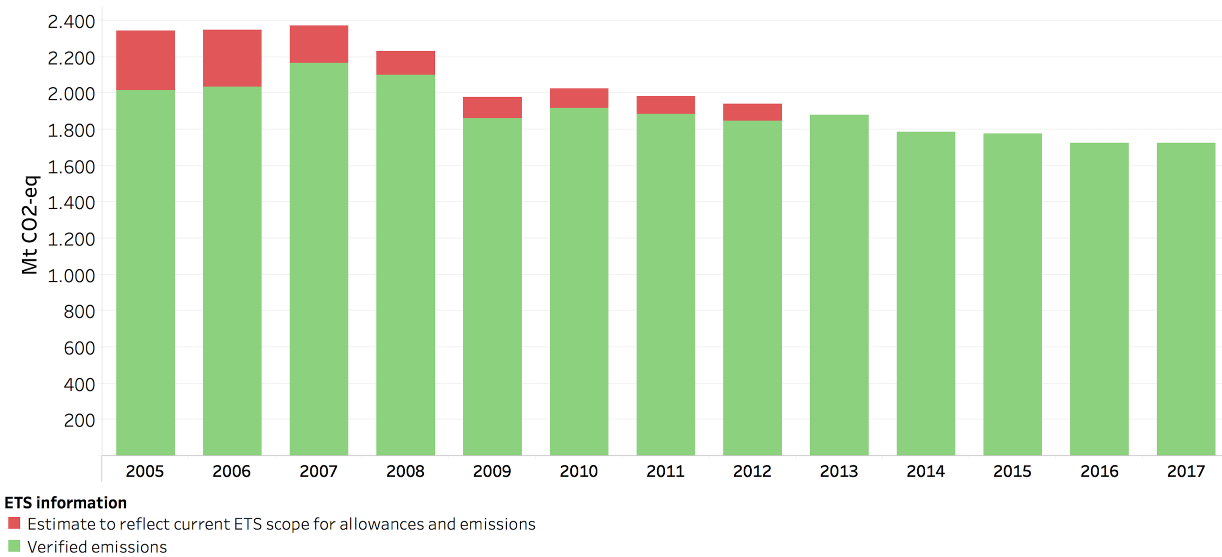

Figure 2 - EU-ETS historical CO2 emissions with scope adjustment. (Crespo and Wang, 2020)

Notwithstanding overall marked reduction, the industry sectors' contributions for the decreasing trend were not proportional. Figure 3 demonstrates that the overall reduction was due to the power generation segment contribution. The segment is the greater emitter, responsible for approximately 66% of EU-ETS emissions in 2017, which represents a clear evolution from the 72% contribution in 2005.

Overall EU emissions related to the production of heat and electricity decreased from 4355 MtCO2 in 1990 to 3352 MtCO2 in 2016. Energy efficiency itself has notably grown, i.e. in 2005 EU production marked more than 900 Mtoe, with a consistent decrease trend leading to approximately 760 Mtoe in 2015 and 755.4 Mtoe in 2016.

Specifically regarding the installations under the EU-ETS, in addition to the contributions verified during phase 1 and 2, the power sector decreased its emissions from 1345 MtCO2 by the end of 2012 to 1148 MtCO2 in 2017, or 14.65% in 5 years, equivalent to a reduction of 20.44% compared to 2005 levels, not considering the scope adjustment. The continued power sector decrease trend, in contrast to the other stationary installations trend, may be explained by a combination of two possibly correlated factors, i.e. changes in the energy source mix and a differentiated policy for carbon allowances allocation (Crespo and Wang, 2020).

The energy sources mix is continuously shifting to greener profiles; in 2005 renewables and fossil fuels (coal, oil, and natural gas) represented approximately 13.3% and 57.3% of the energy matrix, reaching 27.9% and 41.5% by 2016. In the same year, approximately 30% of the electricity consumed in the EU derived from renewable sources (RES), with the RES mix mainly composed by hydropower (36%), wind (32%), solar photovoltaic (12%), and solid biomass (European Environment Agency, 2018b).

And although solid, liquid and gaseous biofuels still provide the largest share of total renewable energy, being heavily used in heating, electricity generation and transport, wind and solar energy relative shares are consistently rising: in 2016, the EU produced 26.0 Mtoe from wind energy, more than five-fold increase compared with 2004; in the same year, solar energy (photovoltaic and thermal) provided 13.4 Mtoe, more than 19 times as much as in 2004. And importantly, as aforementioned from 2013 on the sector was not eligible to be granted allowances for free. (Crespo and Wang, 2020).

The aviation segment still contributes with a small part of to EU-ETS emissions, however it currently shows a sharp increase trend. Estimates contained in the EEA Annual EU GHG Inventory 1990-2016 and Inventory Report 2018 indicates that worldwide international aviation emissions increased 115% between 1990 and 2016 (European Environment Agency, 2018c). During phase 3, so far, EU-ETS aviation emissions showed a consistent increase trend, with a variation of approximately 21.5% between 2013 and 2017.

The aviation permits (EUAA) distribution was practically set on a fixed basis for the current EU-ETS phase, i.e. 36 MtCO2 annually, with 82% of the permits allocated for free, 15% distributed by auctioning, and 3% reserved for distribution to fast-growing aircraft operators and new entrants. When considering EU28, phase 3 allowances supply for aviation covered so far 64.7% of its needs; as a consequence, the aircraft operators had to buy and surrender EUAs as complement, with annual figures around 17 MtCO2. Thus, the aviation industry did not have relevant influence on global EU-ETS performance.

The other industrial stationary installations had a reduction right after the 2008 economic crises, which was followed by a rebound to pre 2008 levels by the end of 2013; since then such emissions remained practically stable. According to the European Environment Agency (2018a), the uncertainty for GHG emissions calculation is about 6%, and for trends calculation is 1%. (Crespo and Wang, 2020).

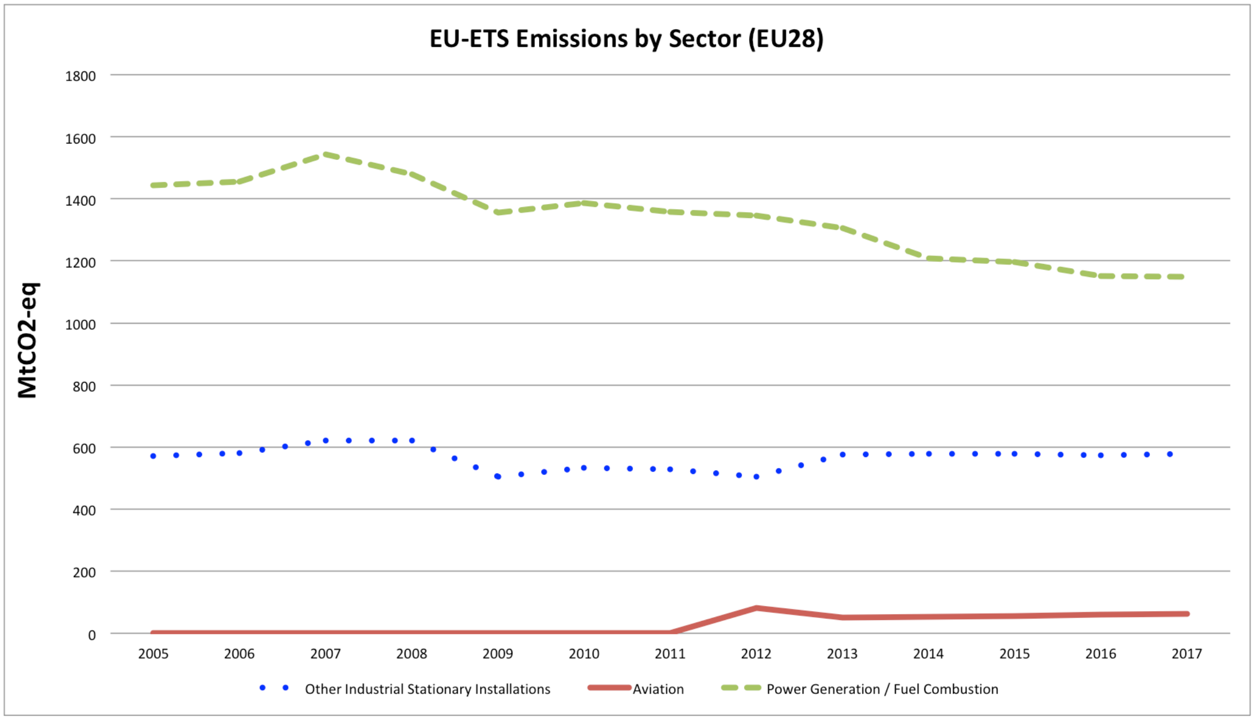

Figure 3 - EU28 emissions by industry sector. (Crespo and Wang, 2020)

Figure 4 allows for a more detailed analysis of the other stationary installations emissions trends. Cement and steel related industries presented an important emissions reduction during EU-ETS first two phases, which was followed by stagnation around 150 MtCO2 in the third phase. Chemical industries in turn presented a marked increase and reached almost 80 MtCO2 in 2017, which provided compensation for the cement and steel industries reductions.

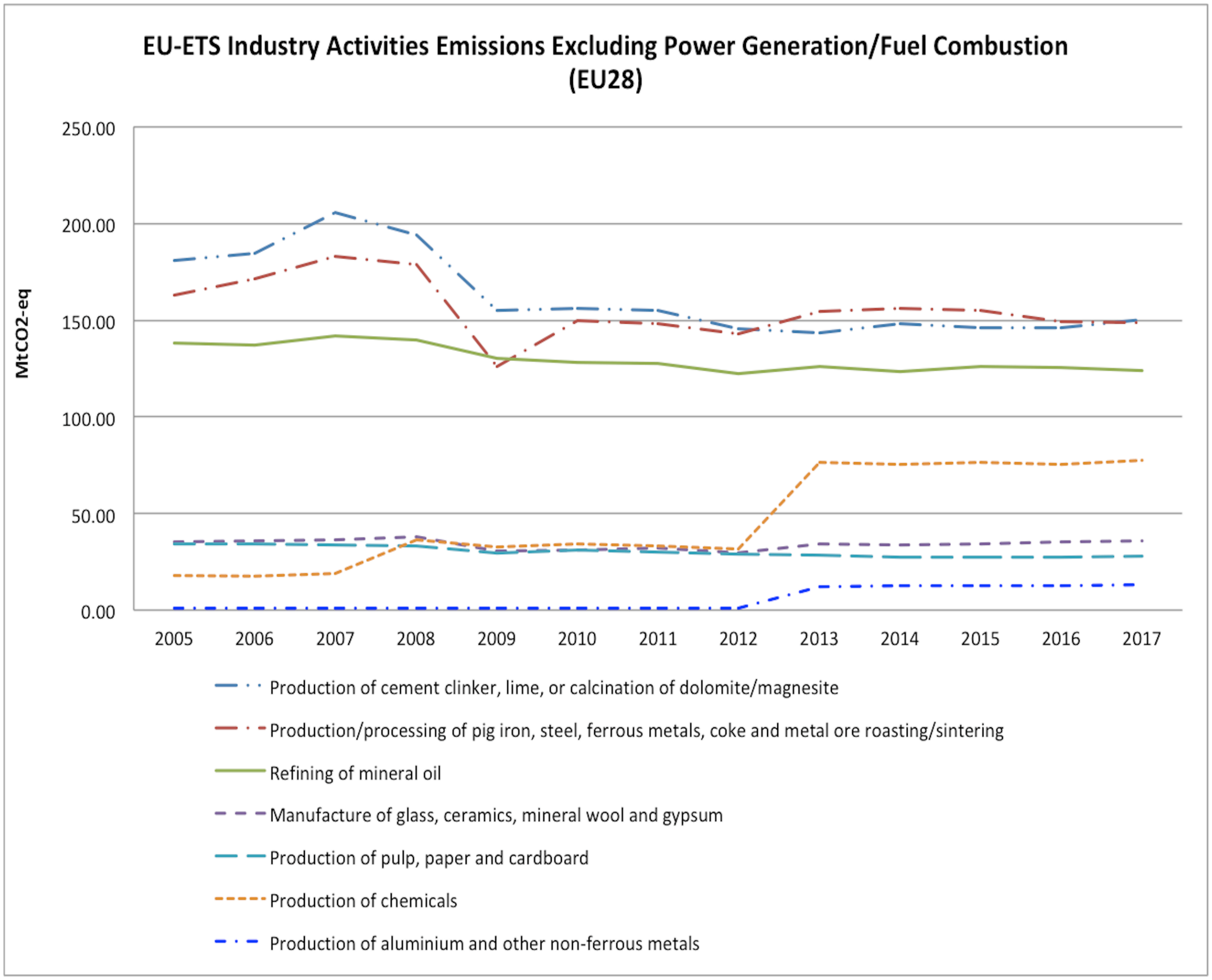

Figure 4 - EU28 emissions by industry segment, excluding the power generation sector. (Crespo and Wang, 2020)

Therefore, it is clear that the EU-ETS did not effectively drive GHG emissions reduction among installations outside the energy sector, and the scheme policy for the allocation of allowances might give some clues about such phenomenon. According to the EEA 2018-14 report (European Environment Agency, 2018d), in 2017 the installations producing iron and steel, coke, and metal ore, as well as the ones producing pulp, paper and cardboard had a substantial balance of free allocations compared to verified emissions, while the plants producing cement and lime, and chemicals had parity. Such conditions may partially explain the trends shown in figure 3, as discussed hereafter.

2.3 EU-ETS Allowances Allocation Issues

In phase 1, the pilot phase, the absence of reliable data on actual emissions and consequent wrong estimations led to allowances surplus that drove its price to zero by 2007. 6370 MtCO2-eq allowances were allocated between 2005 and 2007, for emissions of approximately 6215 MtCO2. In such scenario, carbon price dropped to near €0/tCO2, hence the scheme did not drive a consistent industry greener trend nor presented significant cost-effective results during the pilot phase. During this phase the EU-ETS covered approximately 45% of total EU GHG emissions and presented an increase trend, despite the slight reduction observed on total EU emissions.

Phase 2 had a marked reduction on emissions. With reference to 2005 levels, by the end of phase 2 first year EU-ETS installations emitted 5% less; by the end in 2012 its emissions were 17% lower. Nevertheless such relevant reduction shall be put under perspective, because when the emissions intensity indicator is taken into consideration, it becomes clear that the reduction was mostly due to lower production levels driven by the 2008 economic crises. As can be observed in table 2, the emission intensity of the economy was 72.90% in phase 2 first year and 72.92% in its last year, while EU-ETS contribution to EU emissions as a whole remained stable on about 42%.

Table 1. EU28 total emissions, EU-ETS emissions, EU emission intensity of GDP, and EU-ETS emissions coverage.

Year	EU (EU28) Verified GHG Emissions (with scope adjustment)	EU-ETS (EU28) Verified GHG Emissions (with scope adjustment)	EMISSION INTENSITY (Emissions/GDP - 2005 reference)	EU-ETS Emissions Coverage
2005	5220	2345	100.00%	44.92%
2006	5208	2351	93.58%	45.14%
2007	5160	2371	80.23%	45.95%
2008	5042	2230	72.90%	44.23%
2009	4673	1977	75.60%	42.31%
2010	4777	2024	77.81%	42.37%
2011	4620	1984	69.66%	42.94%
2012	4557	1943	72.92%	42.64%
2013	4462	1882	68.48%	42.18%
2014	4291	1787	63.71%	41.65%
2015	4319	1776	72.80%	41.12%
2016	4293	1724	72.01%	40.16%
2017	4317	1727	69.12%	40.00%

Therefore, although reliable emissions data were available in phase 2, a new large surplus of allowances and credits once again heavily impacted carbon prices. Along with the 2008 economic crises, the Directive 2004/101/EC also contributed to the persistence of such undesirable market imbalance. Total allowances allocation, comprising EUAs, CERs and ERUs, achieved 11373 MtCO2e whilst verified emissions registered 9613 MtCO2. Such oversupply of allowances and the consequential carbon low price continued to negatively impact the scheme effectiveness in terms of emissions reduction accomplishment.

As a whole, the first EU-ETS two phases were marked by difficulties in stabilizing of the carbon price, when the total allocated allowances registered an annual average of approximately 2088 MtCO2, and verified emissions registered an annual average of approximately 1978 MtCO2. In the same period the volume of auctioned allowances (EUA) increased from 0 to 115 MtCO2, while 663 MtCO2e CER and 375 MtCO2e ERU were injected in the market, what clearly contributed to the undesirable and persistent surplus of allowances. By the end of 2012, more than 1 billion allowances were rolled over to the next phase and, in such scenario low-carbon investments were postponed. Figure 5 presents the verified emissions progression, allowances allocation and carbon price for phase 2 and phase 3 up to 2017. (Crespo and Wang, 2020).

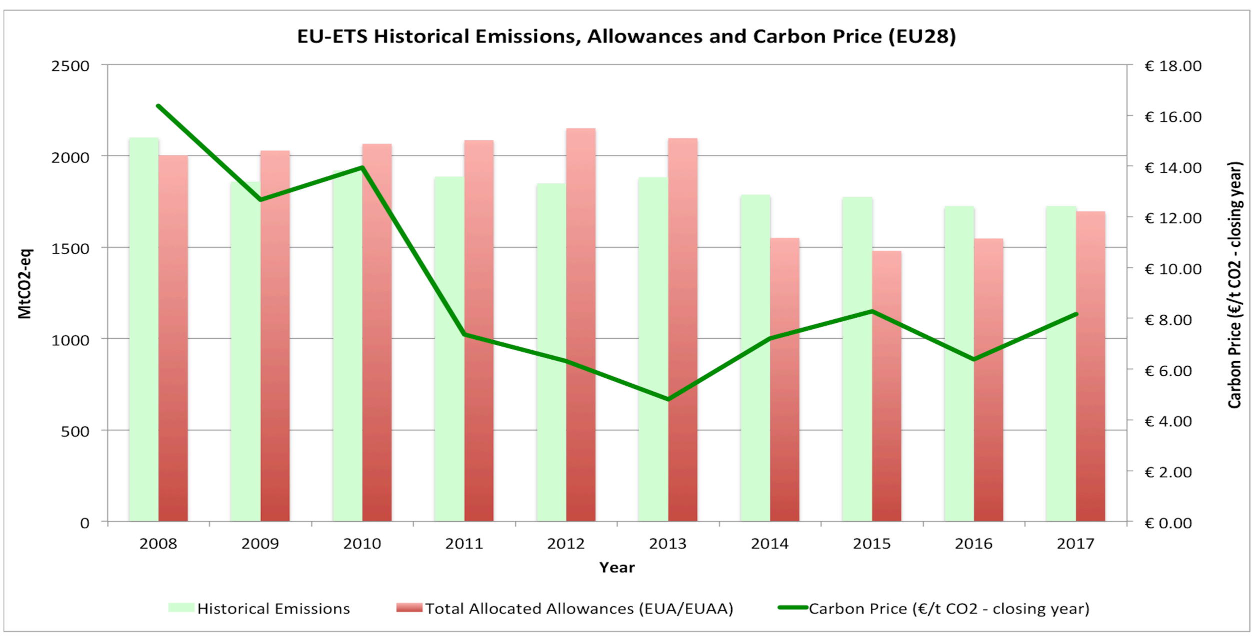

Figure 5 - EU-ETS historical emissions, allocated and surrended allowances, and carbon price 2005-2017. (Crespo and Wang, 2020)

These findings led the European Commission to carry out a thorough review of the system in order to improve its effectiveness for the third and current phase. Auctioning and benchmark respectively replaced free allocation and grandfathering as driving principles for allowances allocation. Hence in the first year of phase 3 the volume of auctioned allowances soared to 1103 $MtCO_2$.

In order to address the persistent allowances surplus, the Commission followed some other strategies such as back-loading, cap and annual linear reduction factor review, scope extension, restriction on international credits utilization and the implementation of discretionary carbon price management mechanisms. Additionally, the power sector installations were enforced to buy all of the required allowances.

A back-loading measure enforced by the Commission regulation (EU) 176/2014 postponed the auction of 900 million allowances, initially planned to be available between 2014 (400 million), 2015 (300 million) and 2016 (200 million), and supposed to be back on market in 2019 (300 million) and 2020 (600 million). The allowances surplus then started to decline in 2015, when the European Union emitted 10% of world GHG, and kept declining for the next two years.

Nevertheless, the drastic reduction on the amount of permits allocated for free and the change from grandfathering to benchmark as the free allocation driving policy did not immediately impact the permits surplus nor the carbon price. In 2017 the allowances surplus still was about 1.6 billion, and this substantial structural supply-demand imbalance keeps distorting the market and compromising the scheme effectiveness as an emissions reduction driver, e.g. other stationary installations emissions are stagnated near 2005 levels.

Such scenario compelled the EU to put in place, from 2019 on, the Market Stability Reserve (MSR), a market resilience-improving mechanism that incorporated the aforementioned back-loaded allowances (European Environment Agency, 2018c). The MSR aims at neutralizing the allowance surplus negative impacts, and at improving the system's resilience to future shocks. Thus an automatic rule-set process will adjust the annual supply of allowances to be auctioned when the number of units in circulation is outside a predefined range, i.e.: a) whenever the surplus exceeds 833 million units, 12% of the allowances in circulation are to be placed in the MSR instead of being auctioned; b) whenever the surplus is less than 400 million units, 100 million allowances are to be released from the MSR via future auctions. The Decision (EU) 2015/1814 even prescribed that the back-loaded permits supposed to re-enter the market in 2019 and 2020, as well as unused NER permits were directly deposited in the MSR.

Besides the lack of accurate emissions information during the pilot phase and the unforeseen economic crises during phase two, it is difficult to state clearly the reasons why the EU-ETS governance framework was not able to address properly the persistent structural market imbalance. Nevertheless, a study developed by the International Emissions Trading Association (IETA) indicates that the effects accrued from the RED and the EED might have contributed for such distortion. According to the IETA estimates (International Emissions Trading Association, 2015), for the period between 2008 and 2020, EED contribution for the surplus could reach about 515 MtCO2, while RED could have reduced the demand for allowances in approximately 210 MtCO2. Therefore, the lack of proper assessment on environmental policies overlapping effects should be considered as one of the reasons why the EU-ETS performance is not as expected.

Finally, the EU-ETS features in support to the avoidance of carbon leakage also seem to jeopardize the scheme effectiveness by contributing for the allowances surplus persistence. The list of flaws may include the inadequate criteria for the definition of the industry segments exposed to carbon leakage risks, and an overestimating process for allowance allocation.

By the end of the current phase though, a combination of factors positively impacted the carbon market. The scheme design improvements put in place during phase 3 combined with the adjustments planned for phase 4 seem to have effectively addressed the concerns towards the structural allowances surplus, which motivated market speculation on the increasing need for permits to cope with ascending industrial output levels. As a result, EUA prices soared from €5.52/tCO2 in January 2017 to €24.10/tCO2 in December 2018. However, the emissions figures for 2018 are yet to be published, thus it is not possible to assess how the carbon prices recent upward movement impacted the EU-ETS emissions trend.

In summary, notwithstanding the planned EU-ETS design evolution and the accompanying policy improvements as regards to the Effort Sharing Decision (ESD), the Renewable Energy Directive (RED) and Energy Efficiency Directive (EED), the EU member States' projections converge to an EU-wide total GHG emissions reduction of at most 32%, which falls short of the 40% target for 2030. EU-ETS specific projections indicate that the stationary installations could reach a 10% reduction on emissions between 2020-2030, which is insufficient for the accomplishment of the 2030 reduction target of 43% compared to 2005 levels.

Therefore the achievement of the EU ambitious targets will require additional policies resulting from new holistic and creative approaches targeting carbon emissions trends prediction and efficient allowances allocation processes. (Crespo and Wang, 2020).

2.4 Carbon Emissions Prediction - Relevant Related Work

A myriad of researches analyzed carbon emissions behavior, and attempted to predict it by means of several different approaches, methods and techniques, and considering different emissions impacting factors (predictors). Econometric approaches were used by Guan et al. (2008), Anger (2010), Li and Lu (2015), Robalino-Lopez et al. (2016), Scott et al. (2017), Mi et al. (2017). And Game Theory emerged as one of the preferred approaches to address decision-making and supply chain challenges linked to carbon emissions and carbon policies, as in Chang and Chang (2016), Yang et al. (2017), Yang et al. (2018), and Xu et al. (2018).

Whereas General Equilibrium Theory (Wang and Wang (2015), Gavard et al. (2016), Zhang et al. (2017)), Operational Research (Cui et al. (2017), Hong et al. (2018)), Index Number Theory (Wang et al. (2017), Solaymani et al. (2019)), Variational Inequality Theory (Allevi et al. (2018)), and Grey Systems Theory (Jiang et al. (2020)) also played an important role in support of such studies, a significant number of researches opted for the application of techniques within the Statistical and Computational Learning domain. Table 2 provides a summary of the reviewed studies.

Table 2. Methodologies, techniques, and predicting variables for carbon emissions predictions.

AUTHOR	PROBLEM SCOPE	PROBLEM ANALYSIS METHODOLOGY	TECHNIQUE
Guan et al. (2008)	Analysis of carbon emissions behavior considering features such as population, carbon intensity, economic production structure, consumption pattern and consumption per capita.	Environmental Analysis / Macroeconomic Analysis	IPAT / Input-output Analysis / Structural Decomposition Analysis
Anger (2010)	Carbon policies impacts on aviation industry CO2 emissions.	Econometrics. General Equilibrium Theory.	Energy-Environment-Economy model for Europe (E3ME).
Chang (2010)	Carbon emissions prediction (predictors: crude oil consumption, coal consumption, natural gas consumption).	Statistical Analysis / Learning	Multivariate co-integration Granger causality / Vector Error Correction Modeling
Wang & Wang (2015)	Price and market strategies impacts on oil refinery, iron / steel processing, cement production and power generation carbon emissions.	General Equilibrium Theory.	Computable General Equilibrium (CGE).
Li & Lu (2015)	Carbon price prediction (predictors: GDP, carbon intensity, energy consumption).	Signal Analysis / Econometrics.	Empirical Model Decomposition (EMD). / Generalized Autoregressive Conditional Heteroskedastic Process (GACH).
A. Robalino-Lopez et al. (2016)	Carbon emissions prediction (predictors: GDP, energy consumption, economy structure, energy intensity).	Systems Theory / Econometrics	Systems Dynamics / Kaya Identity
Chang & Chang. (2016)	Carbon emissions quotas allocation.	Information Theory (Entropy) / Game Theory.	Entropy Analysis / Shapley value.

AUTHOR	PROBLEM SCOPE	PROBLEM ANALYSIS METHODOLOGY	TECHNIQUE
Gavard et al. (2016)	Emissions Trading Systems integration impacts on carbon prices	General Equilibrium Theory.	Computable General Equilibrium (CGE)
Yang et al. (2017)	Supply chain competition considering price and product greening level.	Game Theory.	Stackelberg Game.
Zhang et al. (2017)	Emissions Trading Systems integration and carbon quotas allocation efficiency impacts on carbon emissions.	General Equilibrium Theory.	Computable General Equilibrium (CGE).
Scott et al. (2017)	Industry production driven carbon emissions.	Econometrics.	Environmentally-extended Multi-region Input-Output Analysis (EE-IOA).
Hong et al. (2017)	Carbon allowance price prediction (predictors: oil brent, natural gas, coal).	Statistical Learning.	Predictive Regression Bagged (bootstrap aggregation) / Decision Tree
Cui et al. (2017)	Environmental policies impacts on airline pollution abatement costs.	OR	Data Envelopment Analysis (DEA).
Wang et al (2017)	Carbon emissions prediction based on energy use (predictors: sectoral energy intensity, energy consumption structure, production structure (technology), total production output (economy growth), final demand structure (consumption pattern), total final demand).	Index Number Theory (Decomposition Analysis).	Index Decomposition Analysis (logarithmic mean Divisia index - LMDI) / Structural Decomposition Analysis (D&L method).
Mi et al. (2017)	Analysis of carbon emissions behavior considering the following drivers: population, carbon intensity, consumption pattern and consumption volume.	Environmental Analysis / Macroeconomic Analysis	IPAT / Input-output Analysis / Structural Decomposition Analysis
Liu et al. (2017)	Carbon emissions predictions.	Computational Learning Theory / Statistical Learning Theory / Chaos Theory	Neural Networks
Zhou et al. (2017)	Carbon emissions prediction (predictors: thermal power capacity, thermal power generation, urbanization rate, GDP)	Computational Learning Theory / Statistical Learning Theory	Neural Networks / Particle Swarm Optimization (PSO)
Sun et al. (2017)	Carbon emissions prediction (predictors: coal consumption, primary industry GDP, secondary industry GDP, tertiary industry GDP, population, urbanization level, transport, power generation, steel production, total investments, final consumption).	Computational Learning Theory / Statistical Learning Theory / Grey Systems Theory	Neural Networks / Principal Component Analysis (PCA) / Grey Model
Hong et al. (2018)	Supply chain structure impacts on carbon emissions.	OR	Dynamic Programming.
Allevi et al. (2018)	Closed supply chain carbon emissions analysis.	Variational Inequality Theory.	Partial Differential Equations.
Yang et al. (2018)	Dual supply chain remanufacturing strategy impact on carbon emissions.	Game Theory.	Stackelberg Game.
Zhou et al. (2018)	Carbon emissions prediction (predictors: GDP, urbanization rate, electricity consumption, coal consumption, thermal power capacity)	Statistical Learning / Grey Systems Theory	Support Vector Machine (SVM) / Particle Swarm Optimization / Grey Relation Analysis
Xu et al. (2018)	Centralized/decentralized dual channel supply chain pricing and emissions abatement strategies.	Game Theory.	Stackelberg Game.
Li et al. (2018)	Carbon emissions prediction (predictors: energy consumption, i.e. coal, oil, and natural gas).	Computational Learning Theory / Statistical Learning.	Neural Networks Support Vector Machine (SVM)
Song et al. (2019)	Carbon allowance price prediction (predictors: demand-related policies).	Stochastic Processes.	Fuzzy Stochastic Differential Model.
Solaymani et al. (2019)	Carbon emissions drivers analysis.	Index Number Theory (Decomposition Analysis).	Logarithmic Mean Divisia Index (LMDI) Method.
Sun et al. (2019)	Carbon emissions prediction (predictors: coal consumption, primary sector GDP, secondary industry GDP, tertiary industry GDP, final consumption, population, power generation, exports, urbanization level (%), investments, transportation, fuel and power purchase price index, cement production, urban green areas, total retail sales of consumer goods, finished steel production,).	Computational Learning Theory / Statistical Learning.	Support Vector Machine / Particle Swarm Optimization/ Principal Component Analysis / Neural Networks
Jiang et al.	Carbon emissions prediction (predictors: inward	Grey Systems Theory	Grey Multivariable Verhulst

AUTHOR	PROBLEM SCOPE	PROBLEM ANALYSIS METHODOLOGY	TECHNIQUE
(2020)	foreign direct investment, outward foreign direct investment)		model.
Wen et al. (2020)	Carbon emissions prediction: total population, household consumption level, urbanization level, GDP per capita, primary industry GDP, secondary industry GDP, tertiary industry GDP, commercial department GDP, total energy consumption, and total retail sales of social consumer goods.	Computational Learning Theory / Statistical Learning Theory / Evolutionary Computation	Neural Networks / Particle Swarm Optimization / Random Forest / Support Vector Machine / Genetic Algorithm

The literature review provided fundamental insights on the existing carbon emissions impacting factors and how to apply them in emissions prediction models. It was noted that the researches benefiting from Computational Learning and Statistical Learning theories were the ones providing more information regarding how the predictors (or the availability / choice of different predictors) impacts prediction confidence level and accuracy.

The literature review also allowed us to identify some very important challenges related to carbon emissions prediction, when considering the amount and diversity of potential predictors. Firstly, a particular predictor correlation to a specific target varies depending on the scenario / region. Secondly the systematic generation of trustworthy carbon emissions information started in the 1990 decade, and its availability is restricted to some parts of the world.

Thirdly, carbon emissions can be characterized as a worldwide multisectoral interconnected phenomenon, e.g. the pollution outcomes international flights may have contributing components spread in all continents if we consider the airline headquarters location, the flight route (origin-overfly area-destination), the aircraft manufacturer (engines manufacturer, fuselage manufacturer, tires manufacturer, etc.), the fuel producer (petroleum, biofuels).

As an additional example, consider, a huge transnational enterprise may move its heavily polluting production to regions where carbon policies are less strict or even inexistent (carbon leakage). In such scenario, carbon emissions prediction models should be scalable in order to progressively cover broader scopes and process more data.

However, such required scalability would lead to the use of an increasing number predictors (predicting model features space dimension), what would not be accompanied by additional instances, once the availability of trustworthy data is limited. Thus, any intended predicting model should be capable of addressing data related characteristics such as non-linearity, heteroskedasticity, endogeneity, and dimensionality.

The overall insights accrued from the literature review drove us to choose a computational learning / statistical Learning approach for the design of our prediction framework. It was also noted that, considering the nature of carbon emissions related data, it would be generally impossible to work with any parametric learning method. Additionally, fitting high-dimensional statistical models often requires the use of non-linear parameter estimation procedures (Javanmard and Montanari, 2014). Therefore, we opted for Neural Networks as the core learning model of our proposed predicting framework.

3 RESEARCH DATA

The level of trust attributed to the outcomes of any Artificial Intelligence / Machine Learning (ML) implementation is assessed by processes such as verification and validation. The ML verification is defined as the process of determining that a model implementation and its associated data accurately represent the developer's conceptual description and specifications. The ML validation, often referred as ML evaluation, is described as the process of determining the degree to which a model outcome and its associated data properly address the real world problem from the perspective of the intended uses of the model.

Therefore, the applicability and the reliability of a ML solution is strictly dependent upon the proper combination ML algorithm - data, i.e. the characteristics of the data are crucial in determining the ML algorithm to be used, as well as the features engineering method. Hereafter then we present and analyze the data used to verify and validate the proposed iterative learning framework.

3.1 Learning Framework Validation Data

Our research focused on the European Union - 28 States (EU28), and used datasets comprising data obtained from the European Union (Eurostat), International Energy Agency (IEA), Organization for Economic Co-operation and Development (OECD), and World Bank (WB) databases. The Learning Framework performance evaluation and benchmarking dataset is described as follows.

- Sources: Eurostat (2020), IEA (2020), OECD (2020), World Bank (2020).
- Scope:
  - EU28;
  - 1990 – 2017;
  - Total CO_2 emissions / sectoral CO_2 emissions;
  - 26 economic / energy indicators (candidate predictors).
- Data Aggregation Levels:
  - Regional;
  - Annual;
  - Total Emissions / Energy Industries / Industries / Commerce – Public Services / Transport / Residential / Aviation.

Tables 3 and 4 introduce the prediction targets and potential predictors explored in our research.

Table 3. Learning framework validation prediction targets - MtCO2 / IEA.

T1 - Total CO2 Emissions
T2 - CO2 Emissions from Energy Industries
T3 - CO2 Emissions from Energy Intensive Industries
T4 - CO2 Emissions from Commercial and Public Services
T5 - CO2 Emissions from Transport
T6 - CO2 Emissions from Residences
T7 - CO2 Emissions from Aviation

Table 4. Learning framework validation candidate predictors.

A1 - GDP (constant million 2010 USD / World Bank)	**A14** - Final Consumption (expenditure of households current prices million Euro / Eurostat)
A2 - GDP(current prices million Euro / Eurostat)	**A15** - Final Consumption (expenditure current prices million Euro / Eurostat)
A3 - Population (Eurostat**)**	**A16** - Primary Energy Consumption (Mtoe / IEA)
A4 - Temperature (HDD / Eurostat)	**A17** - Final Energy Consumption (MTtoe / IEA)
A5 - Temperature (CDD / Eurostat)	**A18** - Energy Use (KGOE per capita / World Bank)
A6 - Technology Innovation (GERD per GDP / OECD)	**A19** - Energy Intensity Level of Primary Energy (MJ / per GDP PPP 2011 USD / World Bank)
A7 - Technology Innovation (GERD million PPP 2010 USD / OECD)	**A20** - Energy Intensity Level of Primary Energy (Kgoe per GDP PPP 2011 USD / World Bank)
A8 - Technology Innovation (GERD per GDP / World Bank)	**A21** - Energy Intensity of GDP (Kgoe per thousand Euro Chain Linked Volumes 2010 / Eurostat)
A9 - Technology Innovation (GERD million 2010 USD / World Bank)	**A22** - Coal Total Primary Energy Supply (Ktoe / IEA)
A10 - Technology Innovation (GERD per GDP / Eurostat)	**A23** - Oil Total Primary Energy Supply (Ktoe / IEA)
A11 - Technology Innovation (GDP per direct material input PPP 2010 USD per kg / OECD)	**A24** - Natural Gas Total Primary Energy Supply (Ktoe / IEA)
A12 - Technology Innovation (GDP per direct material input PPP current USD per kg / OECD)	**A25** - Biofuels and Waste Total Primary Energy Supply (Ktoe / IEA)
A13 - Final Consumption (gross national expenditure current USD / World Bank)	**A26** - Non Combustion Electricity Generation (Ktoe / IEA)

3.2 Data Analysis and Descriptive Statistics

In this section we provide a deeper analysis of our data, which corroborated our choice for the design of a learning framework combining neural networks and the RReliefF algorithm. Firstly we submitted the data to a distribution analysis in order to assess the suitability of parametric and non-parametric ML methods. Secondly, prediction targets and candidate predicators were assessed for potential correlation.

3.2.1 Data Distribution Analysis

The prediction targets and the candidate predictors were assessed for Normal, LogNormal, Weibull, and Gamma distributions, by means of the following tests: a) Chi-Square, b) Anderson-Darling, c) Cramer-von Misses, and d) Kolmogorov-Smirnov. The distribution analysis outcomes are presented in Appendix 1, with all tests indicating the non-parametric nature of our research data.

Among such tests, the Chi-Square significance is the strongest indicator that a distribution is a good fit, where a value greater than 0.05 indicates that the data may likely fit the distribution, and the higher the significance the better the distribution fit. Table 5 presents the Chi-Square significance values for our dataset, what corroborate our conclusion on the need for a non-parametric ML method such as NN.

Table 5. Chi-Square distribution test significance values.

Chi-Square Distribution Test - Significance Value									
Prediction Target	Distribution				Feature	Distribution			
	Normal	LogNormal	Gamma	Weibull		Normal	LogNormal	Gamma	Weibull
T1	0	0	0	0.0004	**A1**	0	0	-	0.0004
T2	0.0007	0	0.0001	0.0048	**A2**	0.2875	0.0819	-	0.411
T3	0.0699	0.0286	0.0449	0.1076	**A3**	0.2335	0.2319	-	0.1921
T4	0.0018	0.0017	0.0018	0.0006	**A4**	0.4418	0.4456	0.4445	0.1177
T5	0.2726	0.1867	0.2159	0.4149	**A5**	0.7403	0.9326	0.9064	0.6198
T6	0.0037	0.0006	0.0012	0.0317	**A6**	0.0122	0.0179	0.016	0.0025
T7	0.0013	0	0.0001	0.0052	**A7**	0.643	0.3706	-	0.7653
					A8	0.001	0.0019	0.0015	0.0001
					A9	0.5328	0.5129	-	0.5075
					A10	0.0178	0.0246	0.0223	0.0032
					A11	0.0236	0.0385	0.0332	0.0051
					A12	0.0087	0.0203	0.0158	0.0016
					A13	0.0001	0.0001	-	0.0001
					A14	0.2646	0.0795	-	0.3873
					A15	0.3037	0.082	-	0.4162
					A16	0.5339	0.5798	0.5659	0.2806
					A17	0.6358	0.6357	0.6377	0.5899
					A18	0.3493	0.3115	0.3245	0.5072
					A19	0.3418	0.1561	0.2235	0.4834
					A20	0.4753	0.3137	0.3792	0.5814
					A21	0.488	0.3151	0.3832	0.7899
					A22	0.028	0.0316	-	0.0063
					A23	0	0	-	0.0005
					A24	0.1974	0.0572	-	0.3792
					A25	0.0105	0.0935	-	0.0242
					A26	0.0216	0.0108	-	0.1238

3.2.1 Data Correlation Analysis

Pearson's coefficient is a test that measures the statistical association between two continuous variables as a function of the covariance observed between them. It provides information about the magnitude of the association, or correlation, as well as the direction of the relationship.

The results of the Pearson correlation test are bound by some important assumptions regarding the tested data, i.e. the variables should be normally distributed, a feature linearity and homoskedasticity. The test outcomes are values ranging -1 to +1, where +1 indicates a perfect positive relationship, -1 indicates a perfect negative relationship, and a 0 indicates no relationship exists; strong correlations are indicated by values between ± 0.5 and ± 1. The research data was submitted to the test, and table 6 presents the potential predictors listed in order of correlation strength.

Table 6. Pearson correlation test coefficients for prediction target T1.

Pearson Product-moment Correlation / Target: Total CO2 Emissions (MtCO2)							
Predictor	**Coefficient**	**p-value**		**Predictor**	**Coefficient**	**p-value**	
A18 (WB)	0.9668816	1.07E-09	***	**A7 (OECD)**	-0.8692267	1.23E-05	***
A6 (OECD)	-0.9513449	1.52E-08	***	**A9 (WB)**	-0.8683733	1.29E-05	***
A10 (EU)	-0.9453401	3.38E-08	***	**A25 (IEA)**	-0.8499821	3.05E-05	***
A23 (IEA)	0.9381434	7.88E-08	***	**A3 (EU)**	-0.8264887	7.92E-05	***
A16 (IEA)	0.9357116	1.03E-07	***	**A24 (IEA)**	0.7928254	2.49E-04	***
A8 (WB)	-0.9335975	1.28E-07	***	**A15 (EU)**	-0.7707846	4.74E-04	***
A22 (IEA)	0.9290128	2.02E-07	***	**A14 (EU)**	-0.7617238	6.06E-04	***
A17 (IEA)	0.9266759	2.51E-07	***	**A2 (EU)**	-0.7524735	7.70E-04	***
A11 (WB)	-0.9137785	7.54E-07	***	**A1 (WB)**	-0.6586972	5.52E-03	**
A12 (OECD)	-0.910324	9.84E-07	***	**A13 (WB)**	-0.5127864	4.22E-02	*
A21 (EU)	0.9017806	1.82E-06	***	**A4 (EEA)**	0.3722717	1.56E-01	
A19 (WB)	0.8834384	5.73E-06	***	**A5 (EEA)**	-0.1650201	5.41E-01	
A20 (WB)	0.8834384	5.73E-06	***	**A26 (IEA)**	-0.0055333	9.84E-01	

(*) p-value is less than 0.05
(**) p-value is less than 0.01
(***) p-value is less than 0.001

The analysis of the Pearson's test outcomes flags down some important insights. The predictor A18 (Energy Use) shows the strongest correlation with the total CO2 emissions, what is in accordance with the knowledge accrued from the literature review. However, as regards to the predictor A3 (population), the test result is counterintuitive, as it indicates a strong negative relationship between population and CO2 emissions; the literature review also contradicts such negative correlation.

Figure 3 provides the visualization of the predictors A18 and A3, and corroborates the Pearson's test outcome. A deeper analysis of the test outcome raises another important flag, i.e. the predictor A4 (Temperature HDD) shows an irrelevant correlation with total CO2 emissions, and considering the research scope (Europe 28), such outcome seems inconsistent with the real-world energy consumption dynamics.

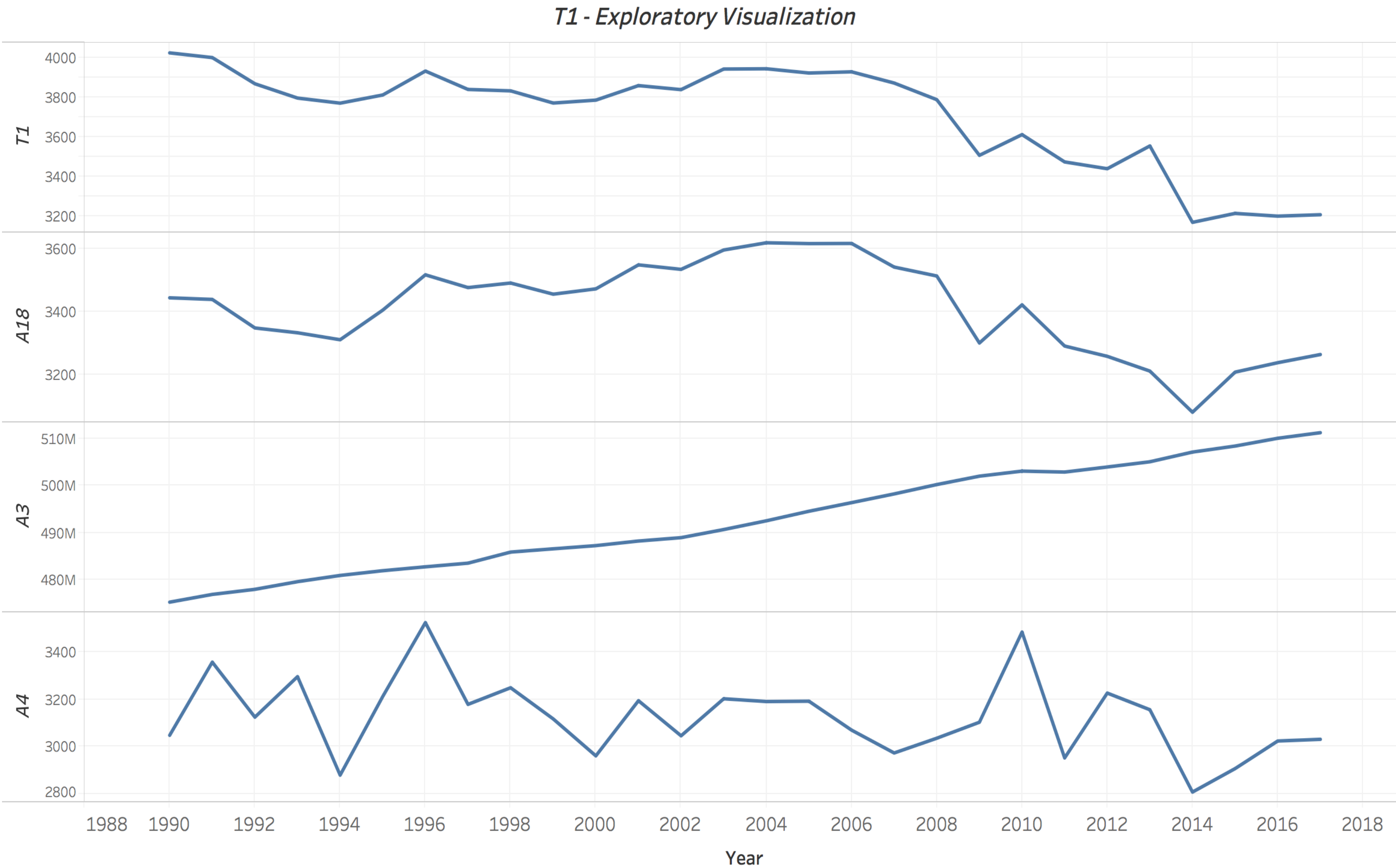

Figure 6 - Exploratory visualization for T1, A18, A3, and A4.

The combined analysis of table 6 and figure 6 indicates potential non-linearity between the variables, as well as eventual additional violations of the Pearson's test assumptions. Thus there is the need for a more sophisticated correlation analysis of the data, and as such, we submitted it to the Spearman correlation test and to the Hoeffding's D Statistic test.

Spearman correlation uses ranks instead of assumptions about the distributions of the two variables and, as such, it analyzes the association between variables according to ordinal measurement levels. Thus, the test does not assume that the variables are normally distributed, and it can be applied to the cases in which the Pearson's assumptions (continuous-level variables, heteroskedasticity, and normality) are not fulfilled.

Similarly to the Pearson's test, Spearman analysis outcomes are values between -1 and +1, and the test results are representative once the data can be ordinally arranged and the scores on one variable can be monotonically related to the other variable.

The Hoeffding's D test (Hoeffding, 1948) measures the independence of the data sets by computing the distance between the product of the marginal distributions under the null hypothesis and the empirical bivariate distribution. The test is able to identify linear / non-linear, monotonic / non-monotonic functions, and also non-functional relationships. The test outcome is a value between -0.5 and +1 where larger values indicate stronger relationships, and there is no information about the variables correlation direction.

We then continued the analysis of the potential abnormal results related to the predictors A3 and A4. Table 7 presents the results of the aforementioned tests, and it is possible to observe that A3 increases its relative correlation level as the test sophistication is improved. Moreover, Spearman test result corroborates the abnormal negative relationship between population and total carbon emissions.

Table 7. Potential predictors ranking according to the specified tests outcomes, for T1.

Pearson Product-moment Correlation / Target: Total CO2 Emissions (MtCO2)			
Predictor	Coefficient	p-value	
A18 (WB)	0.9668816	1.07E-09	***
A6 (OECD)	-0.9513449	1.52E-08	***
A10 (EU)	-0.9453401	3.38E-08	***
A23 (IEA)	0.9381434	7.88E-08	***
A16 (IEA)	0.9357116	1.03E-07	***
A8 (WB)	-0.9335975	1.28E-07	***
A22 (IEA)	0.9290128	2.02E-07	***
A17 (IEA)	0.9266759	2.51E-07	***
A11 (WB)	-0.9137785	7.54E-07	***
A12 (OECD)	-0.910324	9.84E-07	***
A21 (EU)	0.9017806	1.82E-06	***
A19 (WB)	0.8834384	5.73E-06	***
A20 (WB)	0.8834384	5.73E-06	***
A7 (OECD)	-0.8692267	1.23E-05	***
A9 (WB)	-0.8683733	1.29E-05	***
A25 (IEA)	-0.8499821	3.05E-05	***
A3 (EU)	-0.8264887	7.92E-05	***
A24 (IEA)	0.7928254	2.49E-04	***
A15 (EU)	-0.7707846	4.74E-04	***
A14 (EU)	-0.7617238	6.06E-04	***
A2 (EU)	-0.7524735	7.70E-04	***
A1 (WB)	-0.6586972	5.52E-03	**
A13 (WB)	-0.5127864	4.22E-02	*
A4 (EEA)	0.3722717	1.56E-01	
A5 (EEA)	-0.1650201	5.41E-01	
A26 (IEA)	-0.0055333	9.84E-01	

Spearman Rank-order Correlation / Target: Total CO2 Emissions (MtCO2)			
Predictor	Coefficient	p-value	
A18 (WB)	0.970588	4.72E-10	***
A23 (IEA)	0.917647	5.53E-07	***
A16 (IEA)	0.914706	7.01E-07	***
A17 (IEA)	0.9	2.05E-06	***
A6 (OECD)	-0.894118	3.01E-06	***
A10 (EU)	-0.888072	4.37E-06	***
A22 (IEA)	0.879412	7.19E-06	***
A8 (WB)	-0.797059	2.18E-04	***
A21 (EU)	0.788235	2.86E-04	***
A19 (WB)	0.782353	3.41E-04	***
A20 (WB)	0.782353	3.41E-04	***
A9 (WB)	-0.755882	7.06E-04	***
A11 (WB)	-0.752941	7.61E-04	***
A12 (OECD)	-0.752941	7.61E-04	***
A3 (EU)	-0.75	8.20E-04	***
A25 (IEA)	-0.75	8.20E-04	***
A7 (OECD)	-0.747059	8.82E-04	***
A15 (EU)	-0.726471	1.44E-03	**
A2 (EU)	-0.705882	2.25E-03	**
A14 (EU)	-0.705882	2.25E-03	**
A24 (IEA)	0.688235	3.20E-03	**
A1 (WB)	-0.597059	1.46E-02	*
A13 (WB)	-0.505882	4.56E-02	*
A4 (EEA)	0.4	1.25E-01	
A26 (IEA)	0.229412	3.93E-01	
A5 (EEA)	-0.091176	7.37E-01	

Hoeffding's D Correlation / Target: Total CO2 Emissions (MtCO2)			
Predictor	Coefficien	p-value	
A18 (WB)	0.721872	1.00E-08	***
A10 (EU)	0.578183	1.00E-08	***
A6 (OECD)	0.573296	1.00E-08	***
A16 (IEA)	0.526377	1.00E-08	***
A23 (IEA)	0.505369	1.03E-08	***
A21 (EU)	0.478291	2.59E-08	***
A8 (WB)	0.477941	2.62E-08	***
A17 (IEA)	0.445612	7.88E-08	***
A22 (IEA)	0.439309	9.76E-08	***
A9 (WB)	0.433707	1.18E-07	***
A19 (WB)	0.43254	1.23E-07	***
A20 (WB)	0.421919	1.76E-07	***
A7 (OECD)	0.396008	4.26E-07	***
A3 (EU)	0.39274	4.77E-07	***
A25 (IEA)	0.39274	4.77E-07	***
A15 (EU)	0.377451	8.02E-07	***
A11 (WB)	0.360177	1.44E-06	***
A12 (OECD)	0.360177	1.44E-06	***
A2 (EU)	0.312208	7.39E-06	***
A14 (EU)	0.312208	7.39E-06	***
A24 (IEA)	0.236111	1.49E-04	***
A1 (WB)	0.197362	4.52E-04	***
A4 (EEA)	0.076564	2.07E-02	*
A26 (IEA)	0.015173	1.92E-01	
A13 (WB)	0.014006	2.01E-01	
A5 (EEA)	-0.00852	5.27E-01	

As regards to A4, the joint results imply that none of the tests were able to properly assess the correlation level between temperature and CO2 emissions. In such scenario, the next data analysis step comprised the use of a state-of-the-art computationally efficient, non-myopic, and non-parametric algorithm able to indicate and weight complex patterns of association, i.e. the RReliefF algorithm. Once a target variable is defined, RReliefF scores the correlated variables with values ranging from -1 (worst) to +1 (best).

Table 8 presents the outcomes of the aforementioned analysis. The Hoeffding's D test and the RReliefF algorithm do not provide information about the variables correlation direction, thus Pearson's and Spearman's outcomes are presented in terms of absolute value.

Although the RReliefF score for feature A3 does not contradict the information obtained by the other tests, the analysis of the score attributed to feature A4 indicates a very high level of relative correlation between temperature (A4) and CO2 emissions, whilst such condition was not apparent in the other tests outcomes. Consequently, such discrepancy between the tests was further investigated.

Table 8. Data correlation tests comparative perspective for target T1.

Feature	Pearson Correlation	Spearman Correlation	Hoeffding's D Correlation	RReliefF	Feature	Pearson Correlation	Spearman Correlation	Hoeffding's D Correlation	RReliefF
A1	0.6587	0.5971	0.1974	0.0021	**A14**	0.7617	0.7059	0.3122	0.0103
A2	0.7525	0.7059	0.3122	0.0187	**A15**	0.7708	0.7265	0.3775	0.0086
A3	0.8265	0.7500	0.3927	0.0217	**A16**	0.9357	0.9147	0.5264	0.0801
A4	0.3723	0.4000	0.0766	0.1016	**A17**	0.9267	0.9000	0.4456	0.0728
A5	0.1650	0.0912	-0.0085	-0.0181	**A18**	0.9669	0.9706	0.7219	0.0698
A6	0.9513	0.8941	0.5733	0.0520	**A19**	0.8834	0.7824	0.4325	0.0525
A7	0.8692	0.7471	0.3960	0.0295	**A20**	0.8834	0.7824	0.4219	0.0525
A8	0.9336	0.7971	0.4779	0.0392	**A21**	0.9018	0.7882	0.4783	0.0636
A9	0.8684	0.7559	0.4337	0.0319	**A22**	0.9290	0.8794	0.4393	0.0558
A10	0.9453	0.8881	0.5782	0.0281	**A23**	0.9381	0.9176	0.5054	0.0578
A11	0.9138	0.7529	0.3602	0.0553	**A24**	0.7928	0.6882	0.2361	0.1191
A12	0.9103	0.7529	0.3602	0.0609	**A25**	0.8500	0.7500	0.3927	0.0104
A13	0.5128	0.5059	0.0140	-0.0295	**A26**	0.0055	0.2294	0.0152	0.0771

The aggregation level of the data is a characteristic that may adversely bound the effectiveness of such tests. Therefore, the next research step comprised the analysis of the CO2 emissions in a lower level of aggregation, i.e. the test of emissions data of specific industry / economy sectors. Figure 7 shows the comparison between the emissions from commercial and public services (T4) and temperature (A4).

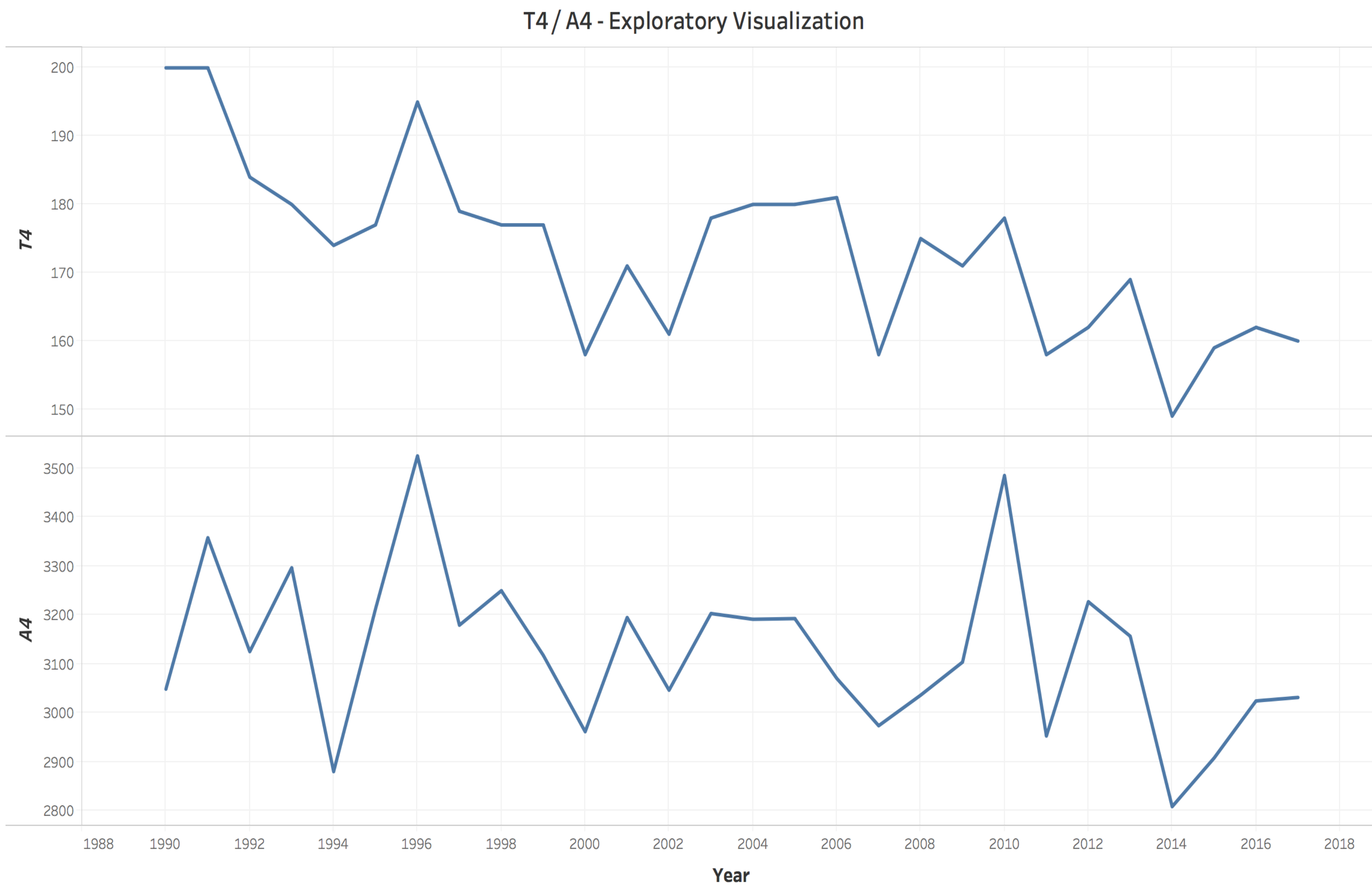

Figure 7 - Exploratory visualization for T4 and A4.

The similarities among the curves are relevant, and table 9 confirms such observation by presenting the results of the Hoeffding's D correlation analysis, where one may observe the feature A4 listed as the most relevant one when T4 is the target variable. The application of the Hoeffding's D test to a carbon emissions dataset featuring a lower level of aggregation confirmed the outcome of the previous RReliefF analysis.

Table 9. Hoeffding's D statistic test for prediction target T4.

Rank	Feature	Measure	p-value		Rank	Feature	Measure	p-value	
1	A4	0.2464	6.94E-05	***	14	A1	0.0716	2.46E-02	*
2	A16	0.2369	1.45E-04	***	15	A9	0.0670	2.87E-02	*
3	A17	0.2055	3.57E-04	***	16	A11	0.0663	2.94E-02	*
4	A24	0.1967	4.60E-04	***	17	A12	0.0663	2.94E-02	*
5	A18	0.1406	2.63E-03	**	18	A3	0.0587	3.82E-02	*
6	A20	0.1228	4.53E-03	**	19	A25	0.0587	3.82E-02	*
7	A19	0.1094	7.01E-03	**	20	A23	0.0579	3.93E-02	*
8	A6	0.1083	7.27E-03	**	21	A15	0.0497	5.23E-02	
9	A10	0.0957	1.10E-02	*	22	A7	0.0409	7.18E-02	
10	A8	0.0909	1.29E-02	*	23	A22	0.0236	1.37E-01	
11	A21	0.0847	1.58E-02	*	24	A13	0.0018	3.36E-01	
12	A2	0.0758	2.12E-02	*	25	A26	0.0000	3.64E-01	
13	A14	0.0758	2.12E-02	*	26	A5	-0.0412	1.00E+00	

Based on such conclusions, the next research step consisted of the expansion of the RReliefF analysis to our research dataset in its entirety, while taking the carbon emissions with a lower level of aggregation, i.e. total emissions split into sectoral emissions (table 1). Table 10 presents the results of the RReliefF scoring for our research data.

And still analyzing the feature A4, it is possible to observe a strong correlation towards the target T6 (residential emissions), what is confirmed by the exploratory visualization in figure 8. Such findings confirmed the applicability of the RReliefF algorithm to assess (score and rank) the correlation level of our research data, and qualified its use in our learning framework features engineering process.

Table 10. RReliefF scores for the research validation dataset.

Continuous Target and Continuous Predictors Variable Importance Weight Analysis_RReliefF							
	Predictor Importance on Target Variable						
Predictor	**T1**	**T2**	**T3**	**T4**	**T5**	**T6**	**T7**
A1	0.0269	0.0441	-0.0015	-0.0334	0.0348	-0.0018	0.0147
A2	0.0264	0.0397	0.0078	-0.0228	0.0316	0.0048	0.0164
A3	0.0373	0.0543	0.02	-0.0283	0.0383	-0.0078	0.0248
A4	0.0469	0.0149	-0.002	0.0891	-0.0086	0.124	-0.0563
A5	-0.1044	-0.0813	-0.0378	-0.065	-0.0236	-0.0839	0.0176
A6	0.0528	0.0355	0.0437	0.0239	0.0241	0.0325	-0.007
A7	0.0425	0.0447	0.0078	-0.0093	0.0278	0.0223	0.0003
A8	0.0568	0.039	0.0532	0.0241	0.0257	0.035	-0.0069
A9	0.0512	0.0533	0.0046	-0.0024	0.0305	0.0271	0.0003
A10	0.0538	0.0396	0.0503	0.0171	0.0333	0.0294	-0.0095
A11	0.067	0.0664	0.0336	0.0025	0.0379	0.0246	-0.0038
A12	0.0656	0.069	0.0349	0.0052	0.0397	0.0275	-0.0049
A13	-0.0161	-0.0136	0.0239	0.0113	0.0154	-0.0284	0.072
A14	0.017	0.0272	0.0149	-0.0204	0.0272	0.0027	0.0131
A15	0.0185	0.0292	0.0158	-0.0204	0.0275	-0.003	0.0219
A16	0.0582	0.0417	0.0455	0.0612	0.0288	0.0486	0.0303
A17	0.0283	-0.0017	0.0298	0.1019	0.0182	0.064	0.013
A18	0.0403	0.0183	0.0279	0.0773	0.0255	0.0571	0.0058
A19	0.0615	0.0582	0.0199	-0.0009	0.0287	0.0424	0.005
A20	0.0197	0.0231	0.0012	-0.0125	0.0159	0.0181	-0.0148
A21	0.0685	0.0622	0.0254	0.0042	0.0283	0.0496	0.0028
A22	0.1227	0.1367	-0.017	-0.0373	0.0652	0.0334	0.0038
A23	0.0476	0.0231	0.0483	0.055	0.0237	0.056	-0.0251
A24	0.0018	-0.0023	0.0091	0.0759	0.0279	0.0519	0.0039
A25	0.0243	0.0326	0.0342	-0.0114	0.0271	-0.0008	0.0117
A26	-0.0316	-0.0168	-0.0262	0.0437	-0.0138	0.0143	-0.0057

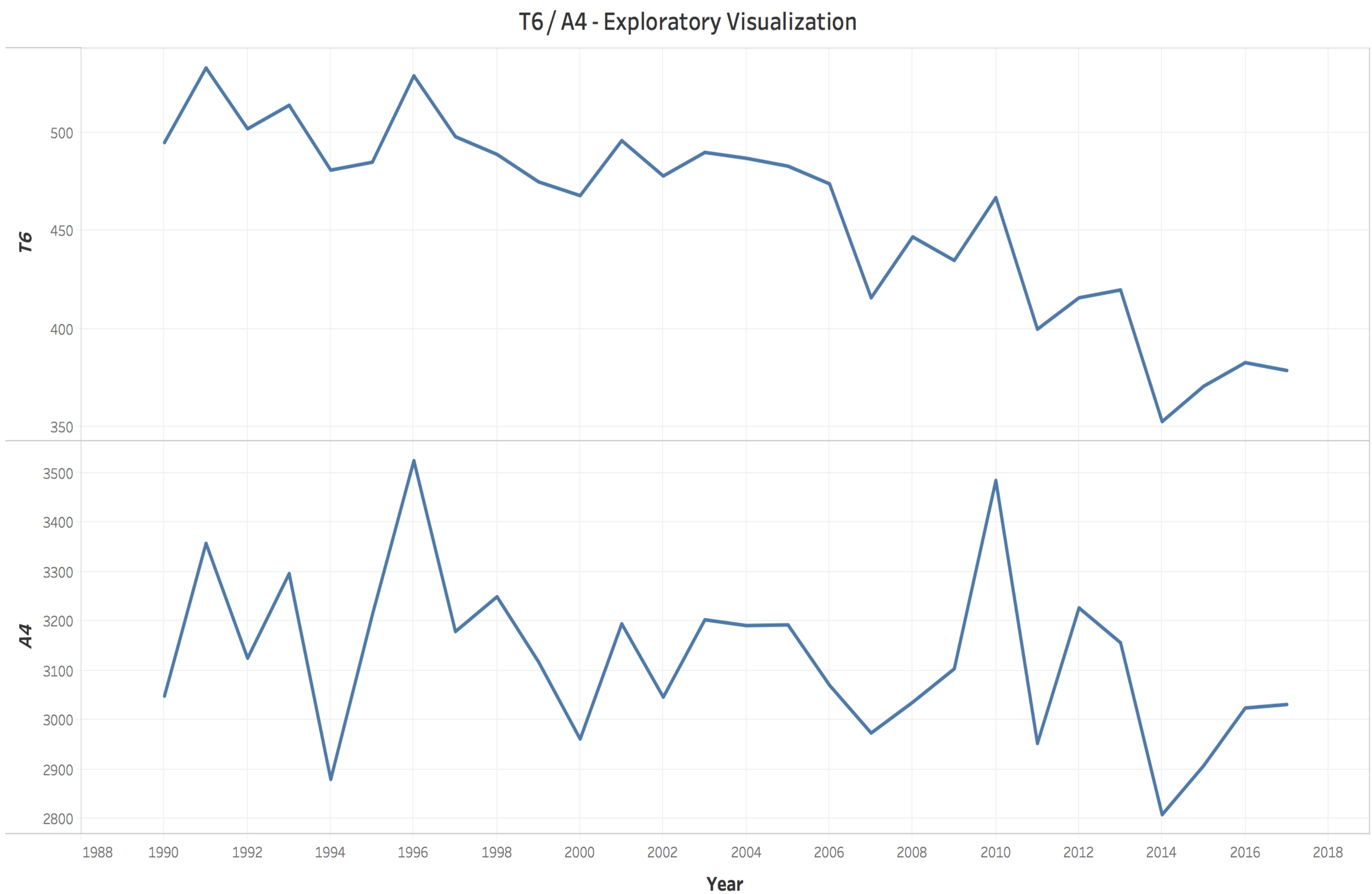

Figure 8 - Exploratory visualization for T6 and A4

4 RESEARCH METHODS

Our research main outcome comprises the design and implemention a computational learning framework for carbon emissions predictions incorporating a RReliefF driven features selection method, and an iterative neural network architecture construction.

The Relief family of algorithms (Kira and Rendell,1992; Robnik-Šikonja and Kononenko, 2003) incorporates the ability to qualify attributes in a dataset as a function of the Euclidean distance computed between neighbouring instances. Such non-parametric and non-myopic algorithms are able to capture non-linear relationships, and run in low-order polynomial time.

The algorithms outcomes are attributes weights probabilistically computed (Robnik-Šikonja and Kononenko, 2003). Figure 9 graphically presents the designed framework, composed by four modules: the Features Engineering Module (FEM), the Model Generation Module (MGM), the Model Evaluation Module (MEM), and the Prediction Explanation Module (PEM).

4.1 Features Engineering and RReliefF Algorithm

In the proposed learning framework, the features engineering and the model generation (i.e. NN architecture design) are iteratively accomplished by two modules, i.e. the Features Engineering Module (FEM) and the Model Generation Module (MGM), as can be observed in figure 9.

The FEM accomplishes the data dimensionality and quality treatment. Such combined treatment is done by a RReliefF driven Backwards Feature Elimination (BFE) aiming at: a) selecting relevant predictors, in order to reduce the dataset features space and avoid the dimensionality curse; b) reducing the computational complexity of the learning algorithm featured in the MGM; c) improving the accuracy of predictions; d) facilitating the interpretation of results, and; e) reducing the data storage space. The feature selection process observes the notation presented in table11.

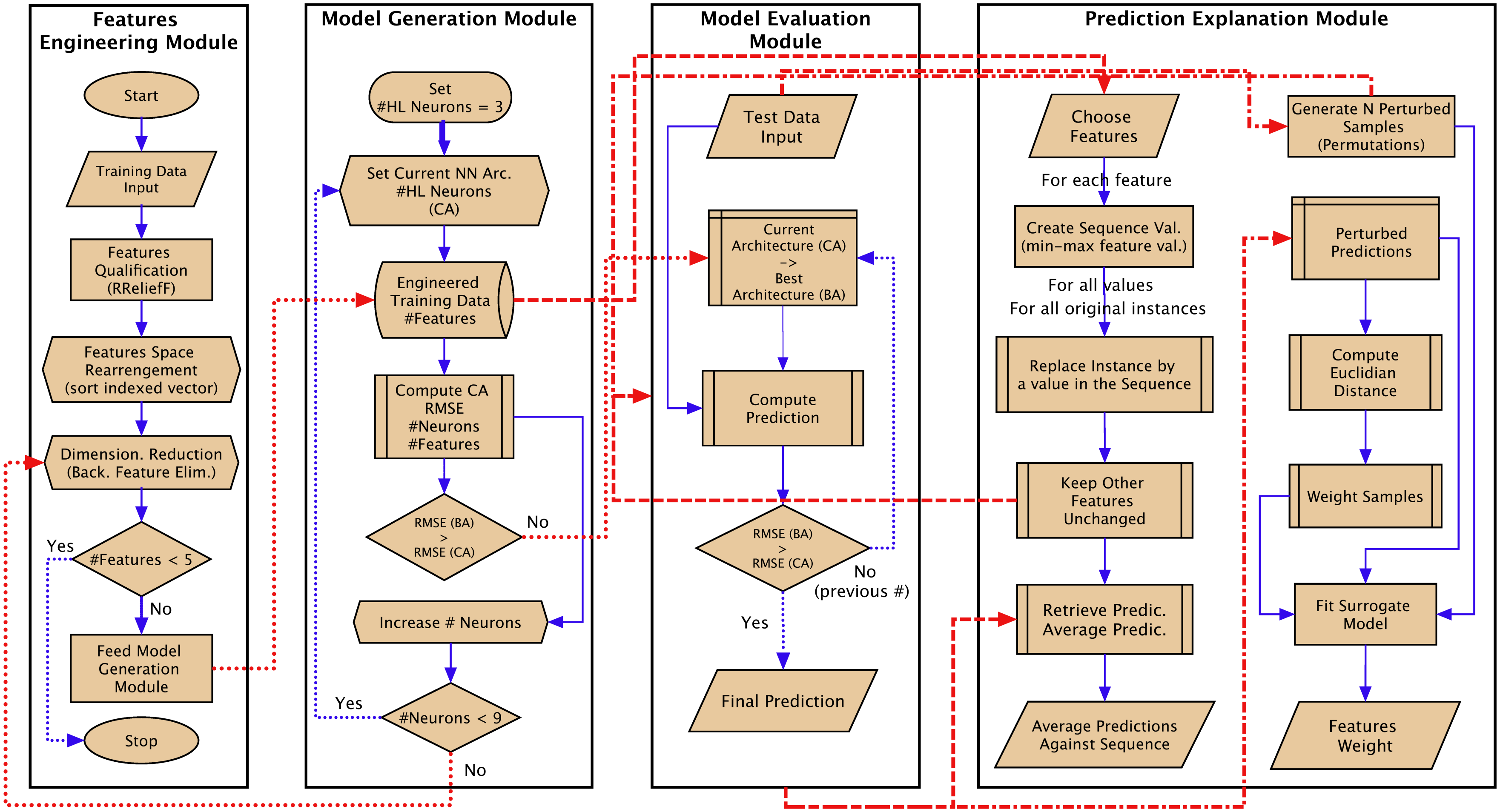

Figure 9 - Computational Learning Framework modules.

Table 11. RRelief algorithm notation.

Number of training instances: n (1)   Number of features (attributes): a (2)

Number of training instances (user defined; $m < n$) used to update W: m (3)

Vector of Attributes (features): $A_1, A_2, \dots, A_a$ (4)

Instance Space (examples): $I_1, I_2, \dots, I_n$ (5)

$R_i \in I$: randomly selected target instance (6)

$\tau(\cdot)$: prediction value (7) k: nearest instances I_j (8)

N_{dC}: weights for different $\tau(\cdot)$ (9) N_{dA}: weights for different attribute (10)

$N_{dC\&dA}[A]$: weights for different prediction and different attribute (11)

$d(i,j) = \frac{d_1(i,j)}{\sum_{l=1}^{k} d_1(i,l)}$ (12) $d_1(i,j) = e^{-\left(\frac{rank(R_i,I_j)}{\sigma}\right)^2}$ (13)

$rank(R_i, I_j)$: rank of instance I_j in a sequence of instances ordered by the distance from R_i (14)

σ: user defined parameter contolling the influence of the distance (15)

$diff\ (A, I_1, I_2) = \frac{|value\ (A,I_1) - value\ (A,I_2)|}{max(A) - min(A)}$ (16)

The RReliefF Algorithm, as presented in figure 10, uses as input a vector of attribute values $[\boldsymbol{A}]$ and predicted value τ for each training instance I, and provide as outcome a vector $\boldsymbol{W}$ containing the score of the attributes.

set all N_{dC}, $N_{dA}[A]$, $N_{dC\&dA}[A]$, $W[A]$ to 0;
for i := 1 **to** m **do begin**
    randomly select instance R_i;
    select **k** instances I_j nearest to R_i;
    for j := 1 **to** k **do begin**
        $N_{dC} := N_{dC} + \text{diff}(\tau(\cdot), R_i, I_j) \cdot d(i,j)$;
        for A := 1 **to** a **do begin**
            $N_{dA}[A] := N_{dA}[A] + \text{diff}(A, R_i, I_j) \cdot d(i,j)$;
            $N_{dC\&dA}[A] := N_{dC\&dA}[A] + \text{diff}(\tau(\cdot), R_i, I_j) \cdot$
                $\text{diff}(A, R_i, I_j) \cdot d(i,j)$;
        end;
    end;
end;
for A := 1 **to** a **do**
    $W[A] := N_{dC\&dA}[A]/N_{dC}$ - $(N_{dA}[A] - N_{dC\&dA}[A])/(m - N_{dC})$;

Figure 10 - RReliefF algorithm (Robnik-Šikonja and Kononenko, 2003).

As observed in the algorithm steps 8 and 9, RReliefF uses equation 16 for the iterative update of features weights according to theirs probabilistic relevance for the predictions. The intuition behind such weights computation as an expression of probabilistic relevance is conveyed by equation 17.

$$W[A] = \frac{P_{diffC|diffA} \cdot P_{diffA}}{P_{diffC}} - \frac{(1 - P_{diffC|diffA}) \cdot P_{diffA}}{1 - P_{diffC}} \qquad (17)$$

In the formulation of equation 17, P_{diffA} represents the probability of having different values of A within the nearest instances, P_{diffC} represents the probability of having a different prediction within the nearest instances, and $P_{diffC\,|\,diffA}$ represents the probability of having a different prediction given a different value of A within the nearest instances.

4.2 Iterative Neural Network Architecture Design

Within the FEM, the initial features A_1 ... A_{26} (potential predictors) are scored by the RReliefF algorithm, the features then are indexed and ranked based on the attributed scores, what leads to a rearranged feature set. Next step, the interaction with the MGM starts, i.e. the rearranged features set is fed to the Backpropagation Neural Network Architecture (NN/BP), the network is trained and the vector containing the current learning framework status (features subset, NN/BP architecture, NN/BP prediction accuracy) is stored. Subsequently, new features subsets are created by backward feature elimination, the NN/BP is trained with the new subset, and the learning framework status vector is updated. The NN/BP featured in the MGM has the following characteristics:

- Feed-forward network $\nu(x)$ defined as follows:

$$\nu(x) := f^L(W^L f^{L-1}(W^{L-1} \ldots f^1(W^1 x) \ldots)) \qquad (18)$$

- Number of layers: 3;
- Hidden layer activation function (transfer function): logistic (sigmoid), defined as follows:

$$f^{L-1}(x_i) = \frac{1}{1 + e^{-x_i}} \qquad (19)$$

- Training method: backpropagation;
- Normalization method: unit interval;
- Training cost (loss) function: residual sum of squares, defined as follows:

$$RSS = \sum_{i=1}^{n} (y_i - \nu(x_i))^2 \qquad (20)$$

where:

y_i is the i^{th} value of the target variable;

x_i is the i^{th} value of the predicting variable;

$\nu(x_i)$ is the predicted value of y_i.

As previously mentioned, the FEM and the MGM interact in an iterative way, and such interaction allows for an innovative BFE/RReliefF driven improvement for the NN/BP, i.e. the number of neurons in the hidden layer is changed along with the features subsets, and the learning framework status vector is updated accordingly. Once framework stop conditions are achieved, the status vector encloses the best features subset and the best NN/BP architecture in terms of prediction accuracy.

4.3 Learning Framework Evaluation

As observed in figure 9, the Model Evaluation Module (MEM) built in the implemented learning framework features the best NN/BP architecture (MGM outcome) and feeds it with the evaluation dataset. The module also features three additional ML models (Support Vector Machine - SVM, Gradient Boosting Machine - GBM, and Random Forest - RF), which are used to complement (benchmarking) the learning framework performance evaluation. The results of the benchmarking are presented in the next subsection, along with the overall assessment of the proposed framework performance.

4.3.1 Original Contribution

To the best of our knowledge, our proposed learning framework is the first to implement an iterative neural network architecture improvement supported by a Backward Feature Elimination search method driven by the RReliefF algorithm (Crespo et al., 2021).

The framework iteratively learns (NN/BP architecture, features subset) on *ad hoc* basis, i.e. specifically for each economy / industry sector. The implemented framework evaluation / validation processes benefited from real world data accrued by the EU, OECD, IEA, and the World Bank. The whole dataset covers the period 1990 - 2017, and the training and test datasets were determined in accordance to the Pareto principle for data sampling.

Table 12 presents the accuracy (Root Mean Square Error - RMSE for the test dataset) of the proposed learning framework for the totality of the EU28 CO2 emissions as well as for sectoral emissions. The table also presents the accuracy for the experiment control NN/BP, the framework featuring NN/BP supported by plain BFE (NN/BP-BFE), and the framework featuring NN/BP supported by RReliefF driven BFE (NN/BP-RReliefF/BFE).

The accuracy figures in table 12 demonstrate the improved performance of the proposed learning framework when compared to the control NN/BP, as well as to other possible framework designs. The table also presents the number of predictors in the learned features subset, and the number of neurons in the hidden layer.

As observed in table 12, the proposed approach combining backward feature elimination, RReliefF feature qualification, and iterative improvement of the NN/BP architecture effectively boosted the carbon emissions prediction accuracy for the EU28 scope dataset.

The computational complexity of the neural network is $O(h^a)$, where h is the number of hidden layers and a is the number of features (predictors), and the training process converged in less than 100 epochs, with a learning rate of 0.1. The RReliefF algorithm computational complexity is $O(n.m.a)$, where n is the number of training instances, and m is the number of training instances used by the algorithm to update the weights. The computational environment featured the CPU Intel i9-9900k supported by the GPU NVIDIA RTX 2080 (8Gb) and 32 Gb DDR4 RAM, and the whole prediction process took approximately 1 hour (average) per prediction target. Appendix 2 encloses complete information about the computational environment used in the research.

Table 12. Computational learning framework evaluation figures (Crespo et al., 2021).

Industry / Economy Sector	Model Parameters / Prediction Accuracy Metric	Methods			
		NN Control	*NN-BFE*	*NN-RReliefF/BFE*	*Proposed Framework*
Total Emissions (T1)	#Predictors	26	15	17	21
	# Neurons HL	3	3	3	7
	RMSE (MtCO2)	692.5226	191.9399	145.2302	143.2545
Energy Industries Emissions (T2)	#Predictors	26	9	24	18
	# Neurons HL	3	3	3	7
	RMSE (MtCO2)	264.1396	55.5251	80.3972	53.0494
Industry Emissions (T3)	#Predictors	26	8	12	20
	# Neurons HL	3	3	3	8
	RMSE (MtCO2)	139.3530	5.6810	7.6481	5.6749
Commercial and Public Services Emissions (T4)	#Predictors	26	11	5	18
	# Neurons HL	3	3	3	5
	RMSE (MtCO2)	15.8050	10.9382	9.0678	6.4312
Transport Emissions (T5)	#Predictors	26	21	14	21
	# Neurons HL	3	3	3	5
	RMSE (MtCO2)	63.3391	29.1528	40.6110	26.5271
Residential (T6)	#Predictors	26	12	12	16
	# Neurons HL	3	3	3	5
	RMSE (MtCO2)	99.7645	24.2505	22.3417	21.9795
Aviation (T7)	#Predictors	26	19	13	12
	# Neurons HL	3	3	3	4
	RMSE (MtCO2)	6.9858	6.9283	6.9406	6.9285

4.3.2 Learning Framework Validation

The validation of the original contribution provided by the proposed learning framework consisted of two different analysis. Firstly, its outcomes were compared to three current mainstream ML models (i.e. SVM, GBM, RF) using our research dataset. Secondly, our accuracy figures were benchmarked against the results of recently published researches targeting carbon emissions prediction.

In the validation process we worked with mean absolute percentage error - MAPE as the accuracy metric, and focused on the prediction target T1 (total CO2 emissions). Thus the best performing model (MAPE performance) designed by our proposed learning framework features 7 neurons in the hidden layer, and 16 predictors out of the candidates presented in table 3, i.e.: A18, A4, A23, A16, A8, A17, A10, A6, A22, A12, A11, A25, A9, A7, A24, and A26.

The trained framework achieved 2.28% accuracy performance (MAPE) on the test dataset, and table 13 allows us to benchmark the result of the proposed learning framework with the results of other NN/BP implementations.

Table 13. Computational learning framework benchmarking figures (MAPE) for prediction target T1 - Total EU28 Carbon Emissions-NN/BP specific (Crespo et al., 2021).

Method / Comparison Parameters		Proposed Framework	NN/BP (Zhou et al., 2017)	NN/BP (Sun et al., 2017)	NN/BP-CT (Liu et al., 2017)	NN/BP -IPSO (Zhou et al., 2017)	NN/BP (Zhou et al., 2018)	NN/BP (Sun et al., 2019)	NN/BP-PCA (Sun et al., 2019)	NN/BP-RF (Wen et al., 2020)
Scope		EU28	China	China	China	China	China	China	China	China
		1990 2017	1993 2014	1980 2014	1960 2011	1993 2014	1995 2014	1990 2016	1990 2016	1997 2017
Test Instances (years)		5	5	5	5	5	5	5	5	4
# Predictors		16 (26)	5	11	3	5	5	24	24	7 (17)
MAPE		2.28	5.07	5.49	3.43	2.53	3.72	4.03	2.87	8.09

Table 14 compares the result of our proposed framework with the results of three ML models (GBM, RF, SVM) supported by plain BFE, and using our research dataset, as well as against the results of recently published researches models other than NN/BP.

Table 14. Computational learning framework benchmarking figures (MAPE) for the prediction target T1 - Total EU28 Carbon Emissions-mainstream ML models (Crespo et al., 2021).

Method / Comparison Parameters		Proposed Framework	GBM-BFE	RF-BFE	SVM-BFE	Econometric / System Dynamics [6]	GM (Sun et al, 2017)	SVM-RF (Wen et al., 2020)	FGMVM (Jiang et al., 2020)
Scope		EU28	EU28	EU28	EU28	Ecuador	China	China	China
		1990 2017	1990 2017	1990 2017	1990 2017	1980 2010	1980 2014	1997 2017	2008 2016
Test Instances (years)		5	5	5	5	-	5	4	2
# Predictors		16 (26)	17 (26)	19 (26)	6 (26)	25	11	7 (17)	3
MAPE		2.28	7.05	7.98	17.58	15.96	5.77	13.37	15.14

The figures in tables 13 and 14 reinforce the relevance of the results accrued by our research, and confirm ANNs as a powerful algorithm capable of processing a large amount of non-linear and non-parametric data. The RReliefF algorithm, in turn, efficiently assess and rank the predicting variables (features) by effectively addressing non-linear relationships, time series, noisy and correlated features, as well as features interactions of high order (complex patterns associations).

The iterative combination of these two algorithms produced a powerful and scalable prediction tool able to process huge datasets featuring complex and incomplete data. The improved *ad hoc* learning capability of our framework makes it potentially applicable to any region in the world, and for any level of data aggregation

Whereas our original contribution represents an important step towards the better design and implementation of environment protection initiatives and policies, its effectiveness would be greatly enhanced once combined with an explainable Artificial Intelligence (XAI) technique, given the black-box nature of ANN algorithms.

4.3 Predictions Explanation

The learning framework evaluation process provided solid evidence on the effectiveness of our proof of concept (POC). However, the framework real-world applicability would immensely benefit from the potential understanding about how predictors (features) influenced the predictions. Such crucial knowledge would be key in supporting the design of effective carbon emissions reduction initiatives, policies and investments.

In such scenario, global and local (i.e. time period and/or feature-wise restricted) predictors impact analysis could greatly support the conception and implementation of broad / focused, short-medium-long term environmental actions, moreover those ones required due to the occurrence of disruptive events such as natural disasters or economic crises.

4.3.1 Explainable Artificial Intelligence - XAI

Within the AI / ML domain, explainability is understood as the extent to which the internal mechanics of an algorithm can be explained in human terms. Additionally, the proper understanding and application of the explainability concept requires the interpretability definition, i.e. the extent to which an AI / ML device allows for the understanding / anticipation of its behavior, upon changes in the inputs or on the algorithmic parameters.

Explainable Artificial Intelligence (XAI) is one of the most recent and relevant research focus within the Computational / Statistical Learning and Data Science domains. Whereas traditional Software Engineering rely on mature testing and verification processes in order to guarantee the quality of the designed applications, AI devices and Machine Learning applications, most of the times, require additional analysis to assess whether they are trustworthy, as regards to the impacts of their outcomes on human beings.

Regarding ML outcomes, it is critically important to ensure that its predictions accuracy performance relies on valid features (predictors) computations, i.e. the ML model is providing the right answer for the right reasons. Such requirement is particularly challenging when dealing with black-box ML models such as Artificial Neural Networks (ANN) and Support Vector Machines (SVM), moreover when their uses take place in areas such as diagnostic medicine, safety and security, public services, finance and insurance, and policy making.

In such context, a ML solution featuring a global XAI capability would reveal the modeled relationship among predictors and prediction targets, yet eventually subject to relevant approximations. Additionally, the inclusion of local XAI capability would allow the model to provide insights accrued from explanations / interpretations derived from specific dataset portions.

Specifically addressing our research, although ANNs are top performing, non-parametric and scalable algorithms, they lack the required algorithmic transparency (in terms of weights and bias) to adequately support policy making and decision-making processes targeting the complex environmental challenges.

Therefore, in order improve the applicability of our POC, tool we added an XAI module (PEM) featuring the capacity to unravel the relationships between the predictors and the predictions in both global and local perspectives.

4.3.2 Global Explanations - Partial Dependency

In order to unravel predictors-predictions relationships on a global level, the Predictions Explanation Module features a partial dependency technique based on Friedman (2001). Consider our prediction function ν (i.e. the ANN), data features $X = [A_1, A_2, \ldots, A_a] = [A_s, A_{-s}]$, where A_s is the feature to have the partial dependency computed, and $A_{-s} = \langle A_1, \ldots, A_{s-1}, A_{s+1}, \ldots, A_a \rangle$ for a total number of features (predictors) a, and n training data records (instances). The partial dependence function ν_s at A_s is then defined by:

$$\nu_s(A_s) = E_{A_{-s}}[\nu(A_s, A_{-s})] = \int \nu(A_s, A_{-s})\, dP(A_{-s}) \qquad (21)$$

As demonstrated by equation 21, the partial dependence ν_s is expressed in terms of the expectation of ν over the marginal distribution of all features in to A_{-s}. Given that each A_s has its own dependence function, which provides the average value of ν when A_s is fixed and A_{-s} varies over its marginal distribution $dP(A_{-s})$. However, the true function ν and $dP(A_{-s})$ are not know, thus the Monte Carlo method is applied and the dependence function is practically estimated by averaging over the training data records:

$$\nu_s(A_s) = \frac{1}{n}\sum_{i=1}^{n} \nu\,(A_s, A_{-s_i}) \qquad (22)$$

Finally, a specific feature global impact on the prediction is computed as the difference between the maximum dependence value minus the It is important to highlight that the partial dependence function relies on the assumption that the features in A are not correlated. Although the violation of such assumption is expected to redound in inconsistent average computations (i.e. unlikely / impossible impact values), the numerical and graphical outcomes of the learning framework allows us to eventually identify and disregard such undesirable results.

4.3.3 Local Explanations - Linear Interpretable Model-agnostic Models - LIME

Regarding local explanations, the implemented XAI module applies a Perturbation Approach, according to which inputs in the neighbourhood of a specific instance are perturbed, and the consequential variations on the outputs are used to assess the predictive impact of this instance (Robnik-Šikonja and Bohanec, 2018).

Among the methods within the XAI Perturbation-based approach, our learning framework was featured with the Local Interpretable Model-agnostic Explanations - LIME (Ribeiro et al., 2016). LIME is a scalable method that creates local interpretable surrogate models (explanations) around a given instance in order to estimate how data points influence the global model predictions.

LIME translates the explanation problem into an optimization problem. The search space comprises explanations generated by the local interpretable surrogate models $g \in G$, where G is a class of interpretable models. Locality is defined by a proximity measure $\pi(x, z)$ expressing the distance between an instance z and x. The interpretability degree of the surrogate model is assessed by means of a complexity measure $\Omega(g)$. Thus, by considering $f(x)$ the model to be explained, the local fidelity measure $\mathcal{L}\ (f, g, \pi)$ express how unfaithful g is in approximating f in the locality π. Finally the LIME outcome ensuring both interpretability and local fidelity is defined by:

$$\varepsilon(x) = \underset{g\, \in\, G}{\arg\min}\, \mathcal{L}(f, g, \pi) + \Omega(g) \quad (23)$$

Within the learning framework XAI module, the model to be explained is defined as $f(x) = \nu(x)$ (i.e. the ANN). G comprises ridge regression models for the perturbed sample $z' \in Z$ (perturbed samples dataset), such that $g(z') = \beta_g\ \cdot\ z'$. The complexity measure $\Omega(g)$ is expressed in terms of non-zero coefficients in the linear model, π is defined by the Euclidian distance, and the local fidelity is computed as square loss. We thus define:

$$\mathcal{L}(f, g, \pi) = \sum_{z, z \in Z} \pi(x, z)\ \ (\nu(z) - g(z'))^2 \quad (24)$$

From a general perspective, for each prediction to be explained, LIME algorithm permutes (perturbation) the observation n times; the statistics for each variable are extracted and permutations are then sampled from the variable distributions. The model to be explained then predicts the outcome of all permuted observations, and the algorithm calculates the Euclidian distance from all permutations to the original observation, and selects the m features with highest absolute weight in a ridge regression fit of the complex model outcome.

Afterwards a simple model is fitted to the permuted data, explaining the complex model outcome with the m features from the permuted data weighted by its distance to the original observation. And finally, the algorithm extracts the feature weights from the simple model and use them to explain the local behavior of the complex model.

5 EXPERIMENTATION RESULTS AND DISCUSSION

Upon validation of the developed learning framework, and in order to reinforce the applicability of our research contribution, we used a different datasets and different prediction targets, as presented hereafter.

5.1 European Union (EU28) Total CO2 Emissions Case

This case study targets EU28 total CO2 emissions (MtCO2, excluding land use, land-use change, and forestry - LULUCF), as recorded by the World Resources Institute's Climate Data Explorer (CAIT). The potential predictors, obtained from the World Bank (WB) database, include 24 candidate indicators, covering the period 1970 - 2014 (as presented in table 15 below).

Table 15. EU28 case study candidate predictors.

Candidate Predictors (prediction model features)	
A1 -Total Energy Use (MtOE / WB)	A13 - Population (WB)
A2 - Fossil Fuel Energy Use (MtOE / WB)	A14 - Temperature (Population Weighted HDD / Eurostat)
A3 - Alternative and Nuclear Energy Use (MtOE / WB)	A15 - Temperature (Population Weighted CDD / Eurostat)
A4 - Combustible Renewables and Waste Energy Use (MtOE / WB)	A16 - GDP (Current M US$ / WB)
A5 - Total Electricity Production (GWh / WB)	A17 - GNI (Current M US$ / WB)
A6 - Total Electricity Use (GWh / WB)	A18 - Final consumption expenditure (current M US$ / WB)
A7 - Electricity Production_Coal (GWh / WB)	A19 - General government final consumption expenditure (current M US$ / WB)
A8 - Electricity Production_Oil (GWh / WB	A20 - Households and NPISHs Final consumption expenditure (current M US$ / WB)
A9 - Electricity Production_Natural Gas (GWh / WB)	A21 - Adjusted net national income (current M US$ / WB)
A10 - Electricity Prodcution_Nuclear (GWh / WB)	A22 - Air transport_Freight (million ton-km / WB)
A11 - Electricity Production_Hydroelectric (GWh / WB)	A23 - Air transport_Passengers carried / WB)
A12 - Electricity Prodcution_Renewables (GWh / WB)	A24 - Education expenditure (current M US$ / WB)

With the object of validating the learning framework with the new dataset, we conducted 4 experiments and analyzed their accuracy performance. The training dataset for the control experiments (i.e. Control 1 and Control 2) consisted of the 1970 - 2005 period instances, and the learning framework predicted CO2 emissions for the period 2006 - 2014. The control experiments configuration relies on the Pareto principle for data sampling, and aims at assessing the framework performance under ideal conditions.

The actual experiments (i.e. Experiment 1 and Experiment 2) have as training input the candidate predictors instances of the 1970 - 2009 period, and the predictions covers the 5 years period 2010 - 2014, what resembles the common EU-ETS CO2 emissions allocation timespan. Table 16 presents the framework accuracy performance, for all experiment configurations.

Table 16. Learning framework accuracy performance for different experiment configurations, for prediction target EU28 Total CO2 emissions.

Experiment Configuration (Prediction			Model Complexity		Best Accuracy Performance				
Experiment	Learning Instances	Predicted Instances	# Predictors (features)	# Neuros HL	Error Type	RMSE (MtCO2)	MAE (MtCO2)	MPE (%)	MAPE (%)
Control 1	36	9	21	9	Test Error	235.4859	187.3018	2.4809	4.9159
Control 2			17	8	Training Error	179.2002	145.3326	0.9703	3.4755
Experiment 1	40	5	19	7	Training Error	234.8836	177.4893	3.3558	4.2183
Experiment 2			22	8	Test Error	155.4359	120.1669	1.0530	3.5018

As can be observed in table 16, the learning framework performed well in all experiment configurations, what confirms the proof of concept (POC) findings presented in chapter 5. Among the actual experiments, Experiment 2 presented the best accuracy performance for all computed metrics.

In order to ensure the value of our implemented learning framework, we benchmarked experiment 2 against two multiple linear regression baseline models. The baseline model 1 features all the 24 candidate predictors for this case study. Baseline model 2 features the 22 predictors as selected by the learning framework, and the results are showed in table 17.

Table 17. Learning framework accuracy performance for different experiment configurations, for prediction target EU28 Total CO2 emissions.

Prediction Target: Total CO2 Emissions								
Experiment	Learning Instances	Predicted Instances	# Predictors (features)	Accuracy Performance				
				Error Type	RMSE (MtCO2)	MAE (MtCO2)	MPE (%)	MAPE (%)
Baseline model 1	40	5	24	Test Error	396.7206	354.2928	-10.3835	10.3835
Baseline model 2			22	Test Error	312.6989	283.5342	-8.2977	8.2977
Experiment 2			22	Test Error	155.4359	120.1669	1.0530	3.5018

Regarding the baseline linear models, regularization techniques (Lasso, Ridge) did not increase the their accuracy performance and, as such, we confirm the value of our research contribution. Therefore, Experiment 2 configuration will be used hereafter in order to present and discuss all the outcomes provided by the implemented learning framework.

5.1.1 Learning Framework Outcomes and Predictions Explanation

Experiment 2 configuration predicted CO2 emissions for the years 2010, 2011, 2012, 2013 and 2014, with accuracy performance of 3.5018% MAPE and 155.4359 MtCO2 RMSE. Although such accuracy performance might reassure the relevance of our research contribution, the potential explanation on how predictors contributed to the predictions would greatly improve its effectiveness in supporting the delineation of environment protection initiatives and policies. Therefore, we present hereafter the outcomes of XAI module featured in our learning framework.

At this point it is extremely important to highlight that the exploration of the XAI domain is in its very beginning. Thus, this part of our contribution is not intended to provide definitive and robust explanations as regards to the predictors impacts. It is rather meant to provide educated insights useful for both research paths, i.e. XAI domain exploration, and Climate Change avoidance efforts.

5.1.1.1 Global Explanation

The XAI global explanation method featured in our learning framework, as presented in section 4.3.2, provided the outcomes summarized in table 18. The features impacts are presented in three different forms, i.e.: a) the absolute partial dependence function outcome values ('Impact'); b) the feature contribution percentage values ('Pct'); and c) the standardized outcome values, with the greater contribution set to 1 (Std_Impact). We then ranked the features according to their standardized impact on the predictions, as presented in figure 11.

Table 18. Predictors global impact- EU28.

Partial Dependence Function Outcomes - Total CO2 Emissions (T1)								
Feature	Impact	Pct_Impact	Std_Impact		Feature	Impact	Pct_Impact	Std_Impact
A1	144.132854	0.03646731	0.21281584		A21	144.694348	0.03660937	0.2136449
A10	318.319437	0.08053856	0.47000678		A22	81.230962	0.02055239	0.11993959
A11	223.392462	0.05652092	0.32984467		A23	138.388991	0.03501404	0.20433488
A13	91.2514313	0.02308769	0.13473507		A24	427.127003	0.10806816	0.63066392
A14	410.683082	0.10390765	0.60638406		A3	112.279696	0.02840808	0.16578384
A16	139.346322	0.03525626	0.2057484		A4	25.8080618	0.00652974	0.03810626
A17	118.048134	0.02986757	0.17430108		A5	108.234275	0.02738455	0.15981067
A18	47.8574516	0.0121085	0.07066275		A6	77.5376221	0.01961793	0.11448628
A19	29.4748616	0.00745749	0.04352039		A7	327.297902	0.08281022	0.48326371
A2	677.265635	0.17135618	1		A8	49.3176515	0.01247795	0.07281877
A20	56.323643	0.01425054	0.0831633		A9	204.37348	0.0517089	0.30176266

The partial dependence function only indicates the absolute impact values, and such values are computed over the whole prediction period; in our research case, the impact figures refer to the period 2010 - 2014. Thereafter, the analysis of the ranked predictors clearly confirms how impacting the use of fossil fuel (feature A2) is. Such finding, however, only corroborates to the common understanding about the CO2 emissions dynamics, what leads us to a deeper analysis of predictors with less clear and/or straightforward impacts.

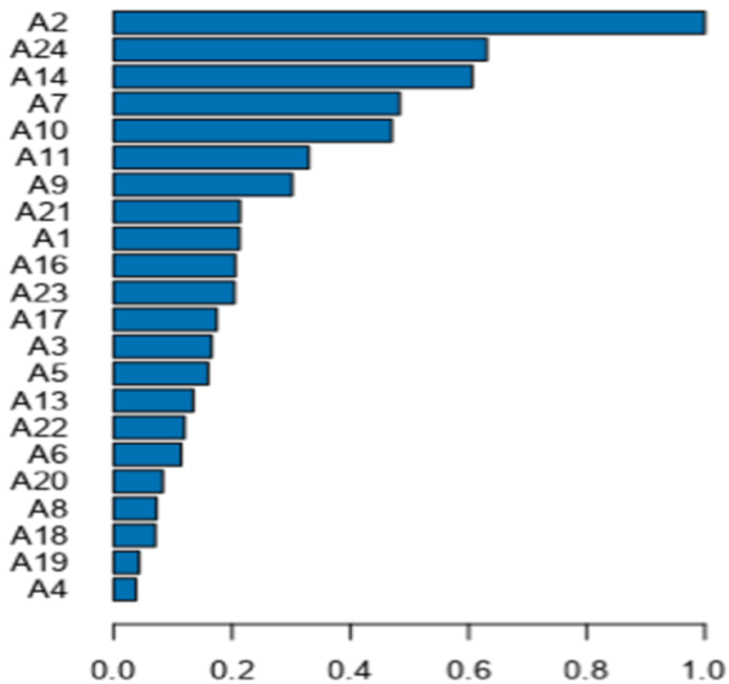

Figure 11 - Standardized features impact - EU28 Total CO2 emissions.

The second greater impacting feature, i.e. education expenditure (A24), makes an interesting research case, and definitely should lead us to further investigation. Figure 12 presents the scatter plot for the scaled values for total CO2 emissions (T1) and A24 for the training dataset. We observe in the figure the following elements: a) the least-squares linear regression curve (solid line); b) a loess non-parametric local regression curve (dashed line); c) the loess curves for the positive and negative root-mean-square residuals from the original loess curve (dot-dashed lines); and d) the univariate marginal boxplots.

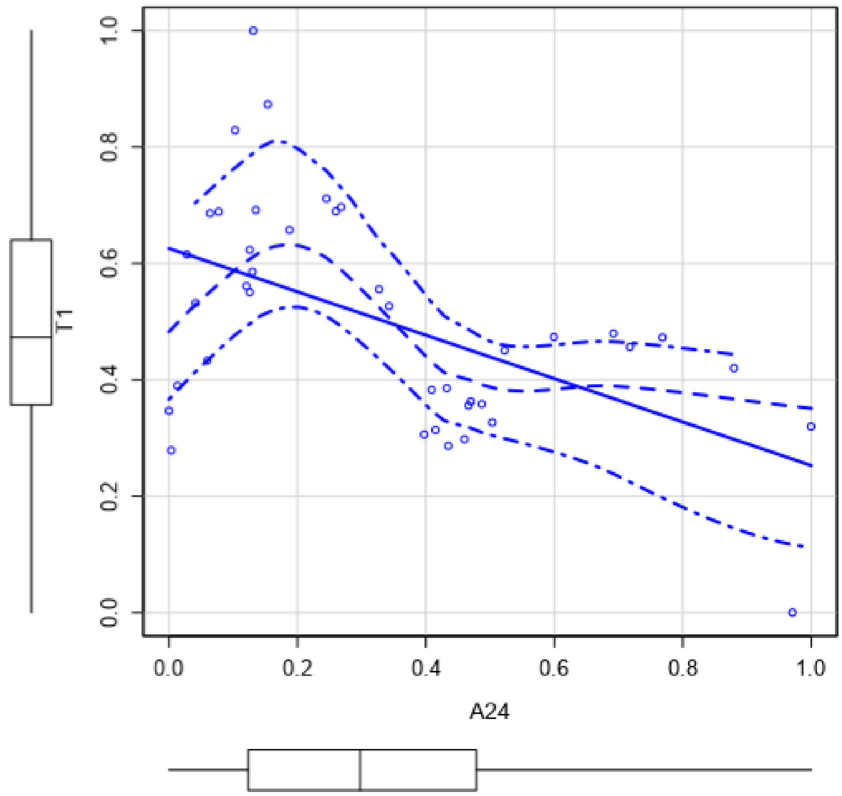

Figure 12 - Scatter plot and linear models for T1 - A24.

The regression curves were studied so that we could assess the possibility of implementing the predictions by means of simpler models. And the loess models on the residuals helped us to understand conditional spread and asymmetry in the error, also in the attempt to potentially solve the prediction problem with less complex models. Such models, however, performed very poorly on test data.

Figure 13 presents the effect plot representing how our neural network architecture modeled the relationship between T1 and A24 in the context of our dataset (training data), considering the data complexities discussed in Chapter 3, and help us understand why the simpler models failed.

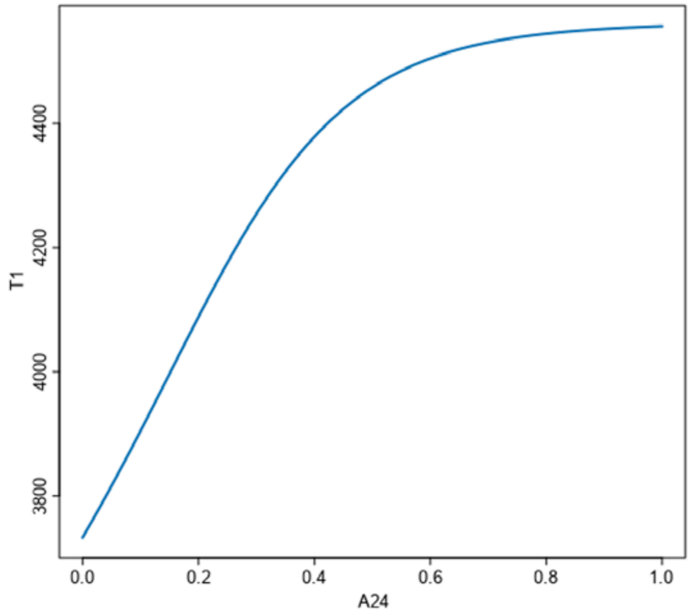

Figure 13 - Effect Plot for T1 - A24.

Figure 13 presents a completely different model when compared to the simpler regression models. Moreover, in figure 14 we observe the outcomes of the partial dependence function, over the learning framework predictions (years 2010-2014), in terms of a partial dependence plot. Such plot depicts how the neural network model fitted the relationship between T1 and 24 over the test dataset, as explained in section 4.3.2, and corroborates the suitability of a more complex ML model.

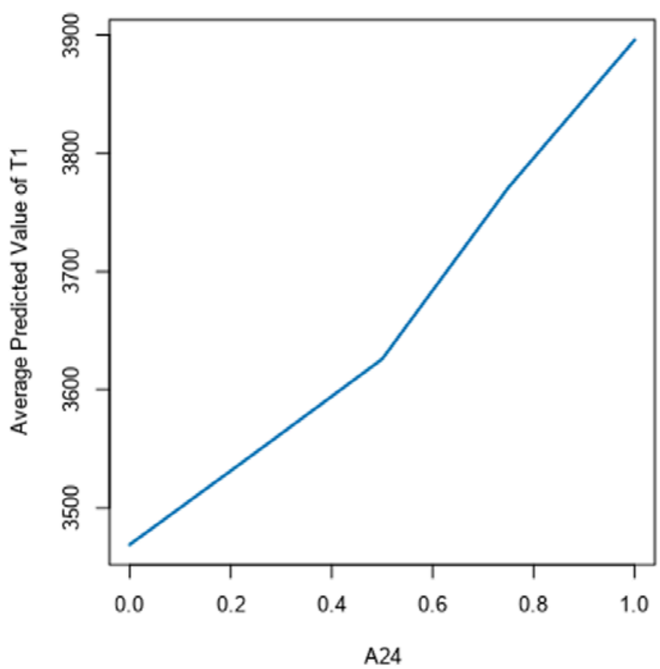

Figure 14 - Partial Dependence Plot for T1 - A24.

The third greater feature A14 (i.e. temperature - HDD) impacting dynamics study is also worth furthering in future work, mainly considering the findings presented in section 3.2.1. The following figure 15 combines the scatter plot, the effect plot, and the partial dependence plot for the predictor A14, and also allows us to accomplish a deeper analysis of its influence of the CO2 emissions.

Based on such analysis, we acknowledged, for instance, how important heating issues (heating methods, heating efficiency, commercial buildings and households thermal preparation, etc.) are in the context of CO2 emissions. We also know that climate and weather phenomena directly determine temperature patterns, usually conditioned by seasonal and / or specific local factors. In such scenario, a more granular analysis would greatly contribute to a better understanding of the predictor-prediction influence dynamics.

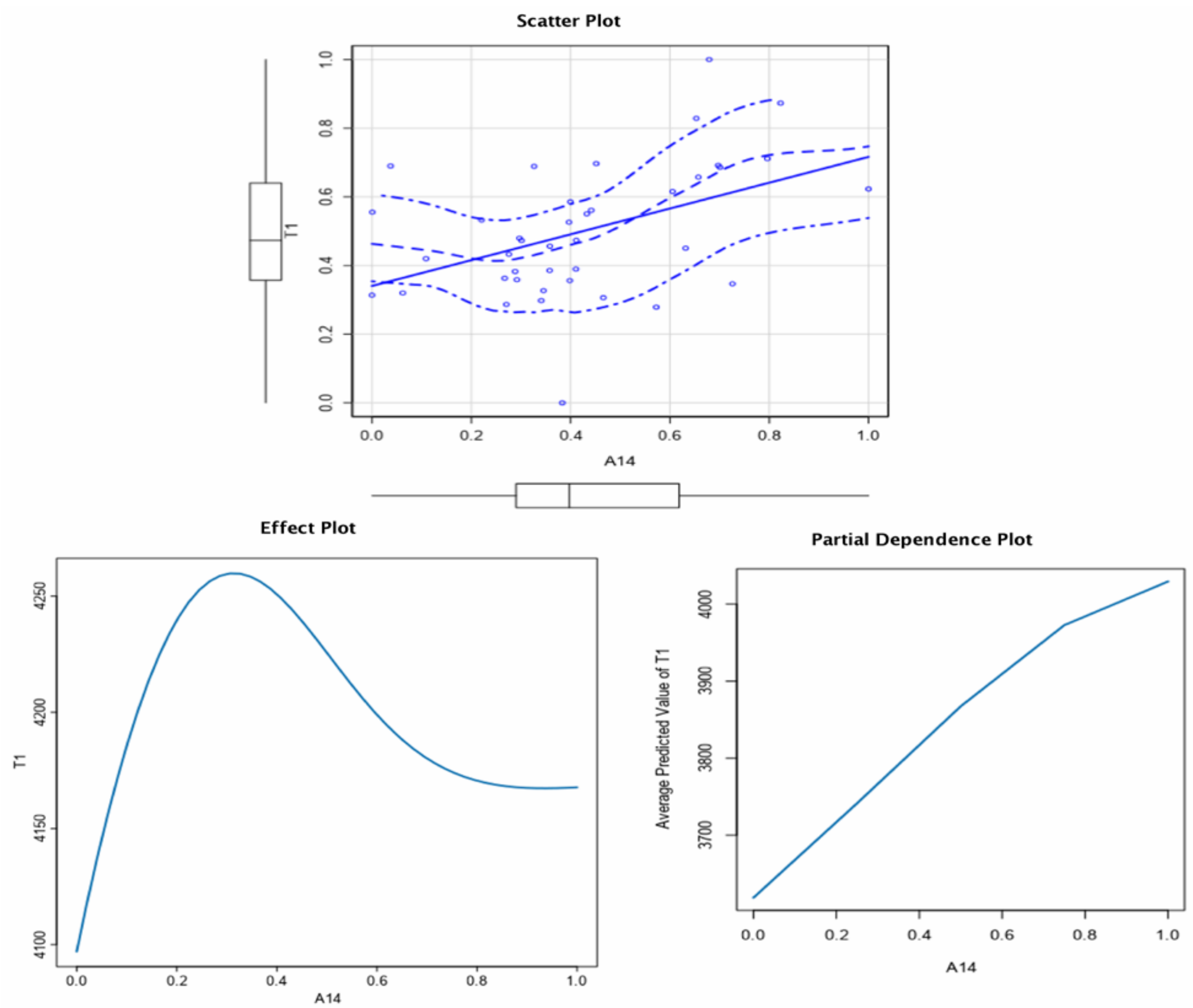

Figure 15 - Scatter Plot, Effect Plot, and Partial Dependence Plot joint presentation for T1 - A14.

When it comes to the further investigation of the predictors impacting dynamics, it is important to bare in mind the ANN capacity to grasp complex non-linear relationships as well as eventual correlations among features. In such context, we might expect, for instance, an increase in energy production from oil leading to a reduction on total predicted CO2 emissions, once such increase drives to the reduction of energy production from coal, which is a more polluting process.

The identification of the aforementioned phenomenon, similarly to the challenges faced on the T1-A14 relationship, requires the analysis of the predictors' impacts on a local level, which may be accomplished by means of the outcomes provided by the local explanation method featured in our learning framework.

5.1.1.2 Local Explanations

In order to explore the potentialities of our learning framework local explanation capability, we will continue the analysis of the relationship between the predictor A14 (temperature HDD) and the total CO2 emissions. As explained in section 4.3.3, tables 19, 20, 21, 22, and 23 compiles the explanations of the predictions for the years 2010, 2011, 2012, 2013, and 2014 respectively, considering the local impact of each of the 22 predictors.

In the tables we can observe the following values: a) the actual emissions; b) the learning framework surrogate linear model intercept (constant); c) the learning framework prediction accomplished by the surrogate linear model; d) the surrogate linear local model R-squared measure (R2); e) the computed features' weights (local Ridge regression model coefficients); f) the influence intervals.

Regarding the influence intervals, the figures presented in the tables indicate the values of the predictor (observed / to be maintained) that had driven / would drive such predictor to impact the prediction as indicated by the attributed feature weight.

We then continued the investigation of temperature HDD (A14) impacts on the predictions, this turn by means of local explainability. The figures in table 19, for instance, indicate that temperature values kept under 0.632 (scaled value) led to a very mild negative impact (i.e. -9.177758829) on total CO2 emissions in 2010.

Table 19. Prediction local explanation - EU28 2010.

T1 - Year (case): 2010						
Actual Emissions	Surrogate Model Intercept	Framework Surrogate Model Prediction	Surrogate Model R2	Feature	Feature Weight	Influence Interval
3709.97065	3612.03796	3658.06924	0.94102422	A2	16.70921252	0.713 < A2
				A14	-9.177758829	0.632 < A14
				A1	26.23353674	0.788 < A1
				A8	102.0943548	0.665 < A8
				A7	-70.18413094	A7 <= 0.644
				A13	43.04655374	A13 <= 0.406
				A24	-128.7303733	A24 <= 0.124
				A11	-202.095464	0.689 < A11
				A16	45.00174737	A16 <= 0.127
				A20	15.64716751	A20 <= 0.137
				A21	87.98202268	A21 <= 0.127
				A4	-17.630824	0.5049 < A4
				A18	53.71611893	A18 <= 0.138
				A17	-131.0937024	A17 <= 0.127
				A19	16.69259266	0.138 < A19 <= 0.400
				A5	23.03029779	0.914 < A5
				A22	-0.007659697	0.741 < A22
				A10	-56.27366059	0.902 < A10
				A6	201.6021454	0.905 < A6
				A3	31.65827713	0.285 < A3 <= 0.766
				A23	19.64687642	A23 <= 0.109
				A9	-21.83605346	0.566 < A9

In table 20, for the year 2011, we observe that temperature values kept under or (at most) equal to 0.337 (scaled value) led to a (slightly greater, whilst still very mild) negative impact (i.e. -18.41449669) on emissions. As regards to 2012 (table 21), values kept between 0.438 and 0.632 lead to a positive impact (i.e. 20.0605607) on emissions. On 2013 though, as presented in table 22, the aforementioned temperature values led to a huge positive impact (i.e. 325.2005964) on total CO_2 emissions. Finally, in the year 2014 (table 23) we observe that temperature values kept under or (at most) equal to 0.337 led to a huge negative impact (i.e. -264.9825967) on the emissions. And such findings indicate consistency between the global and the local explanations implemented techniques. The local explanation tables for the training dataset are compiled in Appendix 4.

Table 20. Prediction local explanation - EU28 2011.

T1 - Year (case): 2011						
Actual Emissions	Surrogate Model Intercept	Framework Surrogate Model Prediction	Surrogate Model R2	Feature	Feature Weight	Influence Interval
3562.25376	3933.65891	3991.24147	0.99827398	A2	-44.708506	0.606 < A2 <= 0.713
				A14	-18.414497	A14 <= 0.337
				A1	-22.844961	0.513 < A1 <= 0.715
				A8	-44.084863	0.461 < A8 <= 0.665
				A7	13.4062302	0.644 < A7 <= 0.797
				A13	-133.90062	A13 <= 0.406
				A24	67.7996364	0.591 < A24
				A11	-2.8847993	A11 <= 0.457
				A16	66.2222044	0.592 < A16
				A20	25.4649633	0.601 < A20
				A21	-121.46384	0.595 < A21
				A4	-44.433791	A4 <= 0.0681
				A18	35.5982139	0.601 < A18
				A17	160.619934	0.592 < A17
				A19	-43.049409	0.592 < A19
				A5	8.3738199	0.372 < A5 <= 0.639
				A22	-44.840295	0.741 < A22
				A10	205.744496	0.274 < A10 <= 0.805
				A6	-42.347954	0.377 < A6 <= 0.638
				A3	15.0122752	A3 <= 0.285
				A23	66.8022629	0.263 < A23 <= 0.609
				A9	-44.48793	0.566 < A9

Table 21. Prediction local explanation - EU28 2012.

T1 - Year (case): 2012						
Actual Emissions	Surrogate Model Intercept	Framework Surrogate Model Prediction	Surrogate Model R2	Feature	Feature Weight	Influence Interval
3513.81632	4630.49356	3812.08003	0.98970941	A2	-268.14672	0.470 < A2 <= 0.606
				A14	20.0605607	0.438 < A14 <= 0.632
				A1	-131.18377	A1 <= 0.513
				A8	-97.512199	0.461 < A8 <= 0.665
				A7	-33.237177	0.865 < A7
				A13	120.685974	A13 <= 0.406
				A24	-148.97633	A24 <= 0.124
				A11	-59.43559	A11 <= 0.457
				A16	-58.506108	A16 <= 0.127
				A20	-33.534844	A20 <= 0.137
				A21	-112.67576	A21 <= 0.127
				A4	91.9854981	0.5049 < A4
				A18	71.9225408	A18 <= 0.138
				A17	-46.053591	A17 <= 0.127
				A19	112.850595	A19 <= 0.138
				A5	-12.209662	0.372 < A5 <= 0.639
				A22	-27.288562	A22 <= 0.140
				A10	-14.089269	A10 <= 0.274
				A6	28.4678414	0.638 < A6 <= 0.905
				A3	-80.055045	A3 <= 0.285
				A23	-4.1697561	0.263 < A23 <= 0.609
				A9	-137.31215	0.224 < A9 <= 0.566

Table 22. Prediction local explanation - EU28 2013.

T1 - Year (case): 2013						
Actual Emissions	Surrogate Model Intercept	Framework Surrogate Model Prediction	Surrogate Model R2	Feature	Feature Weight	Influence Interval
3433.93928	3607.85209	4203.03451	0.98706912	A2	147.718748	A2 <= 0.470
				A14	325.200596	0.438 < A14 <= 0.632
				A1	75.8844676	A1 <= 0.513
				A8	173.586787	A8 <= 0.338
				A7	-34.190307	0.644 < A7 <= 0.797
				A13	-105.17006	0.406 < A13 <= 0.640
				A24	148.949336	0.392 < A24 <= 0.591
				A11	-512.68439	0.689 < A11
				A16	-157.44196	0.592 < A16
				A20	74.5297742	0.404 < A20 <= 0.601
				A21	113.976237	0.595 < A21
				A4	-33.778555	0.5049 < A4
				A18	-32.521886	0.405 < A18 <= 0.601
				A17	16.6719962	0.592 < A17
				A19	13.606445	0.592 < A19
				A5	144.874964	0.372 < A5 <= 0.639
				A22	-134.6204	0.140 < A22 <= 0.363
				A10	145.787843	A10 <= 0.274
				A6	2.07286224	0.377 < A6 <= 0.638
				A3	69.0586435	0.285 < A3 <= 0.766
				A23	-7.071713	0.263 < A23 <= 0.609
				A9	160.742994	0.224 < A9 <= 0.566

Table 23. Prediction local explanation - EU28 2014.

T1 - Year (case): 2014						
Actual Emissions	Surrogate Model Intercept	Framework Surrogate Model Prediction	Surrogate Model R2	Feature	Feature Weight	Influence Interval
3246.99368	4627.91838	3263.07105	0.96633996	A2	-296.64813	A2 <= 0.470
				A14	-264.9826	A14 <= 0.337
				A1	-9.5412737	A1 <= 0.513
				A8	-49.322855	A8 <= 0.338
				A7	-137.60411	A7 <= 0.644
				A13	168.094198	0.805 < A13
				A24	27.1974996	0.591 < A24
				A11	-22.139102	0.689 < A11
				A16	-168.80832	0.592 < A16
				A20	-18.279535	0.601 < A20
				A21	-54.195235	0.595 < A21
				A4	-69.215558	0.5049 < A4
				A18	-37.815498	0.601 < A18
				A17	-135.93829	0.592 < A17
				A19	-33.874442	0.592 < A19
				A5	75.7487551	A5 <= 0.372
				A22	-13.194805	0.363 < A22 <= 0.741
				A10	151.741288	A10 <= 0.274
				A6	-150.4886	A6 <= 0.377
				A3	-80.407627	0.946 < A3
				A23	15.0448258	0.609 < A23
				A9	-260.21791	A9 <= 0.188

5.2 Canada Emissions Case

The learning framework was also applied for the prediction of Canadian emissions. This case study targeted total CO2 emissions, as well as emissions from transportation, and residential buildings and commercial/public services. Table 24 presents the candidate predictors, i.e. Canadian economic/energy indicators gathered from the World Bank databases, covering the period 1960 - 2014.

Table 24. Canada case study candidate predictors.

Candidate Predictors (prediction model features)	
A1 -Total energy use (MtOE / WB)	A13 -Merchandise imports (current M US$ / WB)
A2 - Alternative and nuclear energy use (Mtoe / WB)	A14 - Households and NPISHs Final consumption expenditure (current M US$ / WB)
A3 - Combustible renewables and waste energy use (Mtoe / WB)	A15 - Final consumption expenditure (current M US$ / WB)
A4 - Total electricity production (GWh / WB)	A16 -General government final consumption expenditure (current M US$ / WB)
A5 - Electricity production_Hydroelectric (GWh / WB)	A17 - Urban population (WB)
A6 - Electricity production from oil, gas and coal (GWh / WB)	A18 - Food production index (2004-2006 = 100 / WB)
A7 - Electricity production_natural gas (GWh / WB)	A19 - Aquaculture production (metric tons / WB)
A8 - Electricity production_coal (GWh / WB)	A20 - Transport services (% of commercial service exports / WB)
A9 - Electricity production_oil (GWh / WB	A21 - Transport services (% of commercial service imports / WB)
A10 - Electricity prodcution_Nuclear (GWh / WB)	A22 - Transport services (% of service exports, BoP / WB)
A11 - Electricity production from renewable sources, excluding hydroelectric (GWh / WB)	A23 - Transport services (% of service imports, BoP / WB)
A12 - Merchandise exports (current M US$ / WB)	A24 - Merchandise trade (current M US$ / WB)

Table 25 presents the performance of the learning framework on predicting CO2 emissions, as previously mentioned. The performance figures, for the three predicting targets, demonstrates the consistency and robustness of our research contribution

Table 25. Learning framework accuracy performance for Canada case studies.

Canada Case Studies									
			Model Complexity		Best Accuracy Performance				
Experiment	Learning Instances	Predicted Instances	# Predictors (features)	# Neuros HL	Error Type	RMSE (MtCO2)	MAE (MtCO2)	MPE (%)	MAPE (%)
Canada - Total	50 (1960-2009)	5 (2010-2014)	9	9	test	10.5362	9.9820	1.2744	1.9058
Canada - Transportation			13	9	test	5.2355	4.0486	2.4433	2.4433
Canada - Residential Buildings/Commercial-Public Services			12	8	test	2.9453	2.4345	1.1734	3.2677

5.2.1 Canada Total CO2 Emissions

The learning framework predicted total Canadian CO2 emissions with MAPE performance of 1.9058%. The predicting model features 9 neurons (hidden layer) and 9 predictors, which were ranked by RReliefF as follows: A23 (transport services, % of service imports), A22 (transport services, % of service exports), A20 (transport services, % of commercial service exports), A21 (transport services, % of commercial service imports), A1 (total energy use), A17 (urban population), A6 (electricity production from oil, gas and coal), A8 (electricity production from coal), and A3 (combustible renewables and waste energy).

Table 26 and figure 16 present the global explanation outcomes for the Canadian total CO2 emissions for the predictions 2010 - 2014.

Table 26. Predictors global impact - Canada / total CO2 emissions.

Partial Dependence Function Outcomes - Total CO2 Emissions / 2010 - 2014			
Feature	Impact	Pct_Impact	Std_Impact
A1	16.50184891	0.216323947	0.70326394
A17	23.46465952	0.307599941	1
A20	4.103792775	5.38E-02	0.174892492
A21	6.917601827	9.07E-02	0.294809384
A22	0.717612262	9.41E-03	3.06E-02
A23	6.937871511	9.09E-02	0.295673223
A3	3.489040442	4.57E-02	0.148693419
A6	8.460628872	0.110911004	0.360569002
A8	5.689986775	7.46E-02	0.242491768

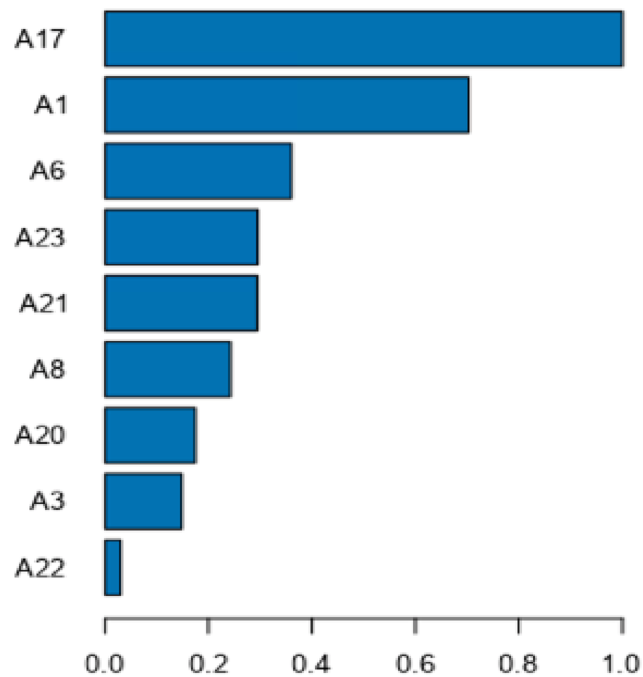

Figure 16 - Standardized features impact - Canada total CO2 emissions.

As can be observed in figure 16, urban population and total energy use were the main drivers of CO2 emissions for the period 2010 - 2014. Such impacts can be better analyzed by means of the local explanations provided by the learning framework, as presented in tables 27, 28, 29, 30, and 31.

Table 27. Prediction local explanation - Canada 2010 / total CO2 emissions.

Total CO2 Emissions - Year (case): 2010 / MtCO2						
Actual Emissions	Surrogate Model Intercept	Framework Surrogate Model Prediction	Surrogate Model R2	Feature	Feature Weight	Influence Interval
527.263262	306.756096	548.3443575	0.78325513	A23	20.2320708	A23 <= 0.143
				A22	19.0529393	A22 <= 0.166
				A20	-13.011613	A20 <= 0.165
				A21	35.4211879	A21 <= 0.132
				A1	126.375308	0.855 < A1
				A17	55.6209404	0.744 < A17
				A6	22.7066019	0.800 < A6
				A8	2.75491345	0.613 < A8 <= 0.763
				A3	-27.564087	0.533 < A3 <= 0.805

Table 28. Prediction local explanation - Canada 2011 / total CO2 emissions.

Total CO2 Emissions - Year (case): 2011 / MtCO2						
Actual Emissions	Surrogate Model Intercept	Framework Surrogate Model Prediction	Surrogate Model R2	Feature	Feature Weight	Influence Interval
522.774854	230.391147	556.1237521	0.83403484	A23	31.4410302	0.143 < A23 <= 0.293
				A22	10.7273701	A22 <= 0.166
				A20	18.7981503	A20 <= 0.165
				A21	-2.585209	0.132 < A21 <= 0.271
				A1	172.766559	0.855 < A1
				A17	113.102245	0.744 < A17
				A6	4.510506	0.800 < A6
				A8	-13.163365	0.613 < A8 <= 0.763
				A3	-9.8646817	0.533 < A3 <= 0.805

Tables 27, 28, 29, 30, and 31 allows for a more detailed perspective on how each predictor impacted the total CO2 emissions in each particular case (year), and the local explanations present a high level of consistency with the global explanation outcomes.

However, we may observe that urban population and total energy use, i.e. predictors A17 and A1 (whilst again indicated as the two most impacting drivers) appeared in a different order, with A1 being identified, from a local explanation perspective, as the most impacting predictor. Such discrepancies are to be subject to future investigation.

Table 29. Prediction local explanation - Canada 2012 / total CO2 emissions.

Total CO2 Emissions - Year (case): 2012 / MtCO2						
Actual Emissions	Surrogate Model Intercept	Framework Surrogate Model Prediction	Surrogate Model R2	Feature	Feature Weight	Influence Interval
517.721728	203.269713	540.9957849	0.84545818	A23	19.8259389	A23 <= 0.143
				A22	-11.774899	A22 <= 0.166
				A20	31.153174	A20 <= 0.165
				A21	28.9831467	A21 <= 0.132
				A1	161.338818	0.855 < A1
				A17	79.1598358	0.744 < A17
				A6	8.42477553	0.565 < A6 <= 0.800
				A8	13.6126907	0.305 < A8 <= 0.613
				A3	7.00259064	0.805 < A3

Table 30. Prediction local explanation - Canada 2013 / total CO2 emissions.

Total CO2 Emissions - Year (case): 2013 / MtCO2						
Actual Emissions	Surrogate Model Intercept	Framework Surrogate Model Prediction	Surrogate Model R2	Feature	Feature Weight	Influence Interval
519.188528	233.145147	539.9633652	0.83471627	A23	36.0820365	A23 <= 0.143
				A22	7.80463291	A22 <= 0.166
				A20	14.8018395	A20 <= 0.165
				A21	36.082037	A21 <= 0.132
				A1	107.478418	0.855 < A1
				A17	60.0863115	0.744 < A17
				A6	6.19191333	0.565 < A6 <= 0.800
				A8	17.5965745	0.305 < A8 <= 0.613
				A3	20.6944551	0.805 < A3

Table 31. Prediction local explanation - Canada 2014 / total CO2 emissions.

Total CO2 Emissions - Year (case): 2014 / MtCO2						
Actual Emissions	Surrogate Model Intercept	Framework Surrogate Model Prediction	Surrogate Model R2	Feature	Feature Weight	Influence Interval
540.614809	234.807686	539.9862407	0.78252619	A23	-8.2660458	A23 <= 0.143
				A22	5.60502543	A22 <= 0.166
				A20	11.9284325	A20 <= 0.165
				A21	10.9882845	A21 <= 0.132
				A1	169.377926	0.855 < A1
				A17	90.1071538	0.744 < A17
				A6	11.4888438	0.800 < A6
				A8	43.8837694	0.305 < A8 <= 0.613
				A3	-29.934835	0.805 < A3

As final insights, both the global and local explanations indicates that urban population, energy production and transportation are important drivers of the Canadian CO2 emissions, thus requiring special attention as regards to the design and implementation of carbon policies and initiatives.

5.2.2 Canada Transportation Sector Emissions

The learning framework predicted Canadian transportation sector CO2 emissions with MAPE performance of 2.4433%. The predicting model features 9 neurons (hidden layer) and 13 predictors, which were ranked by RReliefF as follows: A22 (transport services, % of service exports), A20 (transport services, % of commercial service exports), A23 (transport services, % of service imports), A21 (transport services, % of commercial service imports), A1 (total energy use), A3 (combustible renewables and waste energy), A8 (electricity production from coal), A17 (urban population), A5 (hydroelectricity production), A6 (electricity production from oil, gas and coal), A4 (total electricity production), A2 (alternative and nuclear energy use), and A9 (electricity production from oil).

Table 32 and figure 17 present the global explanation outcomes for the Canadian transportation sector CO_2 emissions for the predictions 2010 - 2014.

Table 32. Predictors global impact - Canada / transport CO2 emissions.

Partial Dependence Function Outcomes -Transport CO2 Emissions / 2010 - 2014			
Feature	Impact	Pct_Impact	Std_Impact
A1	5.304277162	0.190890863	0.856336597
A17	1.81784139	0.06542066	0.293477144
A2	1.712584988	0.061632682	0.27648427
A20	2.014999421	7.25E-02	0.32530686
A21	0.92180542	3.32E-02	0.148818716
A22	0.595833834	2.14E-02	9.62E-02
A23	0.294364934	1.06E-02	4.75E-02
A3	1.654392745	5.95E-02	0.26708956
A4	3.121937568	0.112352605	0.504013895
A5	6.194149802	0.22291569	1
A6	1.697024026	6.11E-02	0.273972067
A8	0.813886067	2.93E-02	0.131395929
A9	1.643864644	5.92E-02	0.265389875

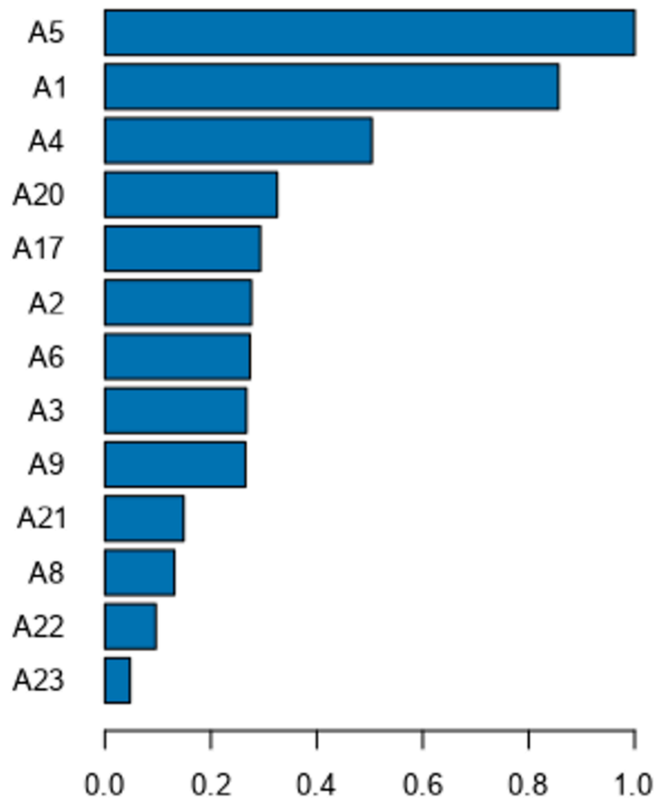

Figure 17 - Standardized features impact - Canada Transport CO2 emissions.

As can be observed in figure 17, electricity production and total energy use were the most important factors for transportation CO2 emissions, in the period 2010 - 2014. Such impacts can be better analyzed by means of the local explanations provided by the learning framework, as presented in tables 33, 34, 35, 36, and 37.

Table 33. Prediction local explanation - Canada 2010 / transport CO2 emissions.

Transport - Year (case): 2010 / MtCO2						
Actual Emissions	Surrogate Model Intercept	Framework Surrogate Model Prediction	Surrogate Model R2	Feature	Feature Weight	Influence Interval
164.671311	76.5880882	169.03715	0.99755481	A22	-3.877988483	A22 <= 0.166
				A20	13.43889475	A20 <= 0.165
				A23	0.443588579	A23 <= 0.143
				A21	-5.643092001	A21 <= 0.132
				A1	49.30024093	0.855 < A1
				A3	-5.885100777	0.533 < A3 <= 0.805
				A8	11.49114891	0.613 < A8 <= 0.763
				A17	13.44215089	0.744 < A17
				A5	-10.57513911	0.849 < A5
				A6	11.73627134	0.800 < A6
				A4	-21.76811904	0.859 < A4
				A2	20.80121646	0.855 < A2
				A9	19.54498551	0.250 < A9 <= 0.403

Table 34. Prediction local explanation - Canada 2011 / transport CO2 emissions.

Transport - Year (case): 2011 / MtCO2						
Actual Emissions	Surrogate Model Intercept	Framework Surrogate Model Prediction	Surrogate Model R2	Feature	Feature Weight	Influence Interval
159.73277	83.1663379	165.394678	0.91199492	A22	-16.555381	A22 <= 0.166
				A20	24.5858122	A20 <= 0.165
				A23	14.8993744	0.143 < A23 <= 0.293
				A21	31.5650105	0.132 < A21 <= 0.271
				A1	48.7720091	0.855 < A1
				A3	12.8068542	0.533 < A3 <= 0.805
				A8	11.7611189	0.613 < A8 <= 0.763
				A17	5.79013813	0.744 < A17
				A5	-16.16365	0.849 < A5
				A6	-9.2580775	0.800 < A6
				A4	-36.491171	0.859 < A4
				A2	5.77857357	0.855 < A2
				A9	4.73772939	A9 <= 0.250

Table 35. Prediction local explanation - Canada 2012 / transport CO2 emissions.

Transport - Year (case): 2012 / MtCO2						
Actual Emissions	Surrogate Model Intercept	Framework Surrogate Model Prediction	Surrogate Model R2	Feature	Feature Weight	Influence Interval
160.453764	81.7620155	164.947719	0.92210452	A22	-1.5124353	A22 <= 0.166
				A20	8.9185495	A20 <= 0.165
				A23	-2.6660927	A23 <= 0.143
				A21	3.36061322	A21 <= 0.132
				A1	41.996091	0.855 < A1
				A3	-3.2322644	0.805 < A3
				A8	7.45107054	0.305 < A8 <= 0.613
				A17	17.3990555	0.744 < A17
				A5	-8.2746889	0.849 < A5
				A6	18.5933879	0.565 < A6 <= 0.800
				A4	5.0561166	0.859 < A4
				A2	-1.5539351	0.855 < A2
				A9	-2.3497643	0.250 < A9 <= 0.403

Table 36. Prediction local explanation - Canada 2013 / transport CO2 emissions.

Transport - Year (case): 2013 / MtCO2						
Actual Emissions	Surrogate Model Intercept	Framework Surrogate Model Prediction	Surrogate Model R2	Feature	Feature Weight	Influence Interval
161.599596	76.6940003	165.64411	0.98213673	A22	-15.28407264	A22 <= 0.166
				A20	0.788742313	A20 <= 0.165
				A23	0.444386721	A23 <= 0.143
				A21	26.87100834	A21 <= 0.132
				A1	43.24603504	0.855 < A1
				A3	-0.297346538	0.805 < A3
				A8	13.09856584	0.305 < A8 <= 0.613
				A17	12.50770695	0.744 < A17
				A5	-20.16688416	0.849 < A5
				A6	18.10622615	0.565 < A6 <= 0.800
				A4	7.777174081	0.859 < A4
				A2	-2.943974714	0.855 < A2
				A9	4.802546374	0.250 < A9 <= 0.403

Table 37. Prediction local explanation - Canada 2014 / transport CO_2 emissions.

Transport - Year (case): 2014 / $MtCO_2$						
Actual Emissions	Surrogate Model Intercept	Framework Surrogate Model Prediction	Surrogate Model R2	Feature	Feature Weight	Influence Interval
168.76135	88.3837607	169.99571	0.91917546	A22	-5.9683494	A22 <= 0.166
				A20	8.69340426	A20 <= 0.165
				A23	12.4600116	A23 <= 0.143
				A21	16.7842689	A21 <= 0.132
				A1	27.0804422	0.855 < A1
				A3	6.17168097	0.805 < A3
				A8	4.32171631	0.305 < A8 <= 0.613
				A17	11.5312003	0.744 < A17
				A5	-12.30918	0.849 < A5
				A6	9.42810137	0.800 < A6
				A4	4.28202308	0.859 < A4
				A2	2.69960938	0.855 < A2
				A9	-3.5629793	0.250 < A9 <= 0.403

Here it is important to make some important remarks, i.e. both the global and local explanations indicates that urban population, energy production and transportation are important drivers of the Canadian CO_2 emissions, thus requiring special attention as regards to the design and implementation of carbon policies and initiatives.

5.2.3 Canada Residential Buildings, Commercial and Public Services Emissions

The learning framework predicted Canadian residential buildings, commercial and public services CO_2 emissions with MAPE performance of 3.2677%. The predicting model features 8 neurons (hidden layer) and 12 predictors, which were ranked by RReliefF as follows: A23 (transport services, % of service imports), A22 (transport services, % of service exports), A20 (transport services, % of commercial service exports), A21 (transport services, % of commercial service imports), A1 (total energy use), A9 (electricity production from oil), A17 (urban population), A8 (electricity production from coal), A6 (electricity production from oil, gas and coal), A3 (combustible renewables and waste energy), A4 (total electricity production), and A5 (hydroelectricity production).

Table 38 and figure 18 present the global explanation outcomes for the Canadian residential buildings, commercial and public services CO_2 emissions for the period 2010 - 2014.

Table 38. Predictors global impact - Canada / residential buildings, commercial and public services CO2 emissions.

Partial Dependence Function Outcomes - Residential Buildings - Commercial and Public Services (T5) / 2010 - 2014			
Feature	Impact	Pct_Impact	Std_Impact
A1	4.35029658	0.17156639	0.81052022
A17	1.02606887	4.05E-02	0.19117077
A20	0.76932664	3.03E-02	0.14333616
A21	3.18881286	0.12575996	0.59411979
A22	1.1504513	4.54E-02	0.21434493
A23	1.15506031	4.56E-02	0.21520366
A3	1.59601161	6.29E-02	0.29735896
A4	3.35300812	0.13223547	0.62471163
A5	0.75717954	2.99E-02	0.14107298
A6	0.5861665	2.31E-02	0.1092109
A8	5.36728942	0.21167441	1
A9	2.05667348	8.11E-02	0.38318662

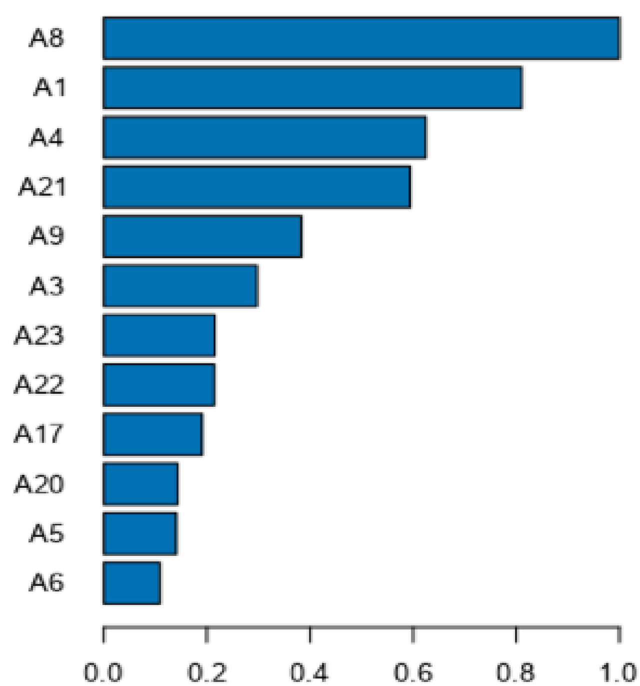

Figure 18 - Standardized features impact - Canada residential buildings, commercial and public services CO2 emissions.

Figure 18 indicates that energy generation and use, and transportation are key factors impacting CO2 emissions in Canada. Such impacts can be better analyzed by means of the local explanations provided by the learning framework, as presented in tables 39, 40, 41, 42, and 43.

Table 39. Prediction local explanation - Canada 2010 / residential buildings, commercial and public services CO2 emissions.

Residential Buildings - Commercial and Public Services - Year (case): 2010 / MtCO2						
Actual Emissions	Surrogate Model Intercept	Framework Surrogate Model Prediction	Surrogate Model R2	Feature	Feature Weight	Influence Interval
72.684752	53.4989426	86.99866786	0.89785987	A23	6.87873336	A23 <= 0.143
				A22	-2.2645985	A22 <= 0.166
				A20	11.8422239	A20 <= 0.165
				A21	1.4666742	A21 <= 0.132
				A1	18.1348675	0.855 < A1
				A9	2.85E-02	0.250 < A9 <= 0.403
				A17	4.06061152	0.744 < A17
				A8	5.62769355	0.613 < A8 <= 0.763
				A6	-5.3170439	0.800 < A6
				A3	8.83770219	0.533 < A3 <= 0.805
				A4	-8.8764002	0.859 < A4
				A5	-6.9192541	0.849 < A5

Table 40. Prediction local explanation - Canada 2011 / residential buildings, commercial and public services CO2 emissions.

Residential Buildings - Commercial and Public Services - Year (case): 2011 / MtCO2						
Actual Emissions	Surrogate Model Intercept	Framework Surrogate Model Prediction	Surrogate Model R2	Feature	Feature Weight	Influence Interval
76.133057	61.0539707	87.19823557	0.65964212	A23	2.13722616	0.143 < A23 <= 0.293
				A22	-13.629856	A22 <= 0.166
				A20	0.60148034	A20 <= 0.165
				A21	-3.5182392	0.132 < A21 <= 0.271
				A1	13.5076743	0.855 < A1
				A9	7.61678142	A9 <= 0.250
				A17	2.84194329	0.744 < A17
				A8	7.37827349	0.613 < A8 <= 0.763
				A6	5.09601879	0.800 < A6
				A3	3.14010691	0.533 < A3 <= 0.805
				A4	-4.8216393	0.859 < A4
				A5	5.79449433	0.849 < A5

Table 41. Prediction local explanation - Canada 2012 / residential buildings, commercial and public services CO2 emissions.

Residential Buildings - Commercial and Public Services - Year (case): 2012 / MtCO2						
Actual Emissions	Surrogate Model Intercept	Framework Surrogate Model Prediction	Surrogate Model R2	Feature	Feature Weight	Influence Interval
69.688505	63.1001871	78.79614622	0.83447909	A23	14.6950619	A23 <= 0.143
				A22	-9.8126521	A22 <= 0.166
				A20	6.1149378	A20 <= 0.165
				A21	-1.2995322	A21 <= 0.132
				A1	25.9086227	0.855 < A1
				A9	6.6245107	0.250 < A9 <= 0.403
				A17	-0.9301557	0.744 < A17
				A8	0.49242417	0.305 < A8 <= 0.613
				A6	-1.9832551	0.565 < A6 <= 0.800
				A3	-1.2067185	0.805 < A3
				A4	-16.942612	0.859 < A4
				A5	-5.9646728	0.849 < A5

Table 42. Prediction local explanation - Canada 2013 / residential buildings, commercial and public services CO2 emissions.

Residential Buildings - Commercial and Public Services - Year (case): 2013 / MtCO2						
Actual Emissions	Surrogate Model Intercept	Framework Surrogate Model Prediction	Surrogate Model R2	Feature	Feature Weight	Influence Interval
71.580904	66.8055092	75.26936623	0.89614686	A23	15.0167766	A23 <= 0.143
				A22	-11.978087	A22 <= 0.166
				A20	-1.6314605	A20 <= 0.165
				A21	-4.9442984	A21 <= 0.132
				A1	20.9141958	0.855 < A1
				A9	-6.8733137	0.250 < A9 <= 0.403
				A17	1.66258621	0.744 < A17
				A8	10.1565083	0.305 < A8 <= 0.613
				A6	-3.3926595	0.565 < A6 <= 0.800
				A3	-0.4386881	0.805 < A3
				A4	1.32616775	0.859 < A4
				A5	-11.35387	0.849 < A5

Table 43. Prediction local explanation - Canada 2014 / residential buildings, commercial and public services CO2 emissions.

Residential Buildings - Commercial and Public Services - Year (case): 2014 / MtCO2						
Actual Emissions	Surrogate Model Intercept	Framework Surrogate Model Prediction	Surrogate Model R2	Feature	Feature Weight	Influence Interval
77.095014	48.8492732	78.35733854	0.88502959	A23	10.1041958	A23 <= 0.143
				A22	-0.6973597	A22 <= 0.166
				A20	-1.6038575	A20 <= 0.165
				A21	9.64758103	A21 <= 0.132
				A1	27.5331084	0.855 < A1
				A9	0.672578	0.250 < A9 <= 0.403
				A17	-2.3457831	0.744 < A17
				A8	3.25237888	0.305 < A8 <= 0.613
				A6	-1.7480318	0.800 < A6
				A3	-1.6217341	0.805 < A3
				A4	-6.9187134	0.859 < A4
				A5	-6.7662972	0.849 < A5

As regards to residential buildings, commercial and public services, both the global and local explanations corroborate the relevance energy production and transportation for the Canadian CO2 emissions scenario.

As final remarks, we highlight that the presented case studies demonstrated the capability of our learning framework to foster the understanding of the carbon emissions drivers' dynamics. The combination of predictions, global model explanations (features global impacts), and local model explanations (features local weights) conform consistent resources in support of new and improved environmental initiatives and policies.

6 CONCLUSIONS AND FUTURE WORK

Environmentally sustainable development is globally recognized as a critical condition for the continuing habitability of the planet, and such fact has been consistently motivating several international efforts aimed at implementing a universally agreed framework able to support economic development and protect the environment concomitantly, such as the Kyoto Protocol.

In such context, the proper understanding of the carbon emissions drivers and its dynamics is a key factor for the design and implementation of effective and efficient initiatives and polices, e.g. carbon markets. Thus, the accurate forecast of such emissions is one of the most important inputs for any decision-making process targeting climate change / global worming avoidance.

Therefore, in our attempt to contribute to such global environmental challenge, we implemented a learning computational framework for carbon emissions predictions. Our framework features the capacity to iteratively improve the prediction features set and the backpropagation neural network (NN/BP) architecture according to the data statistical assessment computed by the RReliefF algorithm.

In order to validate the implemented learning framework, we used real world data obtained from the European Union, International Energy Agency and World Bank, for the period 1990-2017. The learning framework validation process consisted of predictions for 7 different CO2 emissions targets whtihin the EU28 scope, i.e. total, energy industries, industrial, commercial and public services, transport, residential, and aviation. The learning framework's accuracy performance were substantially superior to 3 designed control models.

The outcomes of the learning framework were then evaluated against different NN/BP based solutions (NN/BP, NN/BP-BFE, NN/BP-RReliefF/BFE, NN/BP-CT, NN/BP-IPSO, NN/BP-PCA, NN/BP-RF)), as well as different mainstream machine learning models (GBM-BFE, RF-BFE, SVM-BFE, SVM-RF). Our MAPE accuracy performance for EU28 total CO2 emissions reached 2.28%. Such result demonstrated the effectiveness of our approach in terms of increased prediction accuracy when compared to other current research approaches.

Although the Neural Network and RReliefF iterative integration effectively and efficiently addressed the carbon emissions prediction challenges, the proposition of policy improvements based on such predictions would require further analytical efforts towards a proper understanding of how each predictor contributed to the final predictions.

Therefore, our learning framework was featured with an additional capability designed to provide information on how the predictors impacted the predictions. The prediction module thus computes global model explanations by means of partial dependence functions, and local model explanations by means of the interpretable model-agnostic explanations (LIME) algorithm.

As a complement to the validation process, we conducted 4 additional case studies. In such case studies we targeted: a) EU28 total CO2 emissions with a different database (MAPE accuracy performance of 3.5018%); b) Canada total CO2 emissions (MAPE accuracy performance of 1.9058%); c) Canada transport CO2 emissions (MAPE accuracy performance of 2.4433%); and d) Canada residential buildings, commercial and public services CO2 emissions (MAPE accuracy performance of 3.2677%).

The learning framework outcomes for the case studies consisted of the emissions predictions, as well as the global and the local explanations of such predictions. The framework predictive performance, combined with the machine learning model global explanations (features global impacts), and local model explanations (features local weights) conforms a consistent means to support the design of new and improved environmental initiatives and policies, what allow us to conclude that our research objectives were accomplished.

Finally, the learning framework outcomes are also expected to provide some ground for future researches targeting carbon emissions causality analysis, as well as potential improvements on both ANNs and XAI techniques.

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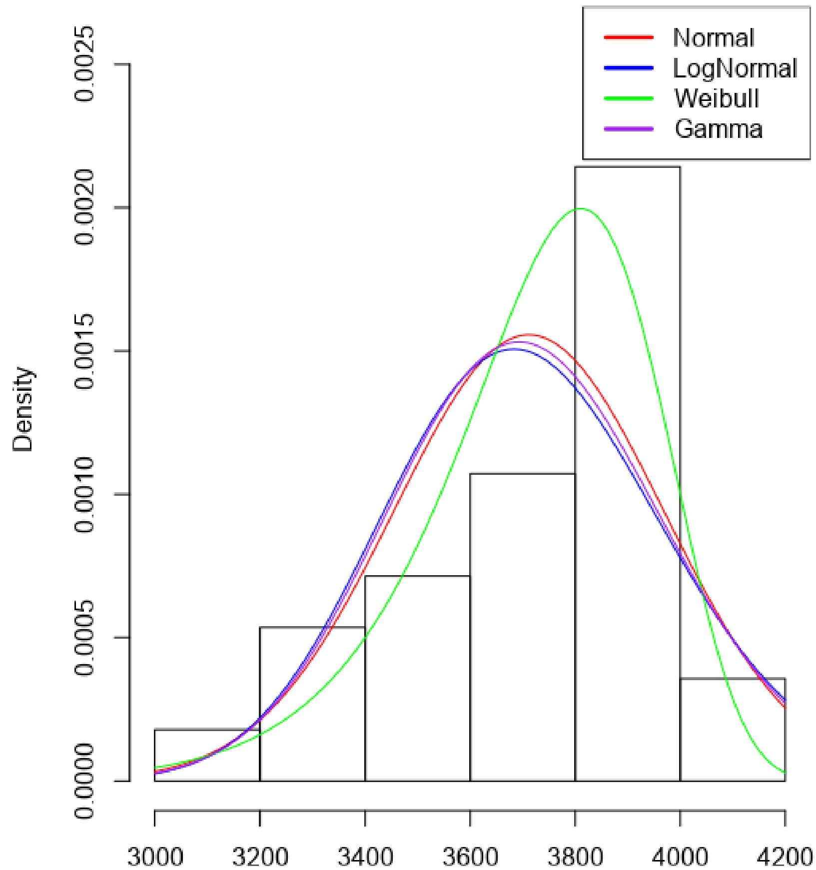
APPENDIX 1 - MODEL VALIDATION DATA DISTRIBUTION ANALYSIS

Distribution Analysis of T1

Skew	-1.02
Number	28.00
Mean	3,711.65
Median	3,804.43
Standard Deviation	261.03
Missing Records	0.00

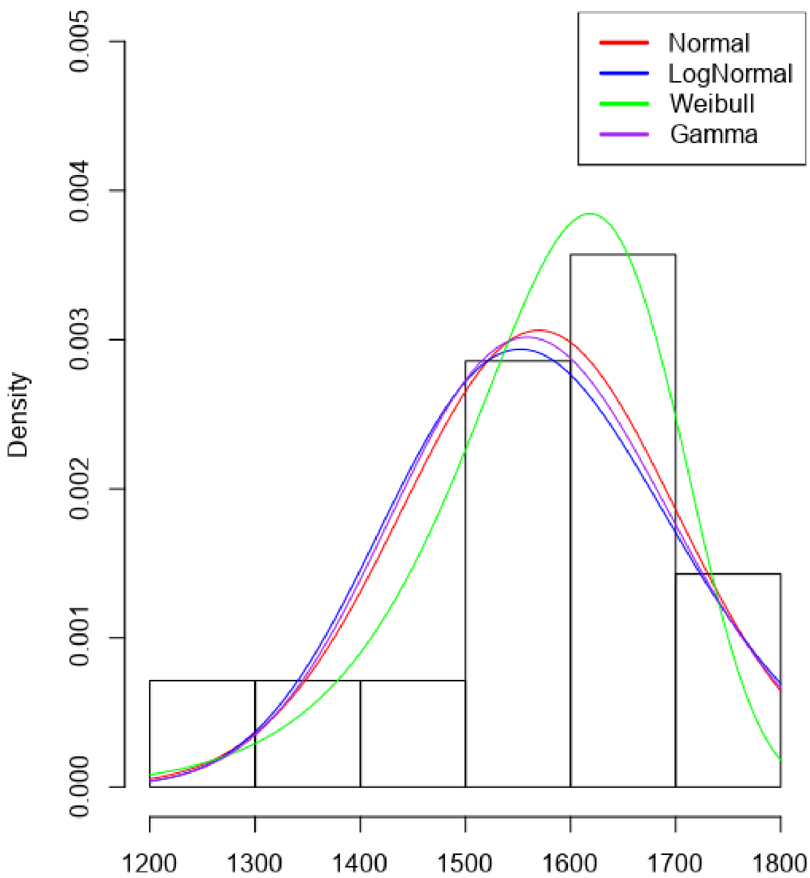


Goodness-of-Fit Statistics

Type	Test	Statistic	Significance
Normal	Anderson-Darling	1.748	< 0.005
LogNormal	Anderson-Darling	2.024	< 0.005
Weibull	Anderson-Darling	1.163	< 0.01
Type	**Test**	**Statistic**	**Significance**
Normal	Chi-Square	28.361	0
LogNormal	Chi-Square	36.024	0
Gamma	Chi-Square	33.070	0
Weibull	Chi-Square	20.426	4e-04
Type	**Test**	**Statistic**	**Significance**
Normal	Cramer-von Mises	0.307	< 0.005
LogNormal	Cramer-von Mises	0.346	< 0.005
Weibull	Cramer-von Mises	0.190	< 0.01
Type	**Test**	**Statistic**	**Significance**
Normal	Kolmogorov-Smirnov	0.270	> 0.15
LogNormal	Kolmogorov-Smirnov	0.283	> 0.15

Distribution Analysis of T2

Skew	-1.07
Number	28.00
Mean	1,569.86
Median	1,599.50
Standard Deviation	132.64
Missing Records	0.00

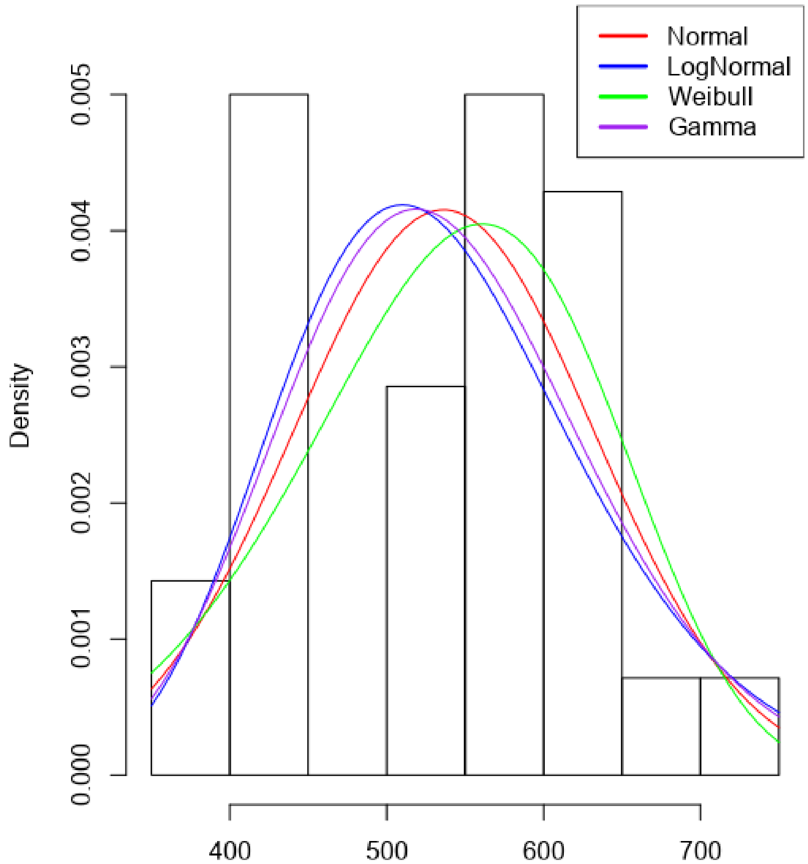


Goodness-of-Fit Statistics

Type	Test	Statistic	Significance
Normal	Anderson-Darling	1.271	< 0.005
LogNormal	Anderson-Darling	1.603	< 0.005
Weibull	Anderson-Darling	0.675	0.0841
Type	**Test**	**Statistic**	**Significance**
Normal	Chi-Square	19.127	7e-04
LogNormal	Chi-Square	25.263	0
Gamma	Chi-Square	22.848	1e-04
Weibull	Chi-Square	14.943	0.0048
Type	**Test**	**Statistic**	**Significance**
Normal	Cramer-von Mises	0.197	0.006
LogNormal	Cramer-von Mises	0.243	< 0.005
Weibull	Cramer-von Mises	0.079	0.2206
Type	**Test**	**Statistic**	**Significance**
Normal	Kolmogorov-Smirnov	0.201	> 0.15
LogNormal	Kolmogorov-Smirnov	0.217	> 0.15

Distribution Analysis of T3

Skew	0.01
Number	28.00
Mean	536.36
Median	558.50
Standard Deviation	97.82
Missing Records	0.00

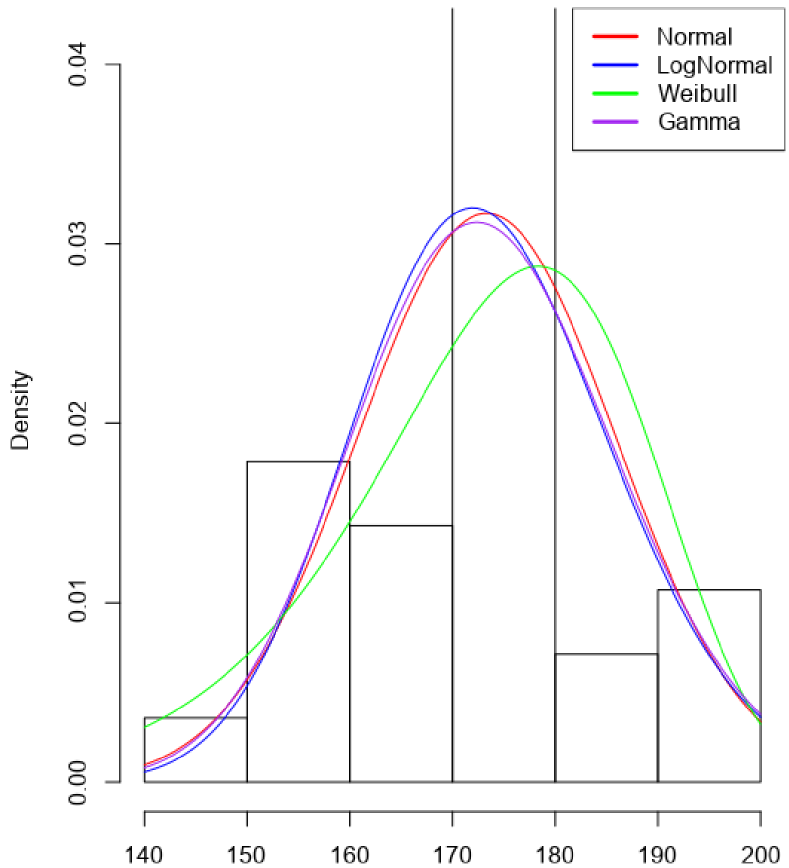


Goodness-of-Fit Statistics

Type	Test	Statistic	Significance
Normal	Anderson-Darling	0.813	0.0373
LogNormal	Anderson-Darling	1.157	0.0051
Weibull	Anderson-Darling	0.631	0.1052
Type	Test	Statistic	Significance
Normal	Chi-Square	8.671	0.0699
LogNormal	Chi-Square	10.823	0.0286
Gamma	Chi-Square	9.748	0.0449
Weibull	Chi-Square	7.595	0.1076
Type	Test	Statistic	Significance
Normal	Cramer-von Mises	0.122	0.0587
LogNormal	Cramer-von Mises	0.186	0.0084
Weibull	Cramer-von Mises	0.083	0.1972
Type	Test	Statistic	Significance
Normal	Kolmogorov-Smirnov	0.151	> 0.15
LogNormal	Kolmogorov-Smirnov	0.153	> 0.15

Distribution Analysis of T4

Skew	0.30
Number	28.00
Mean	173.32
Median	176.00
Standard Deviation	12.82
Missing Records	0.00



Goodness-of-Fit Statistics

Type	Test	Statistic	Significance
Normal	Anderson-Darling	0.668	0.0846
LogNormal	Anderson-Darling	0.656	0.0895
Weibull	Anderson-Darling	0.948	0.0184

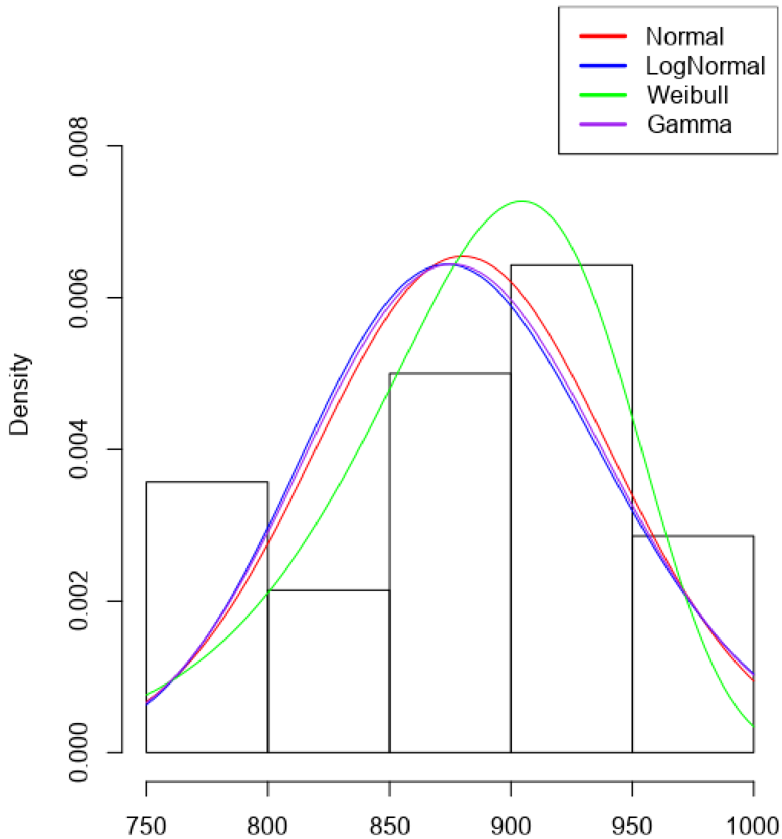
Type	Test	Statistic	Significance
Normal	Chi-Square	14.988	0.0018
LogNormal	Chi-Square	15.093	0.0017
Gamma	Chi-Square	15.040	0.0018
Weibull	Chi-Square	17.435	6e-04

Type	Test	Statistic	Significance
Normal	Cramer-von Mises	0.103	0.1054
LogNormal	Cramer-von Mises	0.108	0.09
Weibull	Cramer-von Mises	0.136	0.0365

Type	Test	Statistic	Significance
Normal	Kolmogorov-Smirnov	0.137	> 0.15
LogNormal	Kolmogorov-Smirnov	0.136	> 0.15

Distribution Analysis of T5

Skew	-0.53
Number	28.00
Mean	880.11
Median	892.50
Standard Deviation	62.06
Missing Records	0.00



Goodness-of-Fit Statistics

Type	Test	Statistic	Significance
Normal	Anderson-Darling	0.629	0.1014
LogNormal	Anderson-Darling	0.790	0.0422
Weibull	Anderson-Darling	0.317	> 0.25

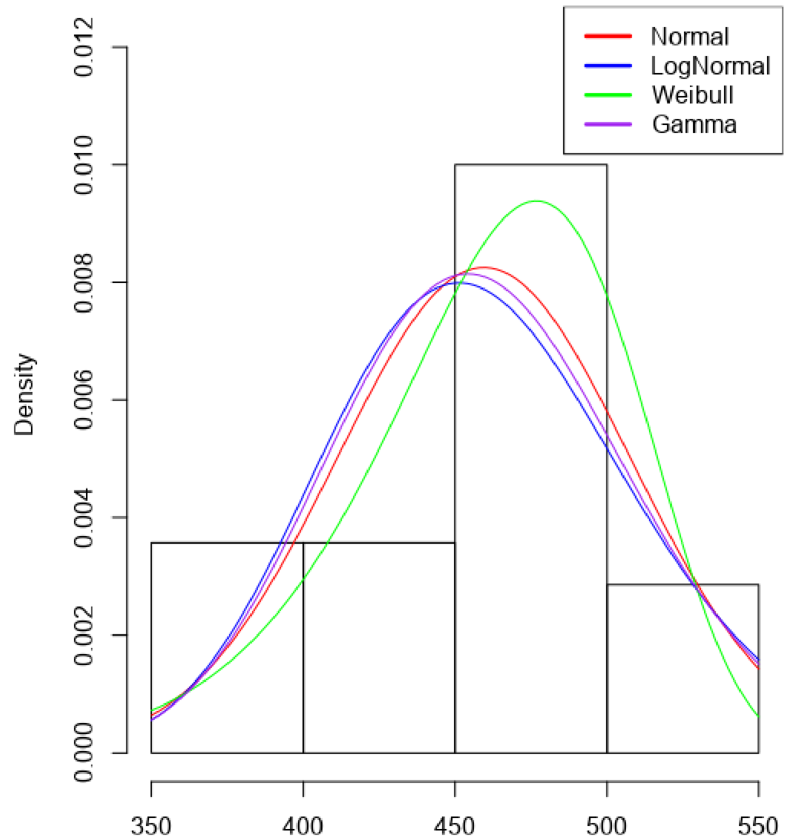
Type	Test	Statistic	Significance
Normal	Chi-Square	5.146	0.2726
LogNormal	Chi-Square	6.171	0.1867
Gamma	Chi-Square	5.784	0.2159
Weibull	Chi-Square	3.934	0.4149

Type	Test	Statistic	Significance
Normal	Cramer-von Mises	0.102	0.1078
LogNormal	Cramer-von Mises	0.129	0.0466
Weibull	Cramer-von Mises	0.040	> 0.25

Type	Test	Statistic	Significance
Normal	Kolmogorov-Smirnov	0.142	> 0.15
LogNormal	Kolmogorov-Smirnov	0.156	> 0.15

Distribution Analysis of T6

Skew	-0.69
Number	28.00
Mean	459.43
Median	476.50
Standard Deviation	49.21
Missing Records	0.00



Goodness-of-Fit Statistics

Type	Test	Statistic	Significance
Normal	Anderson-Darling	1.014	0.012
LogNormal	Anderson-Darling	1.314	< 0.005
Weibull	Anderson-Darling	0.642	0.0978

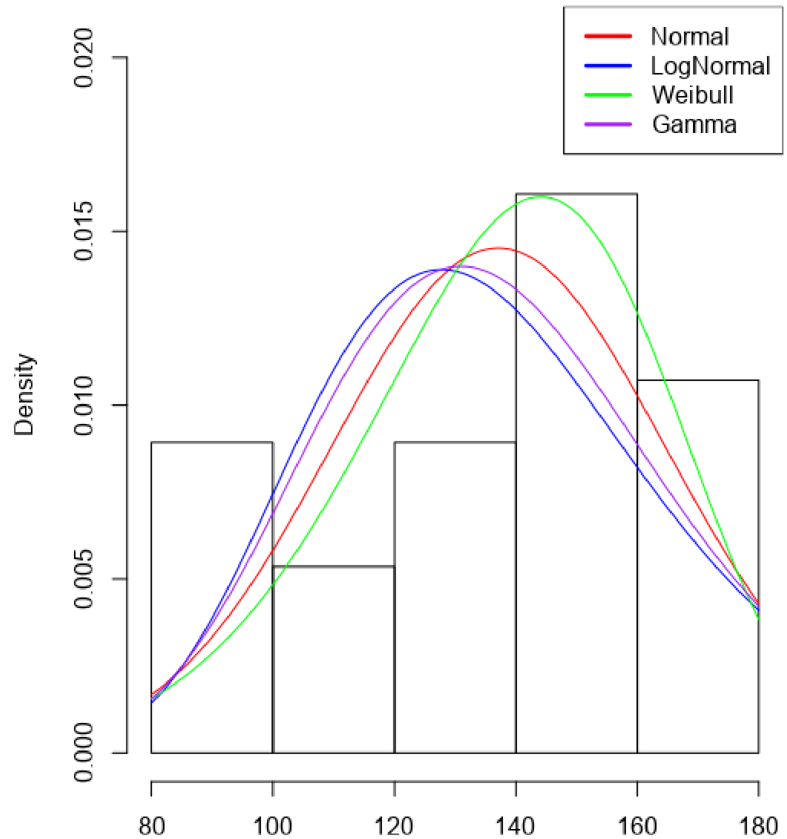
Type	Test	Statistic	Significance
Normal	Chi-Square	15.546	0.0037
LogNormal	Chi-Square	19.473	6e-04
Gamma	Chi-Square	17.973	0.0012
Weibull	Chi-Square	10.583	0.0317

Type	Test	Statistic	Significance
Normal	Cramer-von Mises	0.196	0.0062
LogNormal	Cramer-von Mises	0.245	< 0.005
Weibull	Cramer-von Mises	0.118	0.0646

Type	Test	Statistic	Significance
Normal	Kolmogorov-Smirnov	0.205	> 0.15
LogNormal	Kolmogorov-Smirnov	0.225	> 0.15

Distribution Analysis of T7

Skew	-0.61
Number	28.00
Mean	137.11
Median	144.50
Standard Deviation	27.97
Missing Records	0.00



Goodness-of-Fit Statistics

Type	Test	Statistic	Significance
Normal	Anderson-Darling	1.076	0.0084
LogNormal	Anderson-Darling	1.739	< 0.005
Weibull	Anderson-Darling	0.942	0.0189

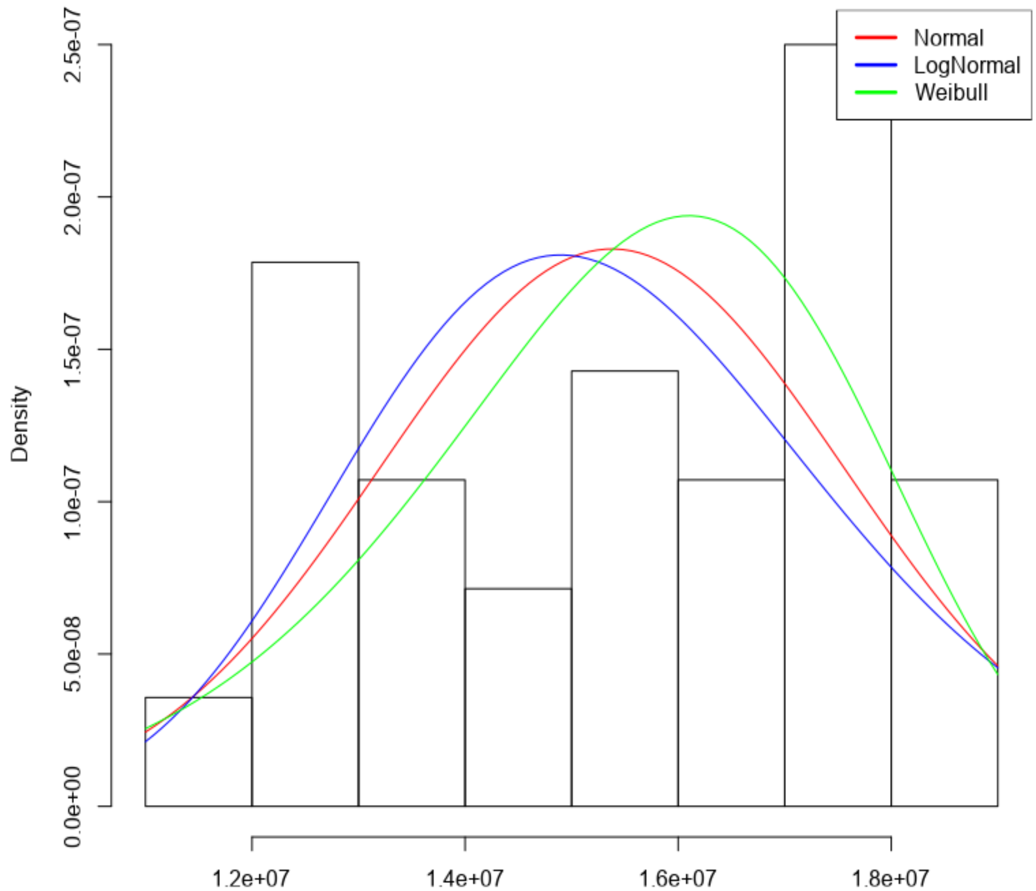
Type	Test	Statistic	Significance
Normal	Chi-Square	17.935	0.0013
LogNormal	Chi-Square	26.380	0
Gamma	Chi-Square	22.822	1e-04
Weibull	Chi-Square	14.770	0.0052

Type	Test	Statistic	Significance
Normal	Cramer-von Mises	0.180	0.0098
LogNormal	Cramer-von Mises	0.275	< 0.005
Weibull	Cramer-von Mises	0.148	0.024

Type	Test	Statistic	Significance
Normal	Kolmogorov-Smirnov	0.195	> 0.15
LogNormal	Kolmogorov-Smirnov	0.218	> 0.15

Distribution Analysis of A1

Skew	-0.28
Number	28.00
Mean	15,378,825.78
Median	15,717,123.54
Standard Deviation	2,220,731.80
Missing Records	0.00

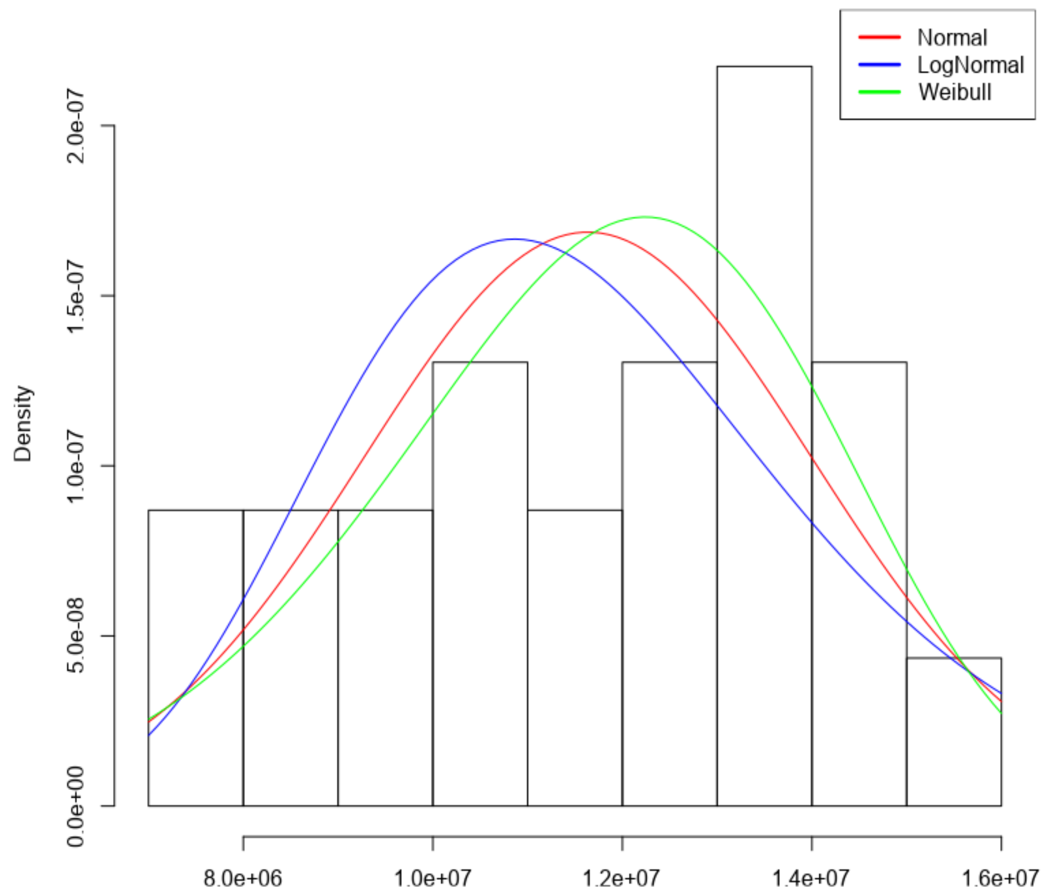


Goodness-of-Fit Statistics

Type	Test	Statistic	Significance
Normal	Anderson-Darling	0.840	0.0318
LogNormal	Anderson-Darling	1.098	0.0074
Weibull	Anderson-Darling	0.695	0.0759
Type	**Test**	**Statistic**	**Significance**
Normal	Chi-Square	26.748	0
LogNormal	Chi-Square	33.069	0
Weibull	Chi-Square	20.358	4e-04
Type	**Test**	**Statistic**	**Significance**
Normal	Cramer-von Mises	0.131	0.0438
LogNormal	Cramer-von Mises	0.172	0.0132
Weibull	Cramer-von Mises	0.106	0.0903
Type	**Test**	**Statistic**	**Significance**
Normal	Kolmogorov-Smirnov	0.149	> 0.15
LogNormal	Kolmogorov-Smirnov	0.166	> 0.15

Distribution Analysis of A2

Skew	-0.25
Number	23.00
Mean	11,634,951.08
Median	12,276,152.80
Standard Deviation	2,418,167.56
Missing Records	5.00

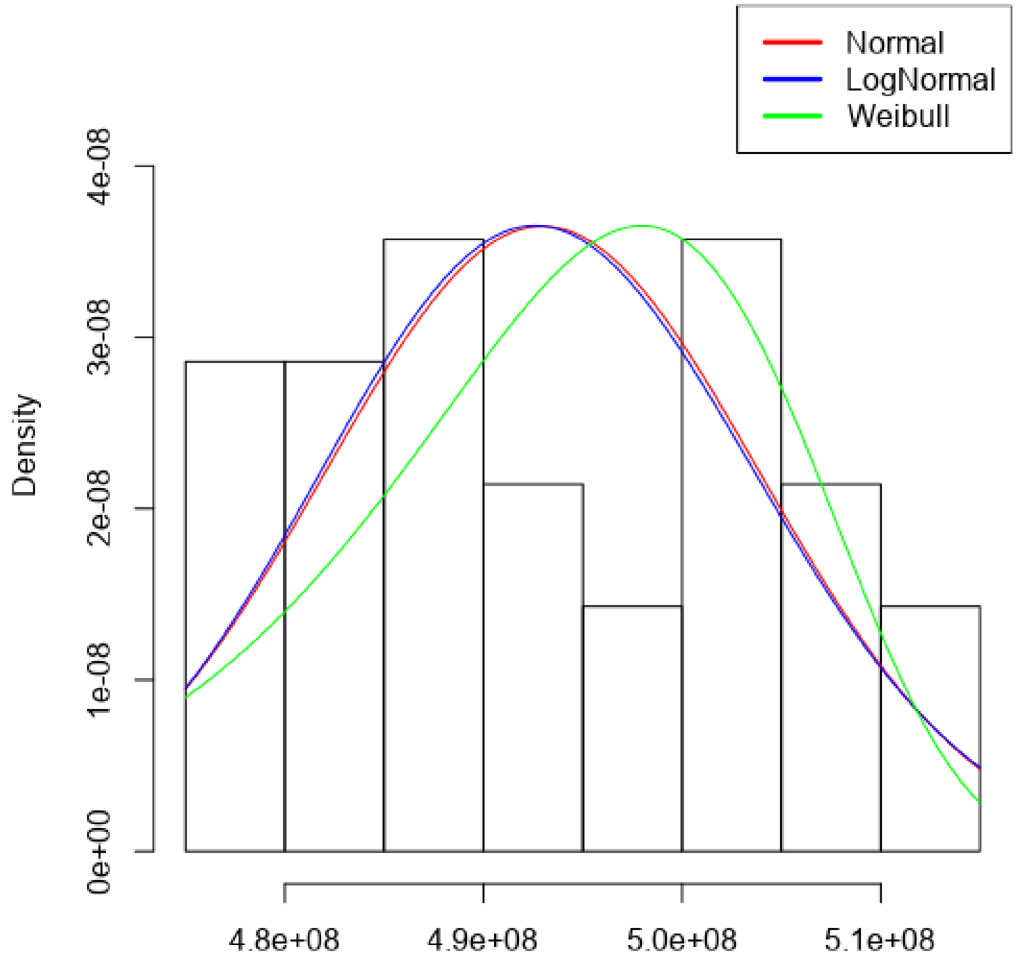


Goodness-of-Fit Statistic

Type	Test	Statistic	Significance
Normal	Anderson-Darling	0.369	0.4452
LogNormal	Anderson-Darling	0.668	0.0848
Weibull	Anderson-Darling	0.303	> 0.25
Type	Test	Statistic	Significance
Normal	Chi-Square	3.770	0.2875
LogNormal	Chi-Square	6.706	0.0819
Weibull	Chi-Square	2.877	0.411
Type	Test	Statistic	Significance
Normal	Cramer-von Mises	0.060	0.3976
LogNormal	Cramer-von Mises	0.105	0.0978
Weibull	Cramer-von Mises	0.046	> 0.25
Type	Test	Statistic	Significance
Normal	Kolmogorov-Smirnov	0.130	> 0.15
LogNormal	Kolmogorov-Smirnov	0.165	> 0.15

Distribution Analysis of A3

Skew	0.08
Number	28.00
Mean	492,968,146.39
Median	491,623,688.00
Standard Deviation	11,135,535.42
Missing Records	0.00

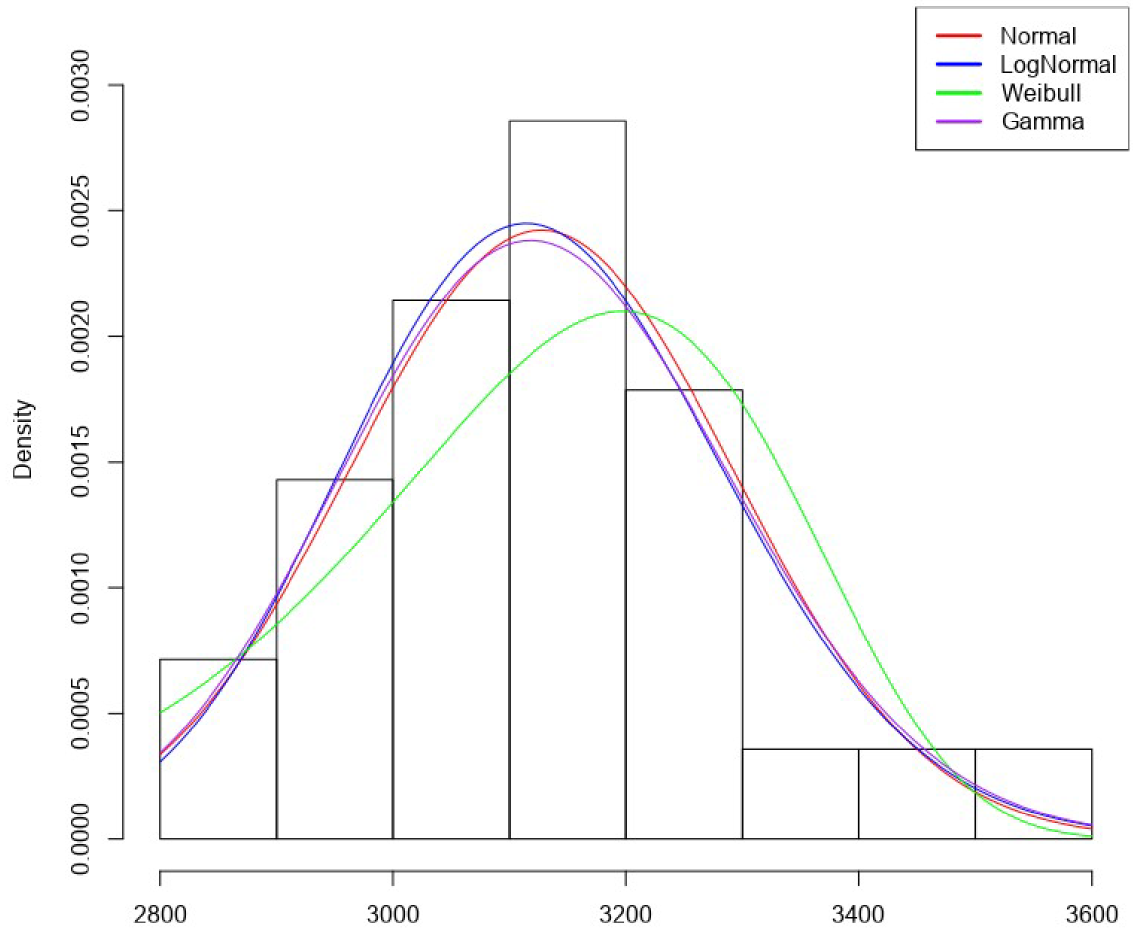


Goodness-of-Fit Statistics

Type	Test	Statistic	Significance
Normal	Anderson-Darling	0.516	0.1994
LogNormal	Anderson-Darling	0.509	0.2075
Weibull	Anderson-Darling	0.618	0.1179
Type	Test	Statistic	Significance
Normal	Chi-Square	5.572	0.2335
LogNormal	Chi-Square	5.591	0.2319
Weibull	Chi-Square	6.096	0.1921
Type	Test	Statistic	Significance
Normal	Cramer-von Mises	0.085	0.1878
LogNormal	Cramer-von Mises	0.083	0.1972
Weibull	Cramer-von Mises	0.103	0.098
Type	Test	Statistic	Significance
Normal	Kolmogorov-Smirnov	0.119	> 0.15
LogNormal	Kolmogorov-Smirnov	0.120	> 0.15

Distribution Analysis of A4

Skew	0.47
Number	28.00
Mean	3,127.31
Median	3,121.67
Standard Deviation	167.72
Missing Records	0.00

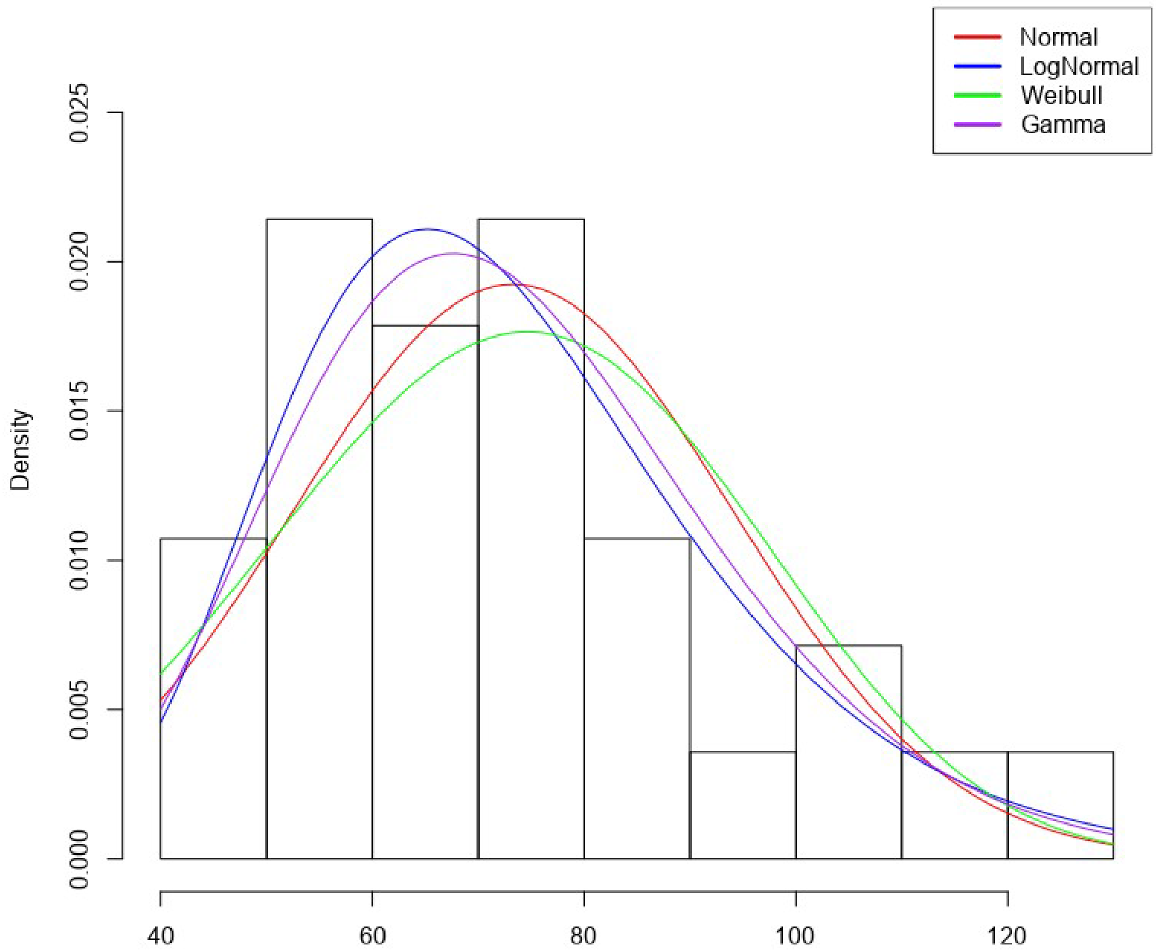


Goodness-of-Fit Statistics

Type	Test	Statistic	Significance
Normal	Anderson-Darling	0.274	> 0.5
LogNormal	Anderson-Darling	0.230	> 0.5
Weibull	Anderson-Darling	0.839	0.0329
Type	**Test**	**Statistic**	**Significance**
Normal	Chi-Square	3.744	0.4418
LogNormal	Chi-Square	3.717	0.4456
Gamma	Chi-Square	3.725	0.4445
Weibull	Chi-Square	7.367	0.1177
Type	**Test**	**Statistic**	**Significance**
Normal	Cramer-von Mises	0.036	> 0.5
LogNormal	Cramer-von Mises	0.032	> 0.5
Weibull	Cramer-von Mises	0.120	0.0593
Type	**Test**	**Statistic**	**Significance**
Normal	Kolmogorov-Smirnov	0.094	> 0.15
LogNormal	Kolmogorov-Smirnov	0.088	> 0.15

Distribution Analysis of A5

Skew	0.65
Number	28.00
Mean	73.28
Median	70.81
Standard Deviation	21.11
Missing Records	0.00

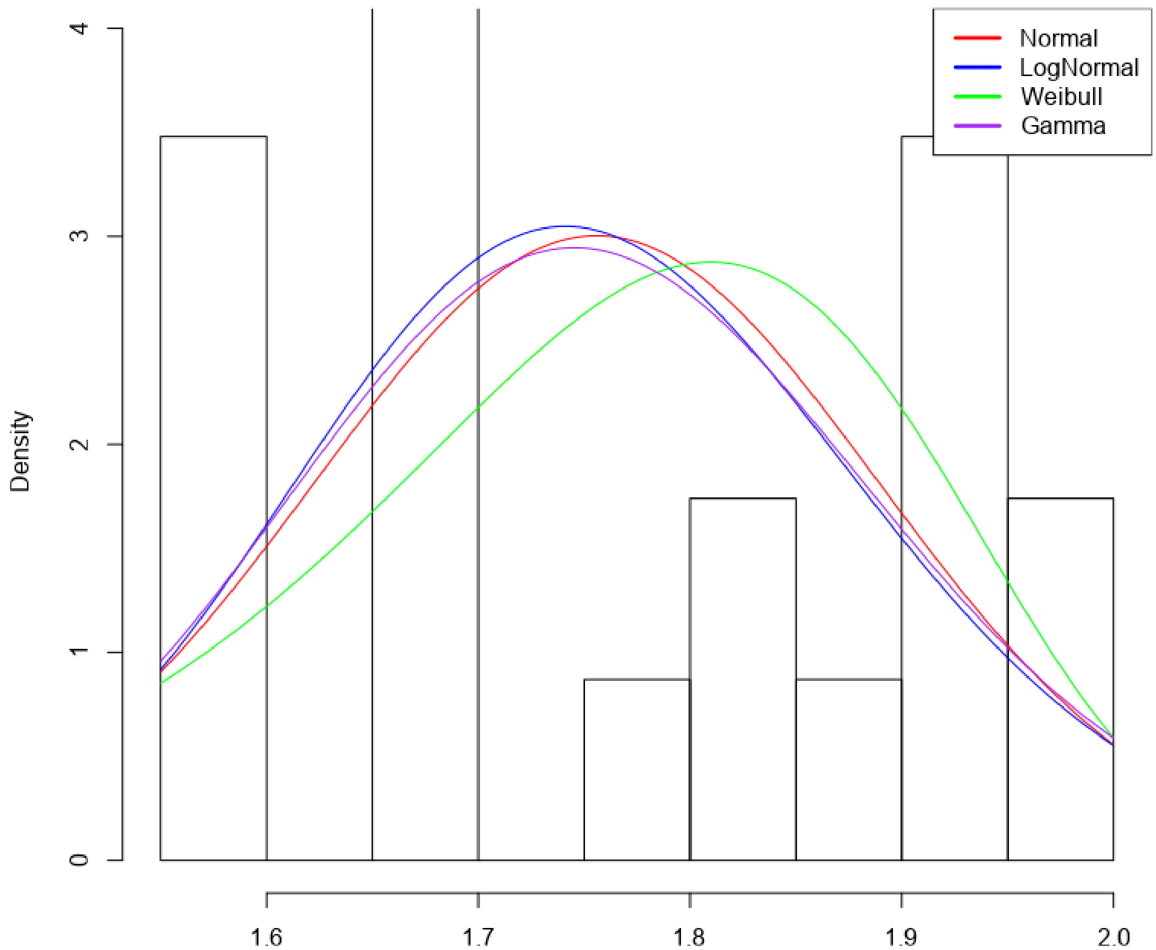


Goodness-of-Fit Statistics

Type	Test	Statistic	Significance
Normal	Anderson-Darling	0.460	0.2692
LogNormal	Anderson-Darling	0.163	> 0.5
Weibull	Anderson-Darling	0.504	0.2228
Type	**Test**	**Statistic**	**Significance**
Normal	Chi-Square	1.975	0.7403
LogNormal	Chi-Square	0.843	0.9326
Gamma	Chi-Square	1.022	0.9064
Weibull	Chi-Square	2.640	0.6198
Type	**Test**	**Statistic**	**Significance**
Normal	Cramer-von Mises	0.070	0.2911
LogNormal	Cramer-von Mises	0.020	> 0.5
Weibull	Cramer-von Mises	0.078	0.2229
Type	**Test**	**Statistic**	**Significance**
Normal	Kolmogorov-	0.126	> 0.15
LogNormal	Kolmogorov-	0.072	> 0.15

Distribution Analysis of A6

Skew	0.35
Number	23.00
Mean	1.76
Median	1.69
Standard Deviation	0.14
Missing Records	5.00

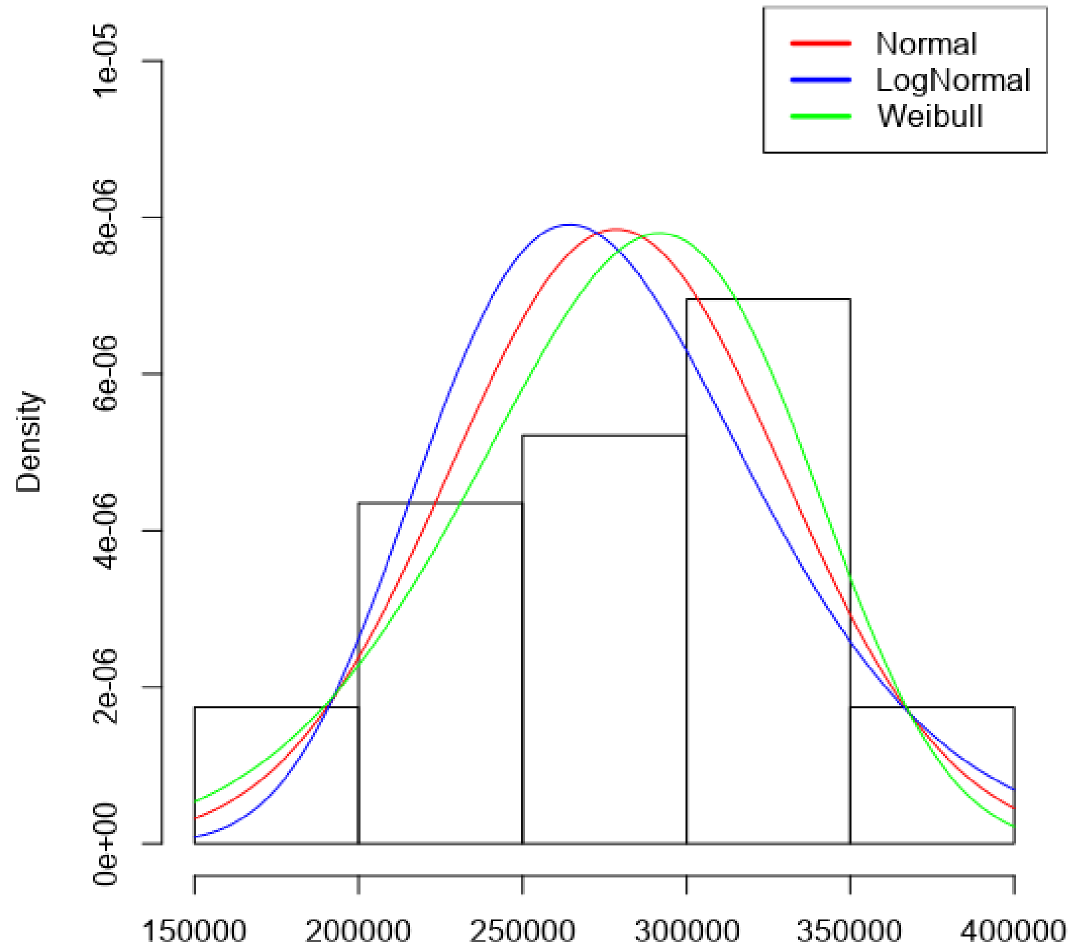


Goodness-of-Fit Statistics

Type	Test	Statistic	Significance
Normal	Anderson-Darling	1.088	0.0079
LogNormal	Anderson-Darling	1.002	0.013
Weibull	Anderson-Darling	1.203	< 0.01
Type	**Test**	**Statistic**	**Significance**
Normal	Chi-Square	10.913	0.0122
LogNormal	Chi-Square	10.083	0.0179
Gamma	Chi-Square	10.323	0.016
Weibull	Chi-Square	14.308	0.0025
Type	**Test**	**Statistic**	**Significance**
Normal	Cramer-von Mises	0.192	0.007
LogNormal	Cramer-von Mises	0.176	0.0116
Weibull	Cramer-von Mises	0.216	< 0.01
Type	**Test**	**Statistic**	**Significance**
Normal	Kolmogorov-Smirnov	0.239	> 0.15
LogNormal	Kolmogorov-Smirnov	0.229	> 0.15

Distribution Analysis of A7

Skew	-0.02
Number	23.00
Mean	278,544.31
Median	277,259.75
Standard Deviation	51,982.41
Missing Records	5.00

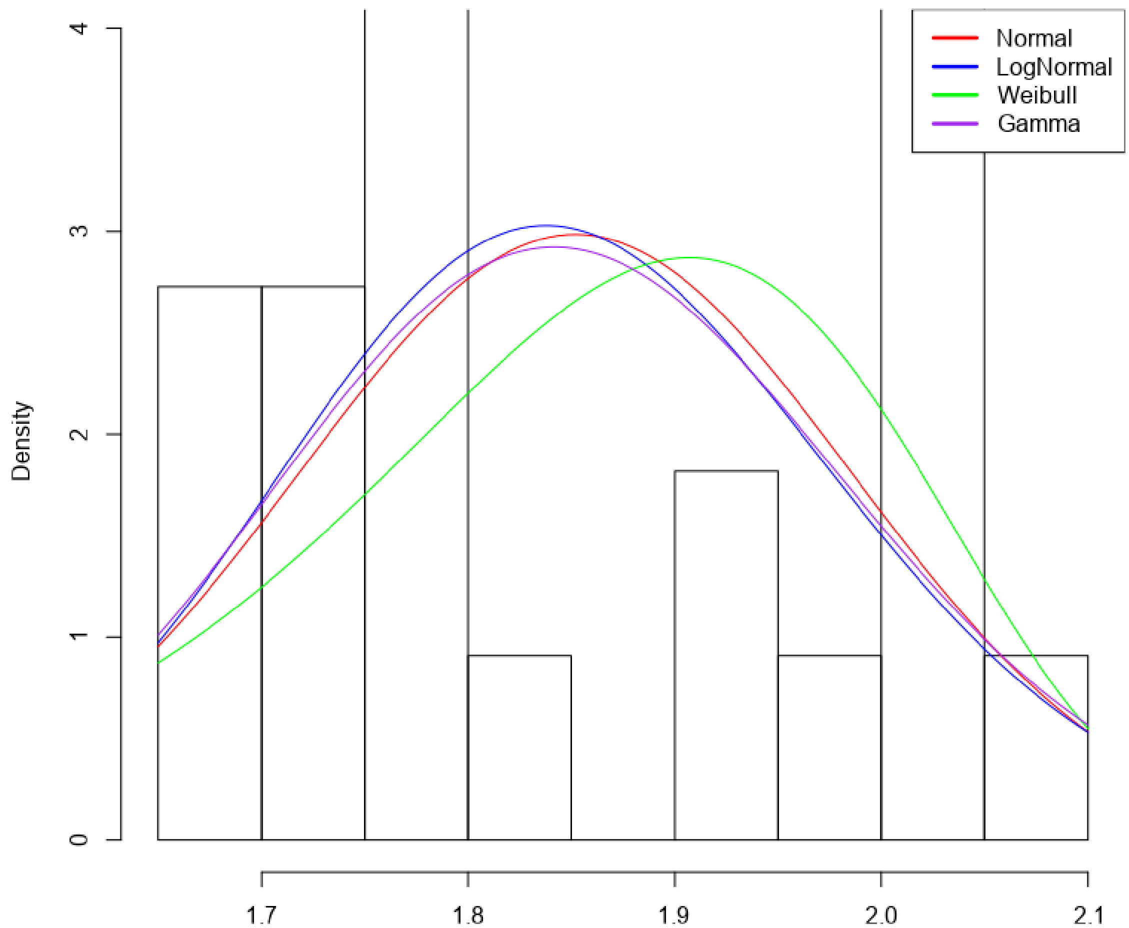


Goodness-of-Fit Statistics

Type	Test	Statistic	Significance
Normal	Anderson-Darling	0.314	> 0.5
LogNormal	Anderson-Darling	0.425	0.338
Weibull	Anderson-Darling	0.301	> 0.25
Type	Test	Statistic	Significance
Normal	Chi-Square	1.673	0.643
LogNormal	Chi-Square	3.140	0.3706
Weibull	Chi-Square	1.149	0.7653
Type	Test	Statistic	Significance
Normal	Cramer-von Mises	0.048	> 0.5
LogNormal	Cramer-von Mises	0.061	0.3898
Weibull	Cramer-von Mises	0.048	> 0.25
Type	Test	Statistic	Significance
Normal	Kolmogorov-Smirnov	0.108	> 0.15
LogNormal	Kolmogorov-Smirnov	0.136	> 0.15

Distribution Analysis of A8

Skew	0.37
Number	22.00
Mean	1.85
Median	1.78
Standard Deviation	0.14
Missing Records	6.00

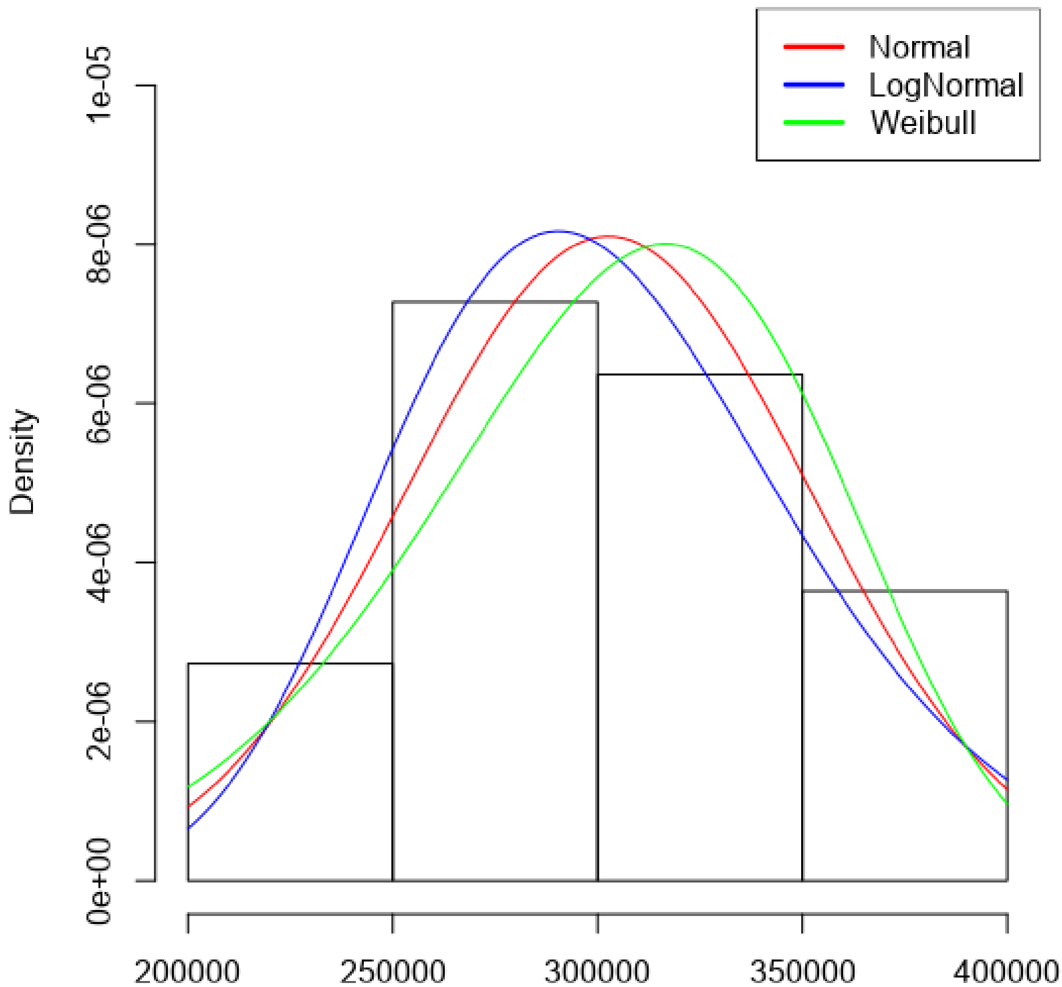


Goodness-of-Fit Statistics

Type	Test	Statistic	Significance
Normal	Anderson-Darling	1.234	< 0.005
LogNormal	Anderson-Darling	1.153	0.0052
Weibull	Anderson-Darling	1.313	< 0.01
Type	**Test**	**Statistic**	**Significance**
Normal	Chi-Square	13.765	0.001
LogNormal	Chi-Square	12.585	0.0019
Gamma	Chi-Square	12.957	0.0015
Weibull	Chi-Square	18.699	1e-04
Type	**Test**	**Statistic**	**Significance**
Normal	Cramer-von Mises	0.218	< 0.005
LogNormal	Cramer-von Mises	0.204	< 0.005
Weibull	Cramer-von Mises	0.232	< 0.01
Type	**Test**	**Statistic**	**Significance**
Normal	Kolmogorov-Smirnov	0.240	> 0.15
LogNormal	Kolmogorov-Smirnov	0.231	> 0.15

Distribution Analysis of A9

Skew	0.01
Number	22.00
Mean	302,573.25
Median	300,911.28
Standard Deviation	50,407.32
Missing Records	6.00

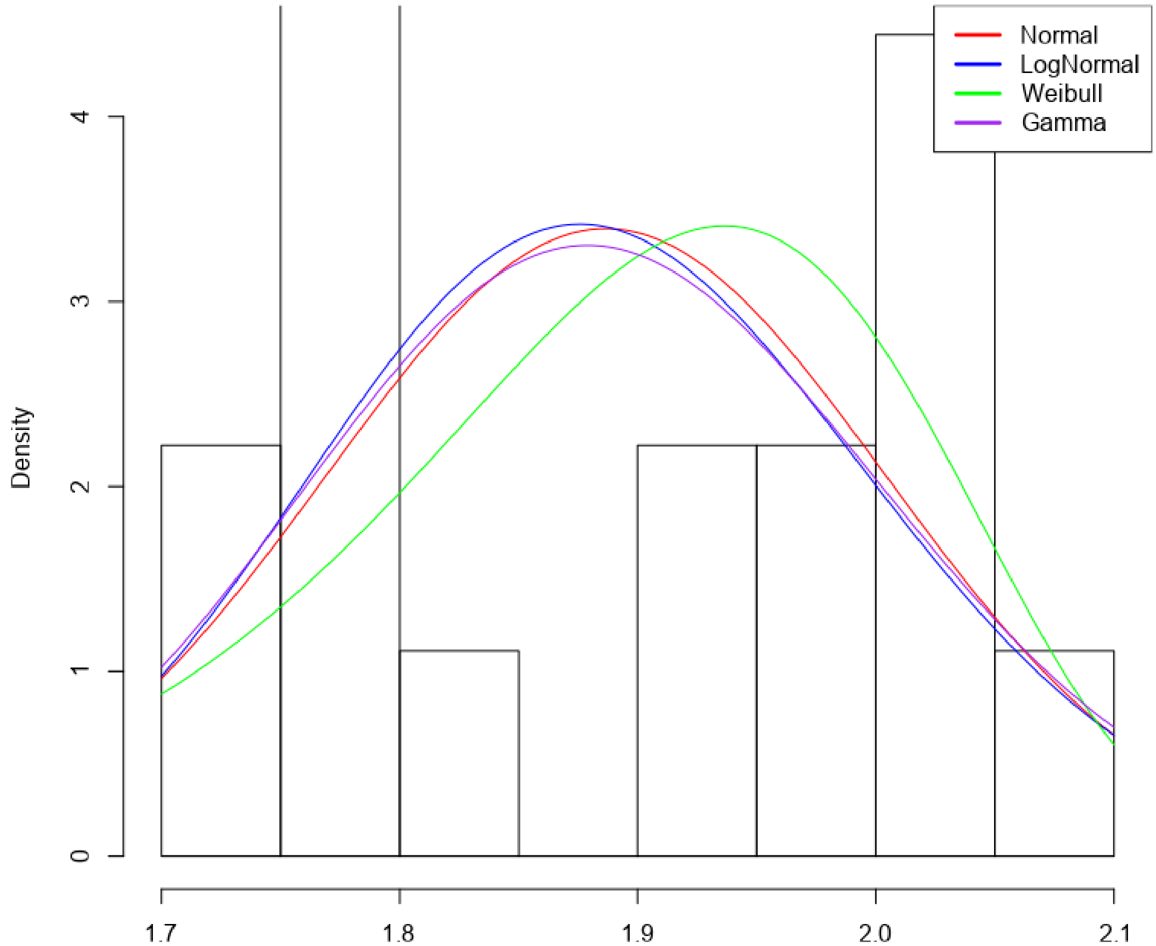


Goodness-of-Fit Statistics

Type	Test	Statistic	Significance
Normal	Anderson-Darling	0.270	> 0.5
LogNormal	Anderson-Darling	0.330	> 0.5
Weibull	Anderson-Darling	0.279	> 0.25
Type	**Test**	**Statistic**	**Significance**
Normal	Chi-Square	1.259	0.5328
LogNormal	Chi-Square	1.336	0.5129
Weibull	Chi-Square	1.357	0.5075
Type	**Test**	**Statistic**	**Significance**
Normal	Cramer-von Mises	0.043	> 0.5
LogNormal	Cramer-von Mises	0.050	> 0.5
Weibull	Cramer-von Mises	0.045	> 0.25
Type	**Test**	**Statistic**	**Significance**
Normal	Kolmogorov-Smirnov	0.109	> 0.15
LogNormal	Kolmogorov-Smirnov	0.115	> 0.15

Distribution Analysis of A10

Skew	0.18
Number	18.00
Mean	1.89
Median	1.88
Standard Deviation	0.12
Missing Records	10.00

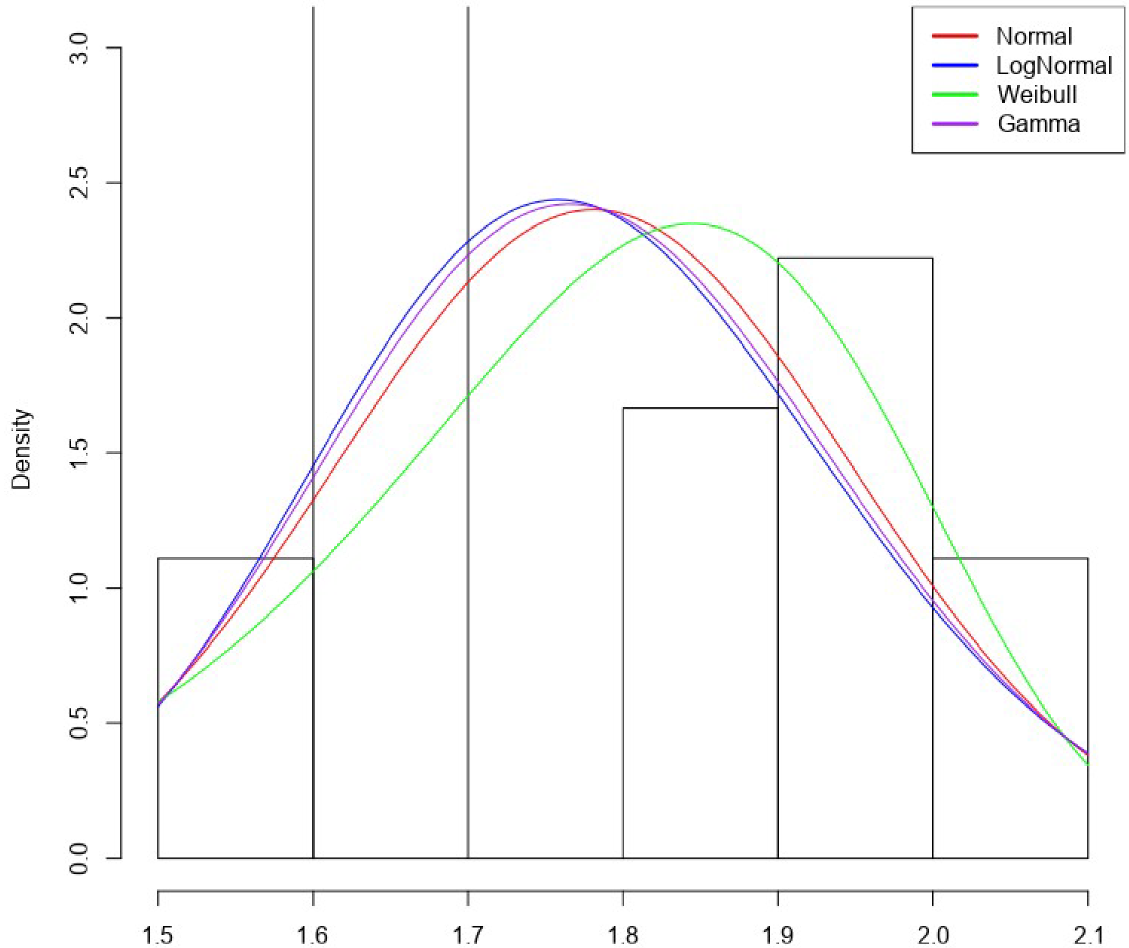


Goodness-of-Fit Statistics

Type	Test	Statistic	Significance
Normal	Anderson-Darling	1.109	0.007
LogNormal	Anderson-Darling	1.104	0.0072
Weibull	Anderson-Darling	1.042	< 0.01
Type	**Test**	**Statistic**	**Significance**
Normal	Chi-Square	10.091	0.0178
LogNormal	Chi-Square	9.388	0.0246
Gamma	Chi-Square	9.602	0.0223
Weibull	Chi-Square	13.779	0.0032
Type	**Test**	**Statistic**	**Significance**
Normal	Cramer-von Mises	0.186	0.0084
LogNormal	Cramer-von Mises	0.186	0.0085
Weibull	Cramer-von Mises	0.173	0.011
Type	**Test**	**Statistic**	**Significance**
Normal	Kolmogorov-Smirnov	0.239	> 0.15
LogNormal	Kolmogorov-Smirnov	0.237	> 0.15

Distribution Analysis of A11

Skew	0.26
Number	18.00
Mean	1.78
Median	1.75
Standard Deviation	0.17
Missing Records	10.00



Goodness-of-Fit Statistics

Type	Test	Statistic	Significance
Normal	Anderson-Darling	0.979	0.0152
LogNormal	Anderson-Darling	0.954	0.0175
Weibull	Anderson-Darling	0.944	0.0187

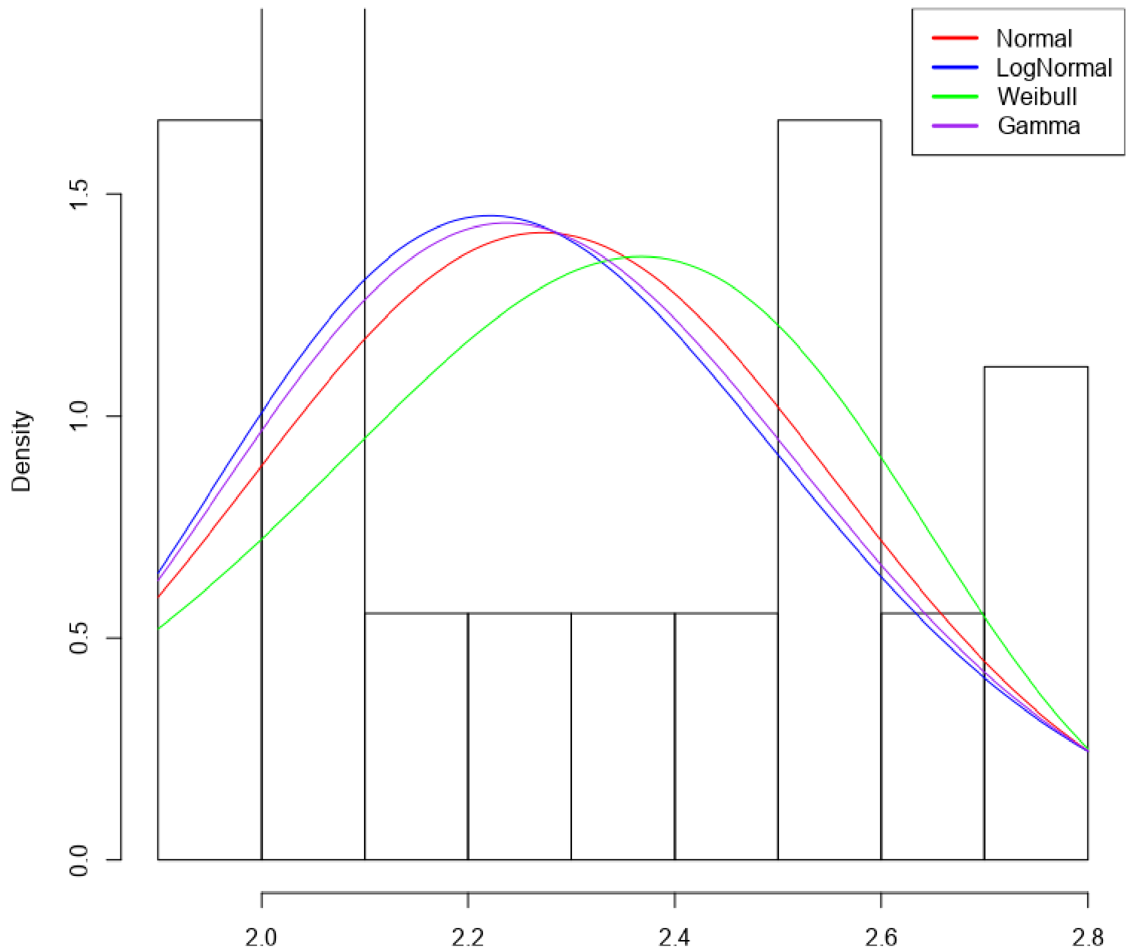
Type	Test	Statistic	Significance
Normal	Chi-Square	9.475	0.0236
LogNormal	Chi-Square	8.398	0.0385
Gamma	Chi-Square	8.721	0.0332
Weibull	Chi-Square	12.813	0.0051

Type	Test	Statistic	Significance
Normal	Cramer-von Mises	0.167	0.0158
LogNormal	Cramer-von Mises	0.165	0.017
Weibull	Cramer-von Mises	0.157	0.0191

Type	Test	Statistic	Significance
Normal	Kolmogorov-Smirnov	0.229	> 0.15
LogNormal	Kolmogorov-Smirnov	0.225	> 0.15

Distribution Analysis of A12

Skew	0.34
Number	18.00
Mean	2.27
Median	2.19
Standard Deviation	0.29
Missing Records	10.00



Goodness-of-Fit Statistics

Type	Test	Statistic	Significance
Normal	Anderson-Darling	1.008	0.0125
LogNormal	Anderson-Darling	0.957	0.0172
Weibull	Anderson-Darling	0.985	0.0149

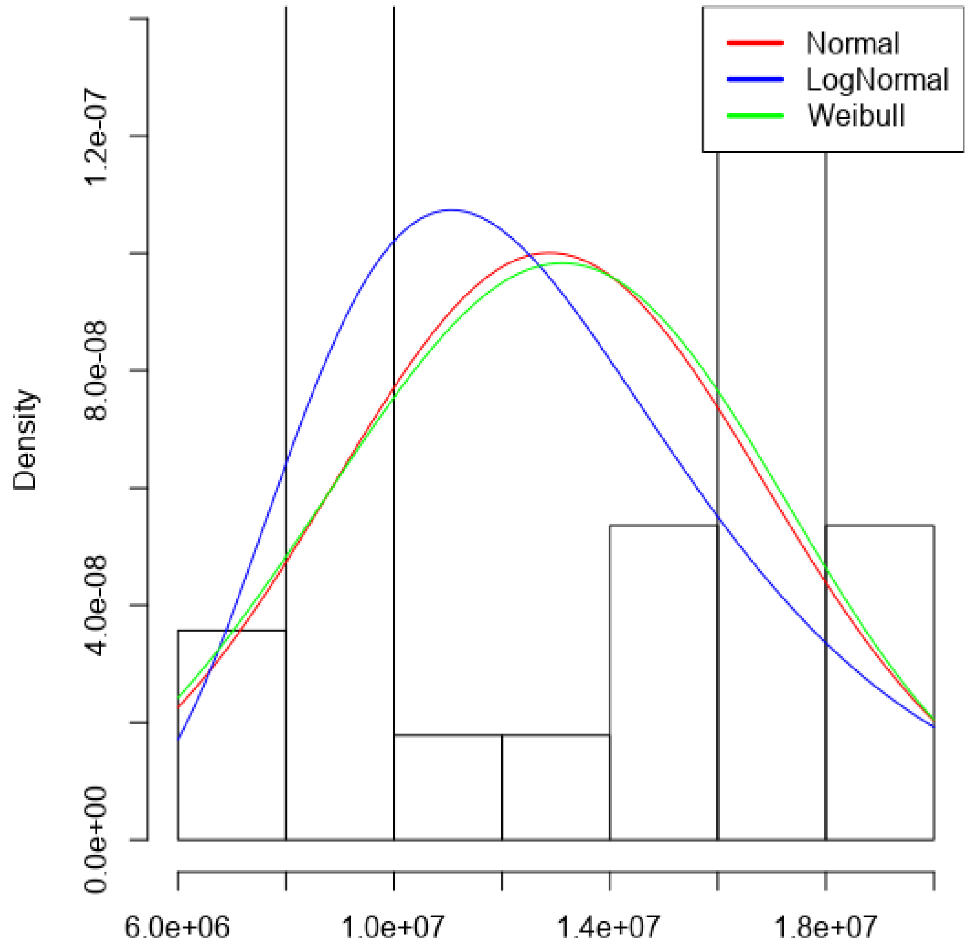
Type	Test	Statistic	Significance
Normal	Chi-Square	11.655	0.0087
LogNormal	Chi-Square	9.801	0.0203
Gamma	Chi-Square	10.355	0.0158
Weibull	Chi-Square	15.283	0.0016

Type	Test	Statistic	Significance
Normal	Cramer-von Mises	0.167	0.0156
LogNormal	Cramer-von Mises	0.160	0.0191
Weibull	Cramer-von Mises	0.163	0.0162

Type	Test	Statistic	Significance
Normal	Kolmogorov-	0.234	> 0.15
LogNormal	Kolmogorov-	0.229	> 0.15

Distribution Analysis of A13

Skew	0.10
Number	28.00
Mean	12,879,007.77
Median	12,729,436.44
Standard Deviation	4,059,494.75
Missing Records	0.00

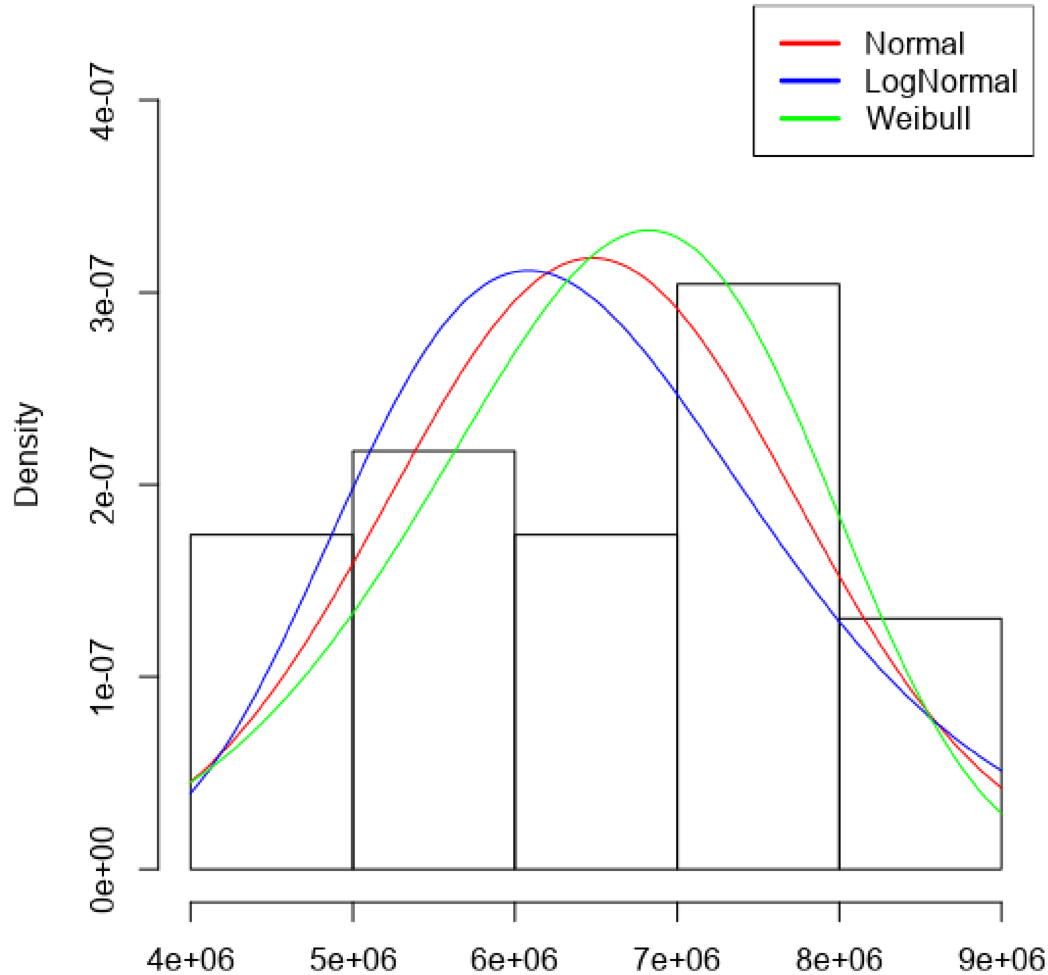


Goodness-of-Fit Statistics

Type	Test	Statistic	Significance
Normal	Anderson-Darling	1.777	< 0.005
LogNormal	Anderson-Darling	2.054	< 0.005
Weibull	Anderson-Darling	1.718	< 0.01
Type	Test	Statistic	Significance
Normal	Chi-Square	24.705	1e-04
LogNormal	Chi-Square	23.676	1e-04
Weibull	Chi-Square	24.238	1e-04
Type	Test	Statistic	Significance
Normal	Cramer-von Mises	0.304	< 0.005
LogNormal	Cramer-von Mises	0.355	< 0.005
Weibull	Cramer-von Mises	0.294	< 0.01
Type	Test	Statistic	Significance
Normal	Kolmogorov-Smirnov	0.252	> 0.15
LogNormal	Kolmogorov-Smirnov	0.249	> 0.15

Distribution Analysis of A14

Skew	-0.34
Number	23.00
Mean	6,477,584.49
Median	6,831,333.30
Standard Deviation	1,283,106.32
Missing Records	5.00



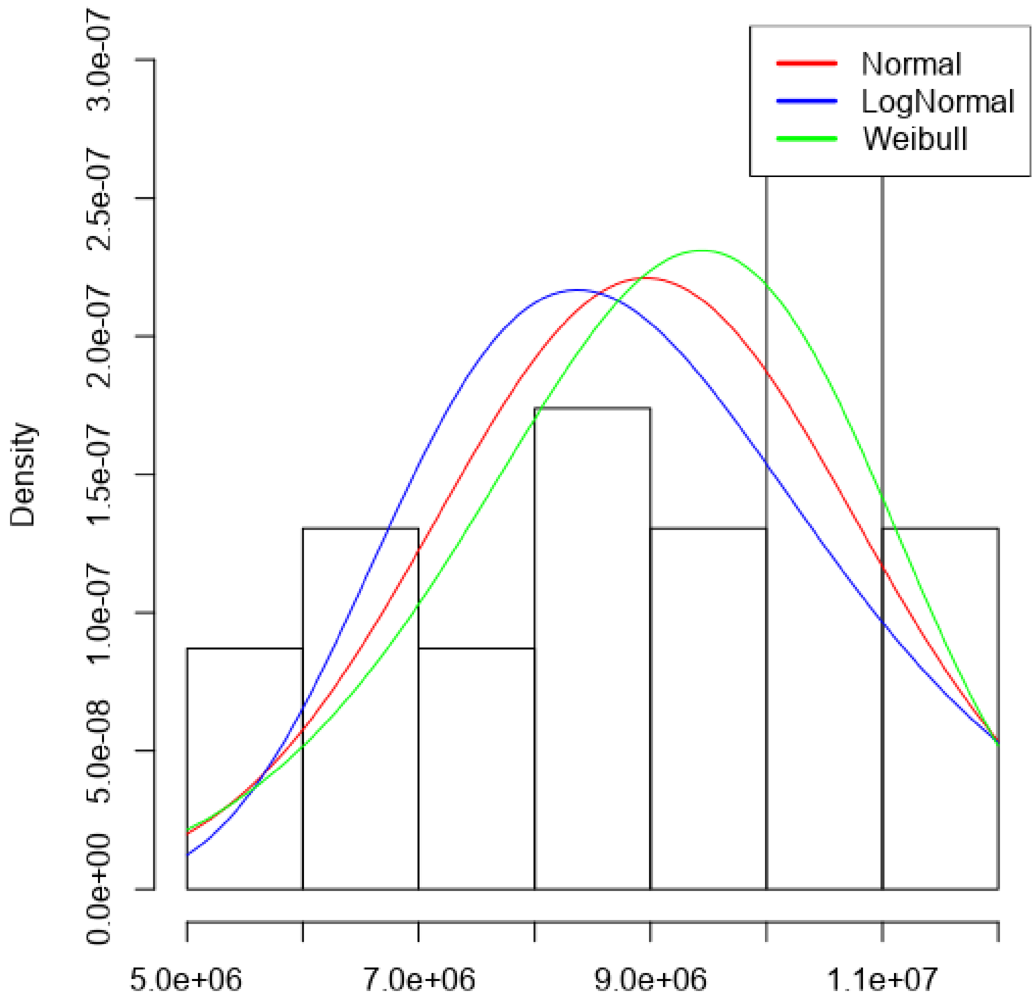
Goodness-of-Fit Statistics

Type	Test	Statistic	Significance
Normal	Anderson-Darling	0.402	0.3825
LogNormal	Anderson-Darling	0.715	0.0652
Weibull	Anderson-Darling	0.324	> 0.25
Type	Test	Statistic	Significance
Normal	Chi-Square	3.971	0.2646
LogNormal	Chi-Square	6.773	0.0795
Weibull	Chi-Square	3.028	0.3873
Type	Test	Statistic	Significance
Normal	Cramer-von Mises	0.065	0.3425
LogNormal	Cramer-von Mises	0.111	0.0838
Weibull	Cramer-von Mises	0.051	> 0.25
Type	Test	Statistic	Significance
Normal	Kolmogorov-Smirnov	0.139	> 0.15
LogNormal	Kolmogorov-Smirnov	0.167	> 0.15

Distribution Analysis of A15

Skew	-0.34
Number	23.00
Mean	8,960,342.15
Median	9,417,402.25

Standard Deviation	1,845,801.94
Missing Records	5.00

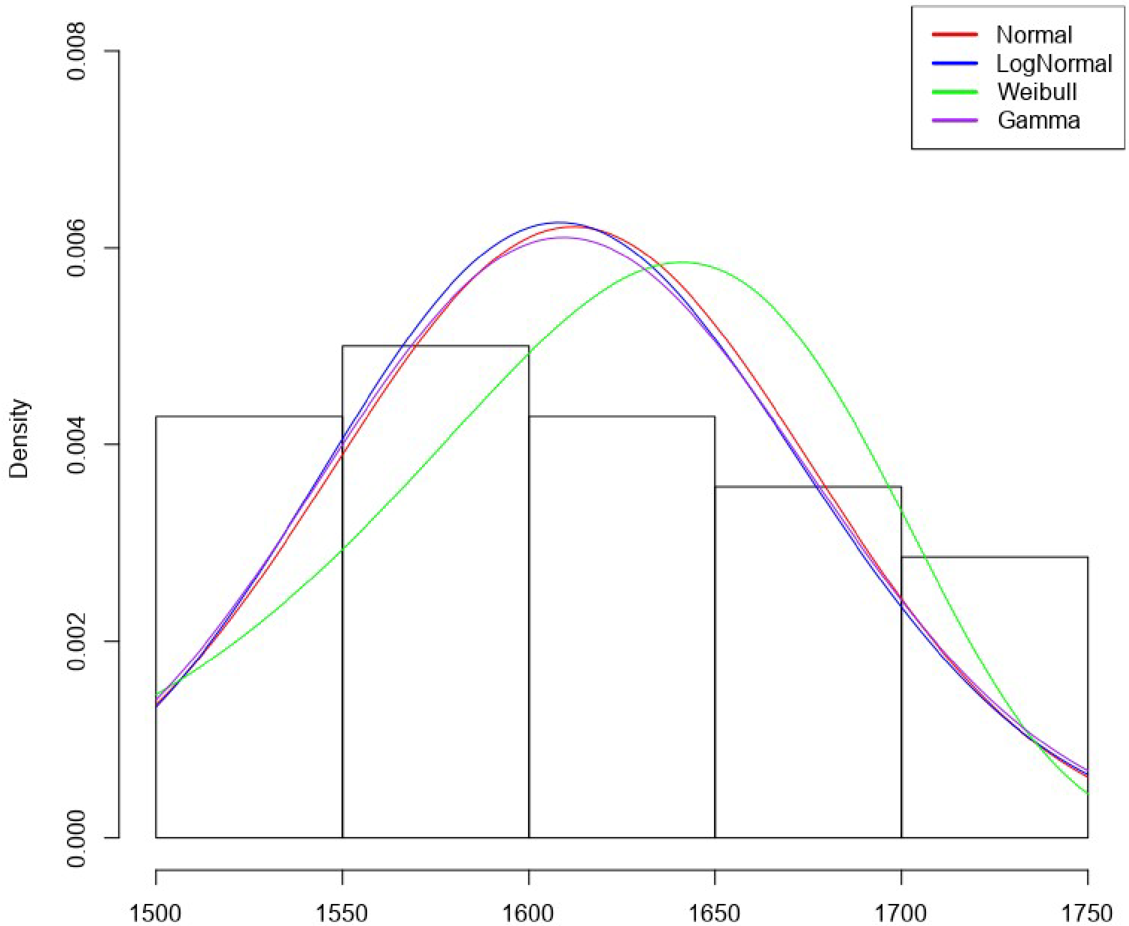


Goodness-of-Fit Statistics

Type	Test	Statistic	Significance
Normal	Anderson-Darling	0.450	0.289
LogNormal	Anderson-Darling	0.786	0.0431
Weibull	Anderson-Darling	0.378	> 0.25
Type	**Test**	**Statistic**	**Significance**
Normal	Chi-Square	3.635	0.3037
LogNormal	Chi-Square	6.703	0.082
Weibull	Chi-Square	2.845	0.4162
Type	**Test**	**Statistic**	**Significance**
Normal	Cramer-von Mises	0.073	0.2601
LogNormal	Cramer-von Mises	0.122	0.0588
Weibull	Cramer-von Mises	0.059	> 0.25
Type	**Test**	**Statistic**	**Significance**
Normal	Kolmogorov-Smirnov	0.143	> 0.15
LogNormal	Kolmogorov-Smirnov	0.174	> 0.15

Distribution Analysis of A16

Skew	0.35
Number	28.00
Mean	1,612.02
Median	1,603.87
Standard Deviation	65.39
Missing Records	0.00

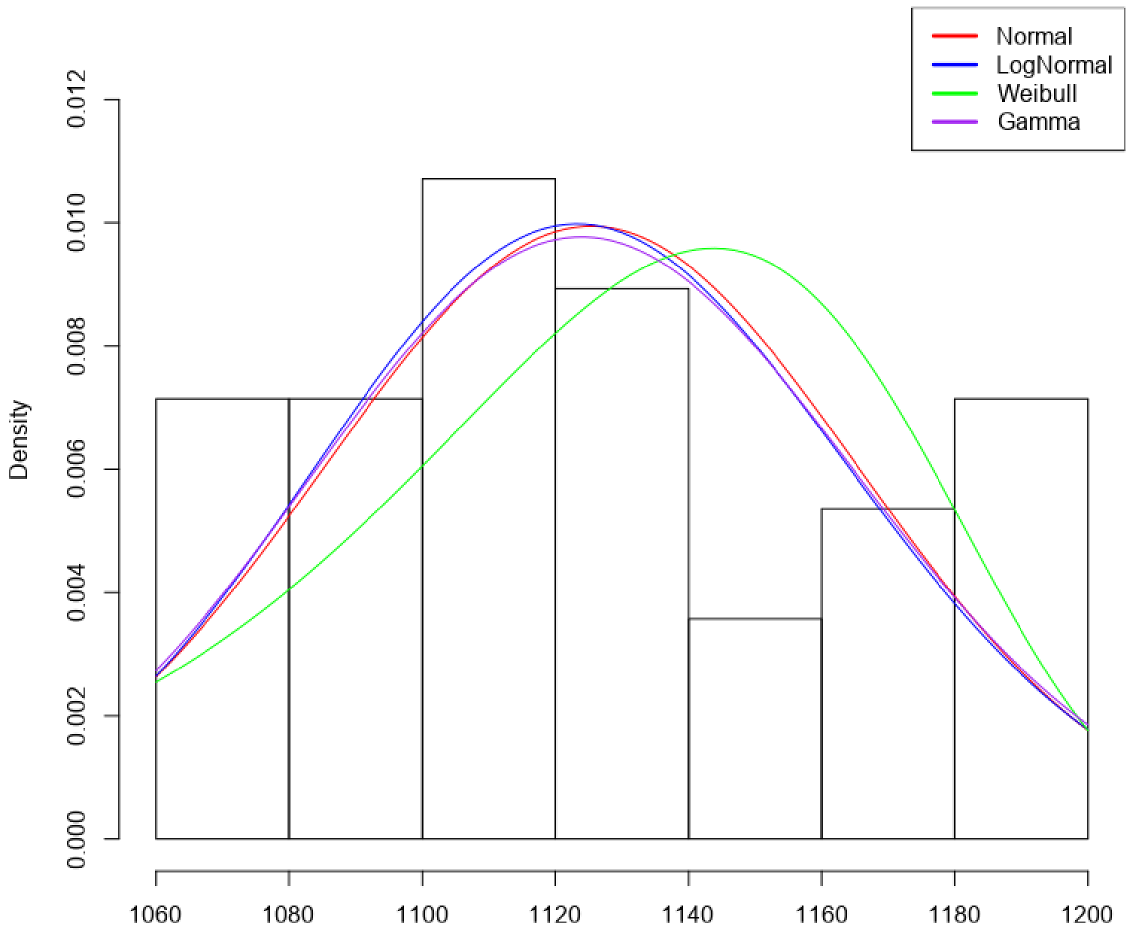


Goodness-of-Fit Statistics

Type	Test	Statistic	Significance
Normal	Anderson-Darling	0.560	0.1513
LogNormal	Anderson-Darling	0.508	0.2085
Weibull	Anderson-Darling	0.877	0.025
Type	**Test**	**Statistic**	**Significance**
Normal	Chi-Square	3.145	0.5339
LogNormal	Chi-Square	2.870	0.5798
Gamma	Chi-Square	2.952	0.5659
Weibull	Chi-Square	5.066	0.2806
Type	**Test**	**Statistic**	**Significance**
Normal	Cramer-von Mises	0.081	0.2072
LogNormal	Cramer-von Mises	0.072	0.27
Weibull	Cramer-von Mises	0.143	0.0288
Type	**Test**	**Statistic**	**Significance**
Normal	Kolmogorov-Smirnov	0.121	> 0.15
LogNormal	Kolmogorov-Smirnov	0.119	> 0.15

Distribution Analysis of A17

Skew	0.20
Number	28.00
Mean	1,125.39
Median	1,120.95
Standard Deviation	40.86
Missing Records	0.00

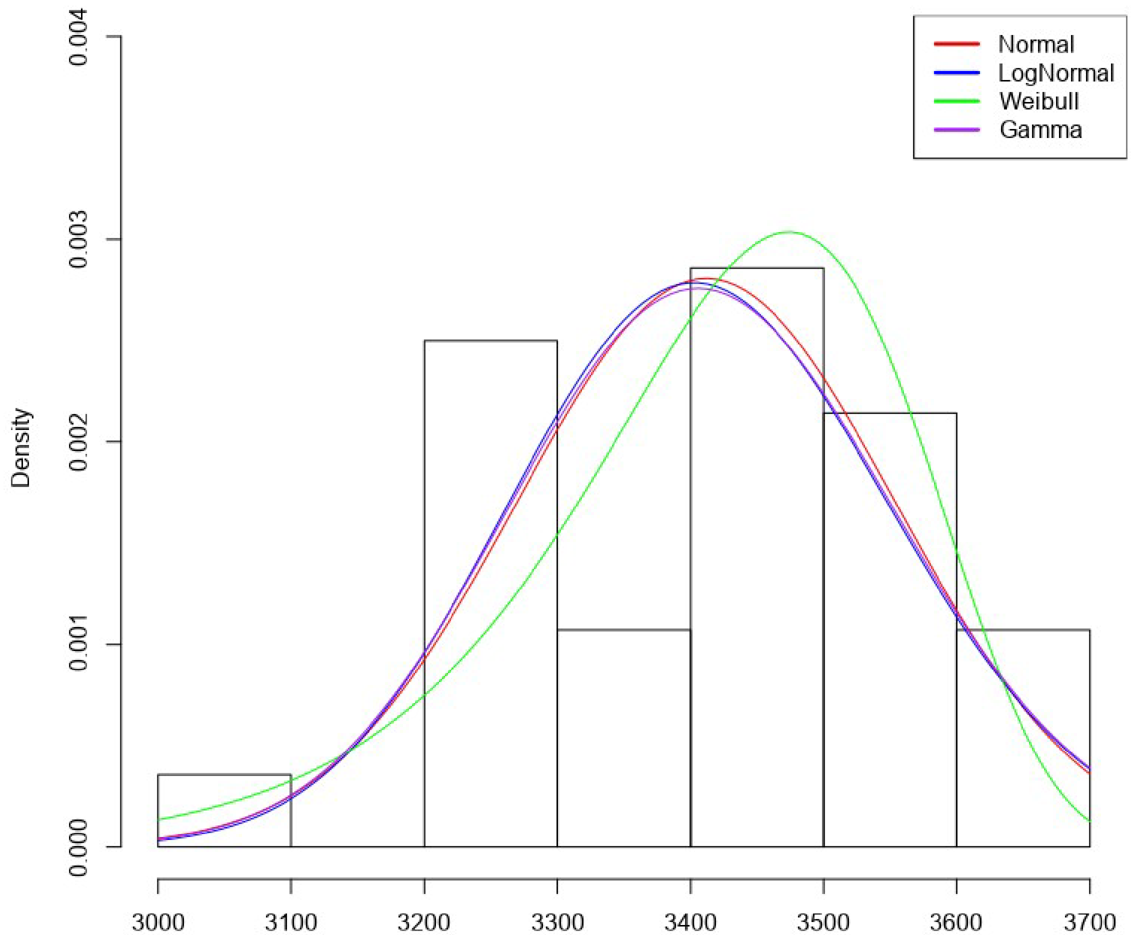


Goodness-of-Fit Statistics

Type	Test	Statistic	Significance
Normal	Anderson-Darling	0.461	0.2669
LogNormal	Anderson-Darling	0.434	0.3191
Weibull	Anderson-Darling	0.741	0.0568
Type	**Test**	**Statistic**	**Significance**
Normal	Chi-Square	2.549	0.6358
LogNormal	Chi-Square	2.550	0.6357
Gamma	Chi-Square	2.539	0.6377
Weibull	Chi-Square	2.811	0.5899
Type	**Test**	**Statistic**	**Significance**
Normal	Cramer-von Mises	0.063	0.3642
LogNormal	Cramer-von Mises	0.058	0.4236
Weibull	Cramer-von Mises	0.123	0.0526
Type	**Test**	**Statistic**	**Significance**
Normal	Kolmogorov-Smirnov	0.104	> 0.15
LogNormal	Kolmogorov-Smirnov	0.103	> 0.15

Distribution Analysis of A18

Skew	-0.38
Number	28.00
Mean	3,411.78
Median	3,440.74
Standard Deviation	144.80
Missing Records	0.00

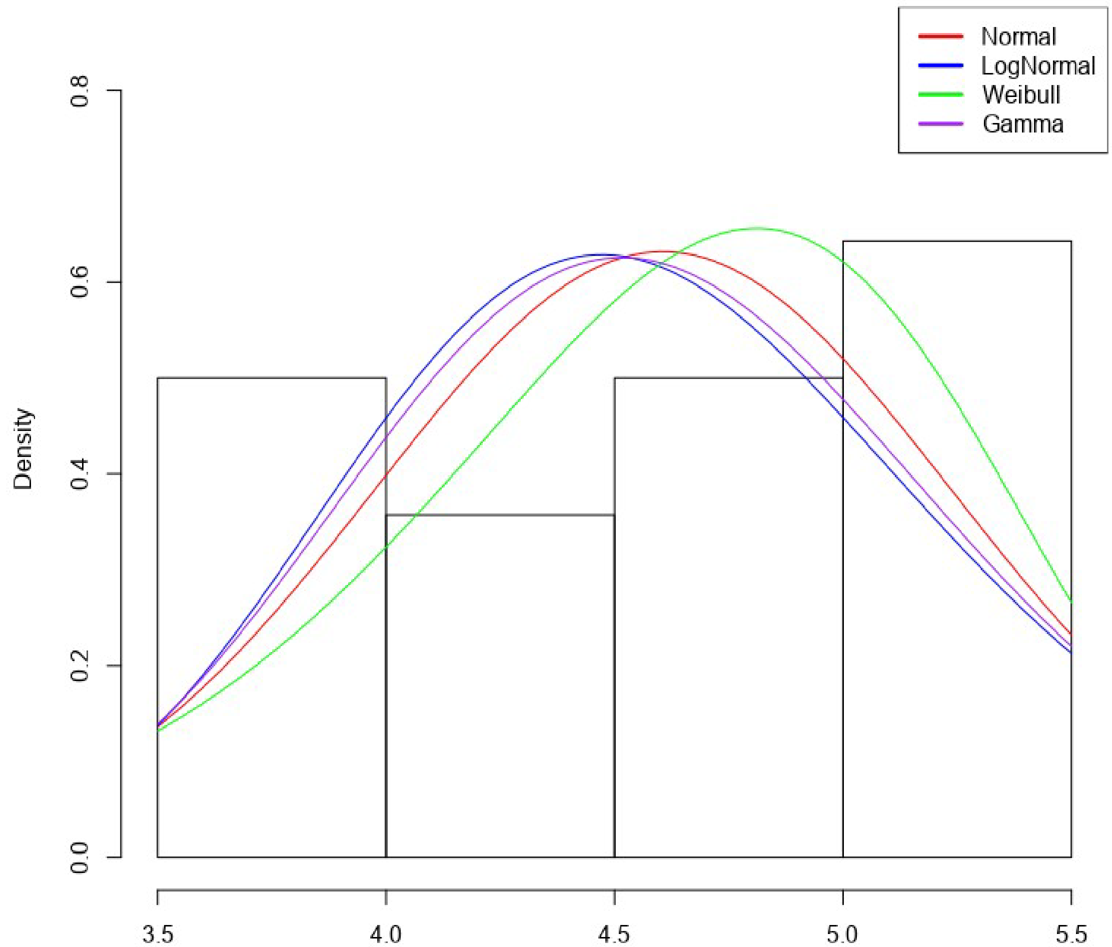


Goodness-of-Fit Statistics

Type	Test	Statistic	Significance
Normal	Anderson-Darling	0.423	0.3412
LogNormal	Anderson-Darling	0.465	0.2599
Weibull	Anderson-Darling	0.348	> 0.25
Type	**Test**	**Statistic**	**Significance**
Normal	Chi-Square	4.444	0.3493
LogNormal	Chi-Square	4.772	0.3115
Gamma	Chi-Square	4.655	0.3245
Weibull	Chi-Square	3.311	0.5072
Type	**Test**	**Statistic**	**Significance**
Normal	Cramer-von Mises	0.071	0.2865
LogNormal	Cramer-von Mises	0.079	0.2231
Weibull	Cramer-von Mises	0.048	> 0.25
Type	**Test**	**Statistic**	**Significance**
Normal	Kolmogorov-Smirnov	0.109	> 0.15
LogNormal	Kolmogorov-Smirnov	0.117	> 0.15

Distribution Analysis of A19

Skew	-0.18
Number	28.00
Mean	4.61
Median	4.71
Standard Deviation	0.64
Missing Records	0.00



Goodness-of-Fit Statistics

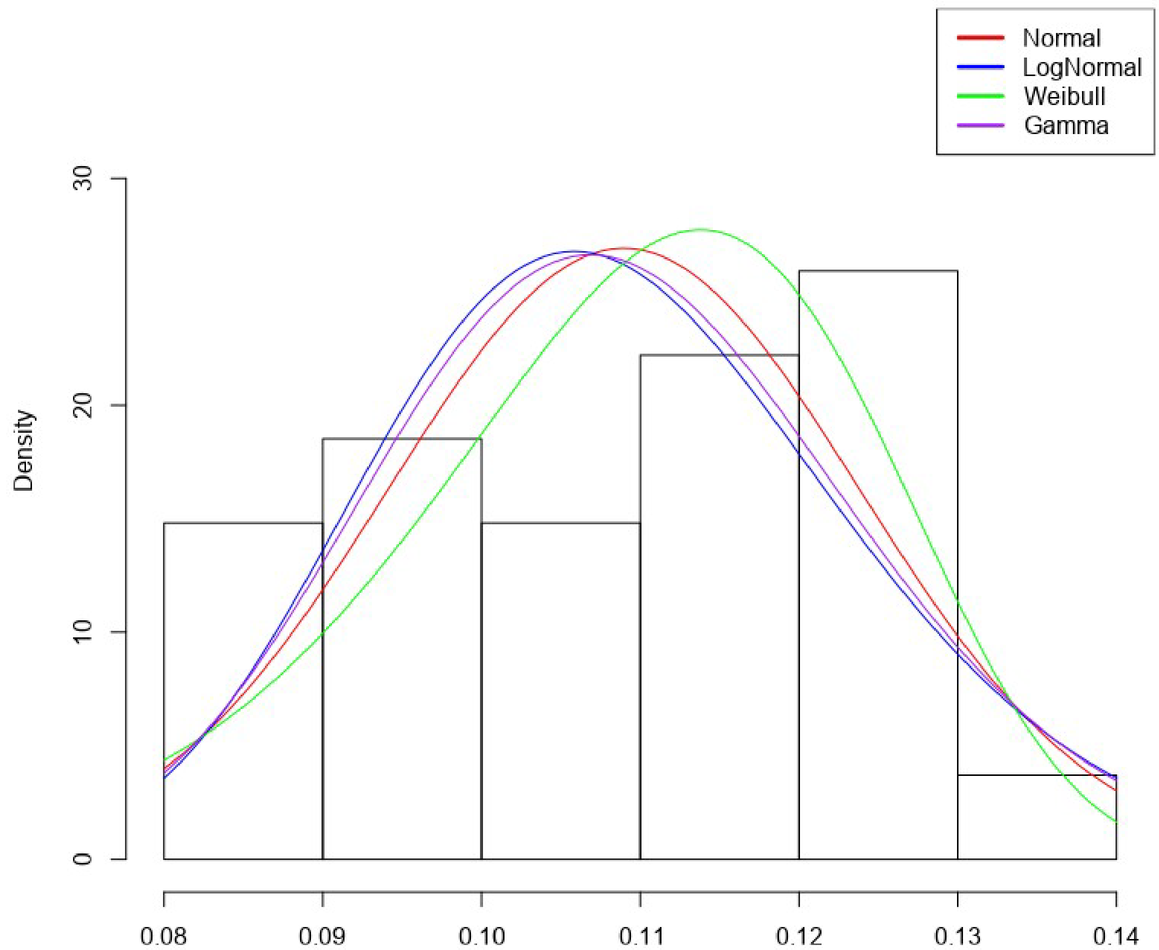
Type	Test	Statistic	Significance
Normal	Anderson-Darling	0.650	0.0923
LogNormal	Anderson-Darling	0.769	0.0466
Weibull	Anderson-Darling	0.661	0.0899

Type	Test	Statistic	Significance
Normal	Chi-Square	4.506	0.3418
LogNormal	Chi-Square	6.642	0.1561
Gamma	Chi-Square	5.691	0.2235
Weibull	Chi-Square	3.464	0.4834

Type	Test	Statistic	Significance
Normal	Cramer-von Mises	0.091	0.1486
LogNormal	Cramer-von Mises	0.111	0.0832
Weibull	Cramer-von Mises	0.092	0.1517

Type	Test	Statistic	Significance
Normal	Kolmogorov-Smirnov	0.126	> 0.15
LogNormal	Kolmogorov-Smirnov	0.133	> 0.15

Distribution Analysis of A20



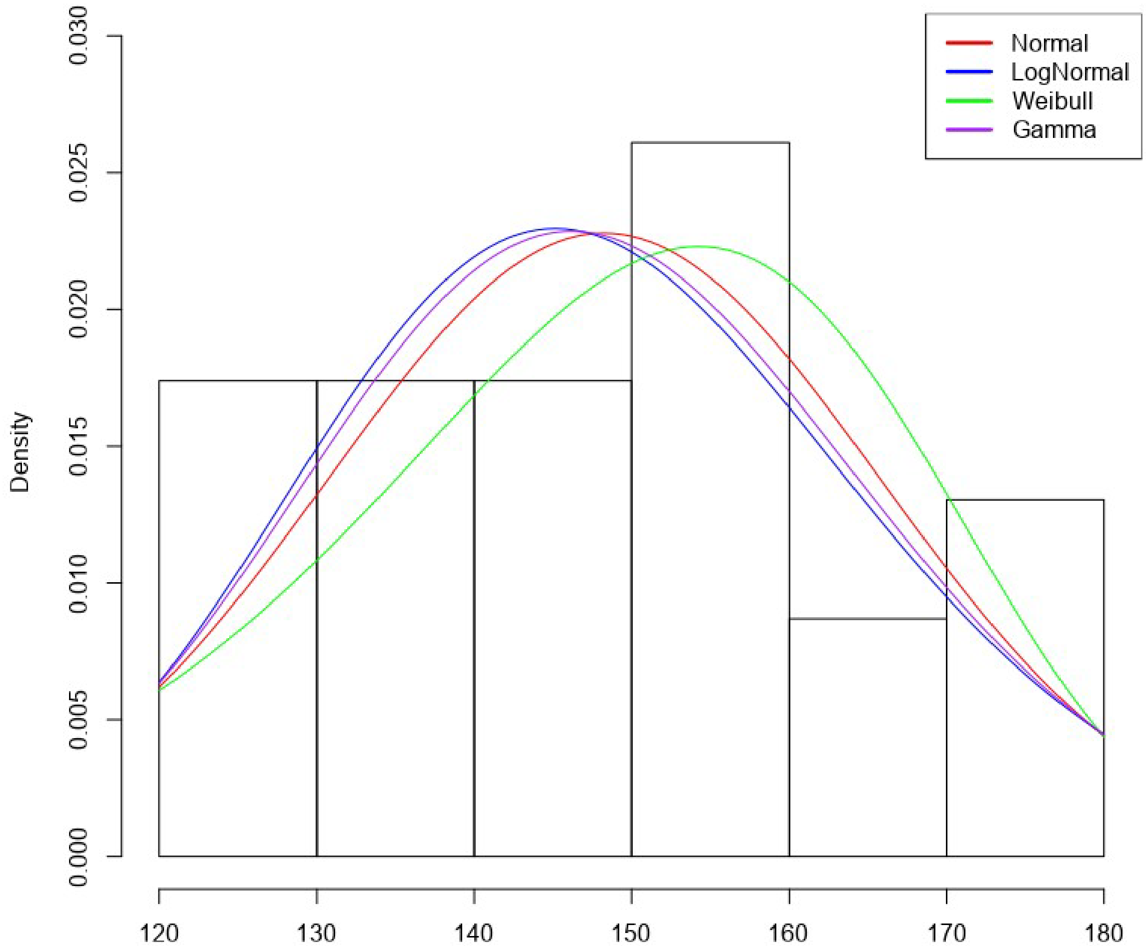
Skew	-0.17
Number	27.00
Mean	0.11
Median	0.11
Standard Deviation	0.02
Missing Records	1.00

Goodness-of-Fit Statistics

Type	Test	Statistic	Significance
Normal	Anderson-Darling	0.515	0.2002
LogNormal	Anderson-Darling	0.601	0.1211
Weibull	Anderson-Darling	0.541	0.1885
Type	**Test**	**Statistic**	**Significance**
Normal	Chi-Square	3.517	0.4753
LogNormal	Chi-Square	4.752	0.3137
Gamma	Chi-Square	4.203	0.3792
Weibull	Chi-Square	2.861	0.5814
Type	**Test**	**Statistic**	**Significance**
Normal	Cramer-von Mises	0.076	0.2376
LogNormal	Cramer-von Mises	0.092	0.1467
Weibull	Cramer-von Mises	0.078	0.222
Type	**Test**	**Statistic**	**Significance**
Normal	Kolmogorov-Smirnov	0.117	> 0.15
LogNormal	Kolmogorov-Smirnov	0.122	> 0.15

Distribution Analysis of A21

Skew	0.07
Number	23.00
Mean	148.25
Median	149.57
Standard Deviation	17.90
Missing Records	5.00



Goodness-of-Fit Statistics

Type	Test	Statistic	Significance
Normal	Anderson-Darling	0.329	> 0.5
LogNormal	Anderson-Darling	0.367	0.4487
Weibull	Anderson-Darling	0.349	> 0.25

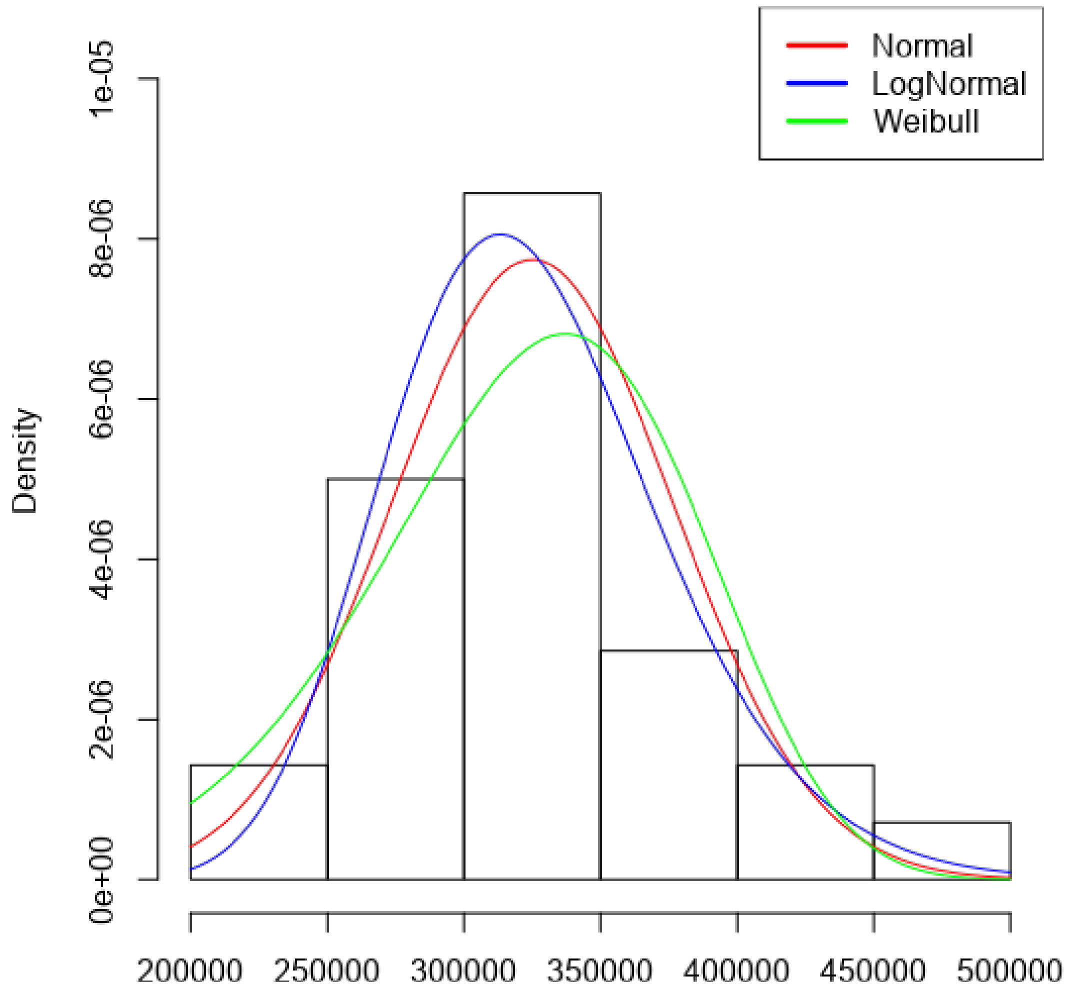
Type	Test	Statistic	Significance
Normal	Chi-Square	2.430	0.488
LogNormal	Chi-Square	3.544	0.3151
Gamma	Chi-Square	3.055	0.3832
Weibull	Chi-Square	1.047	0.7899

Type	Test	Statistic	Significance
Normal	Cramer-von Mises	0.049	> 0.5
LogNormal	Cramer-von Mises	0.055	0.452
Weibull	Cramer-von Mises	0.049	> 0.25

Type	Test	Statistic	Significance
Normal	Kolmogorov-Smirnov	0.106	> 0.15
LogNormal	Kolmogorov-Smirnov	0.123	> 0.15

Distribution Analysis of A22

Skew	0.59
Number	28.00
Mean	325,040.18
Median	322,506.50
Standard Deviation	52,462.21
Missing Records	0.00

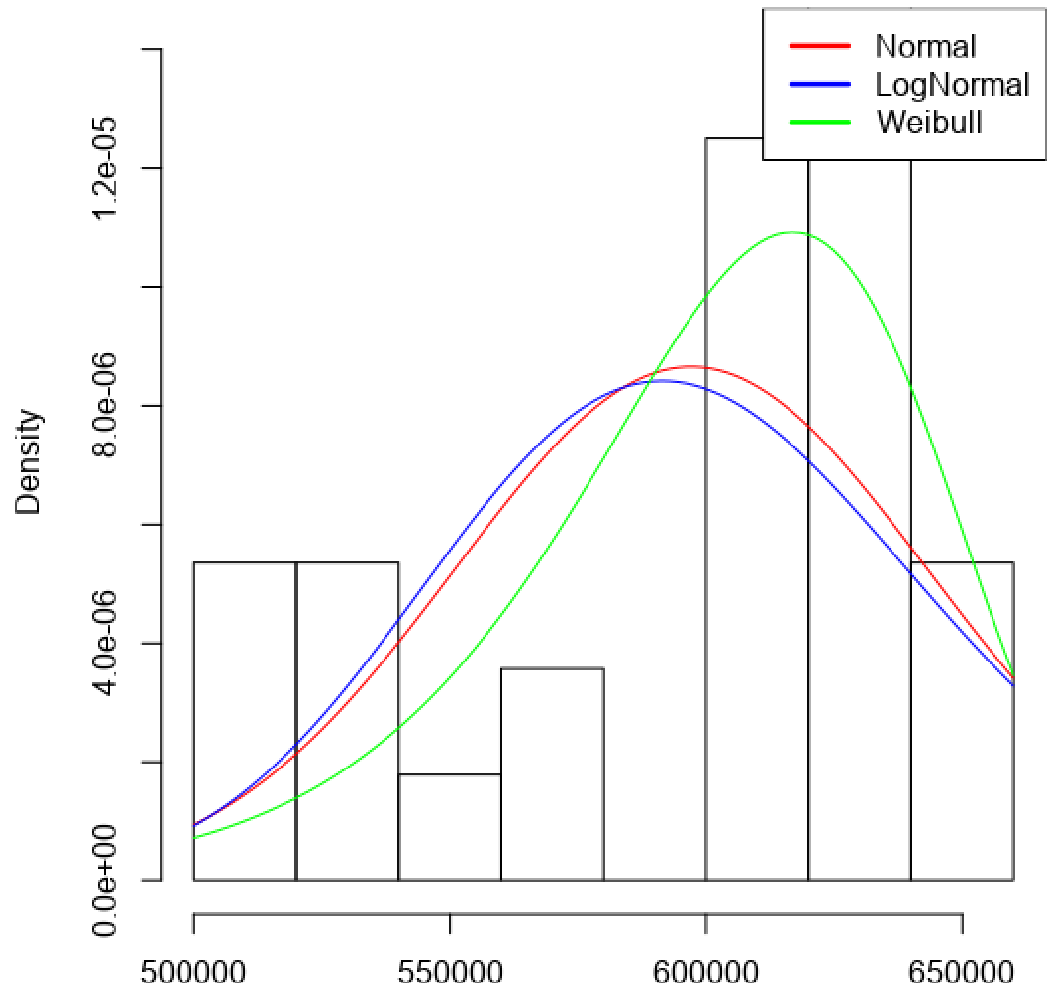


Goodness-of-Fit Statistics

Type	Test	Statistic	Significance
Normal	Anderson-Darling	0.362	0.4589
LogNormal	Anderson-Darling	0.234	> 0.5
Weibull	Anderson-Darling	0.694	0.0763
Type	**Test**	**Statistic**	**Significance**
Normal	Chi-Square	10.876	0.028
LogNormal	Chi-Square	10.586	0.0316
Weibull	Chi-Square	14.326	0.0063
Type	**Test**	**Statistic**	**Significance**
Normal	Cramer-von Mises	0.060	0.4019
LogNormal	Cramer-von Mises	0.042	> 0.5
Weibull	Cramer-von Mises	0.113	0.074
Type	**Test**	**Statistic**	**Significance**
Normal	Kolmogorov-Smirnov	0.153	> 0.15
LogNormal	Kolmogorov-Smirnov	0.122	> 0.15

Distribution Analysis of A23

Skew	-0.82
Number	28.00
Mean	597,070.29
Median	610,794.50
Standard Deviation	46,942.50
Missing Records	0.00



Goodness-of-Fit Statistics

Type	Test	Statistic	Significance
Normal	Anderson-Darling	1.921	< 0.005
LogNormal	Anderson-Darling	2.196	< 0.005
Weibull	Anderson-Darling	1.592	< 0.01

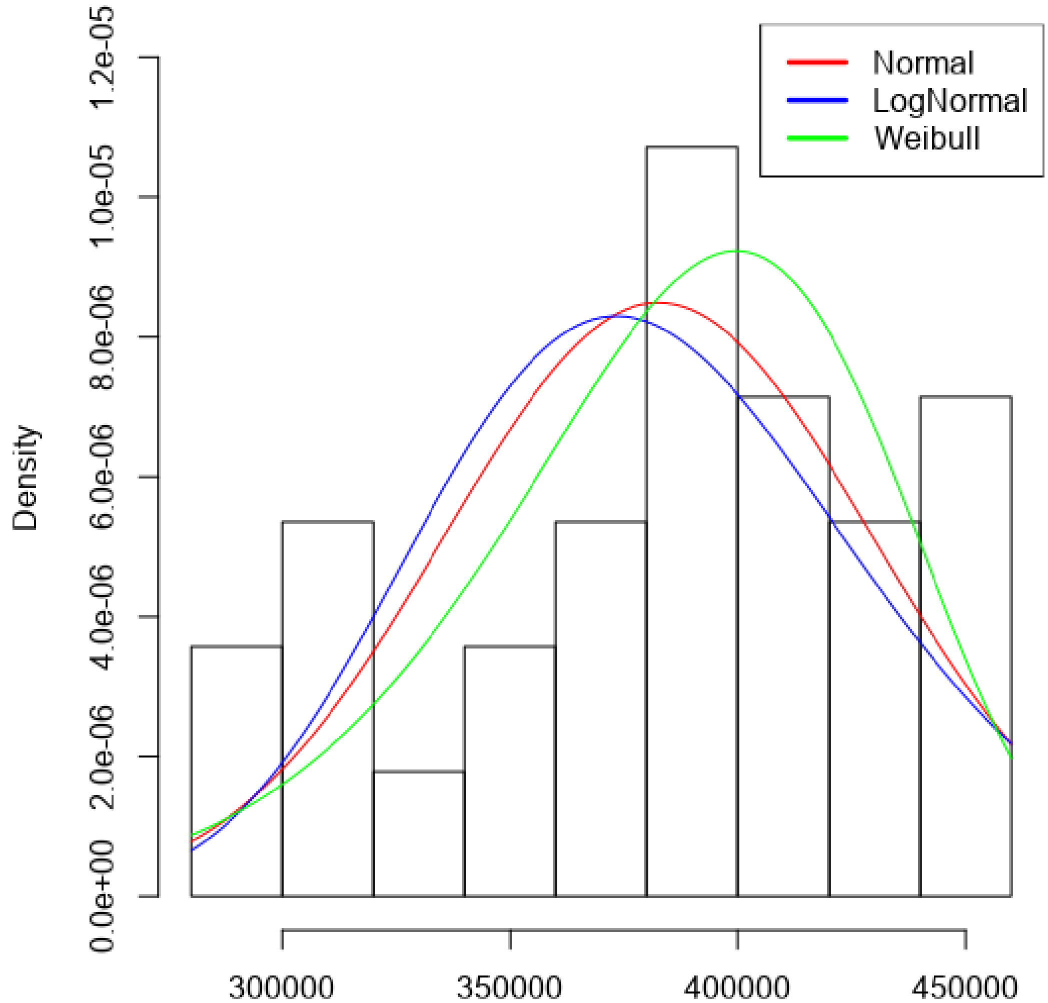
Type	Test	Statistic	Significance
Normal	Chi-Square	27.747	0
LogNormal	Chi-Square	31.821	0
Weibull	Chi-Square	20.082	5e-04

Type	Test	Statistic	Significance
Normal	Cramer-von Mises	0.326	< 0.005
LogNormal	Cramer-von Mises	0.371	< 0.005
Weibull	Cramer-von Mises	0.234	< 0.01

Type	Test	Statistic	Significance
Normal	Kolmogorov-Smirnov	0.255	> 0.15
LogNormal	Kolmogorov-Smirnov	0.270	> 0.15

Distribution Analysis of A24

Skew	-0.45
Number	28.00
Mean	382,520.00
Median	390,437.50
Standard Deviation	47,855.79
Missing Records	0.00



Goodness-of-Fit Statistics

Type	Test	Statistic	Significance
Normal	Anderson-Darling	0.592	0.1275
LogNormal	Anderson-Darling	0.881	0.0242
Weibull	Anderson-Darling	0.408	> 0.25

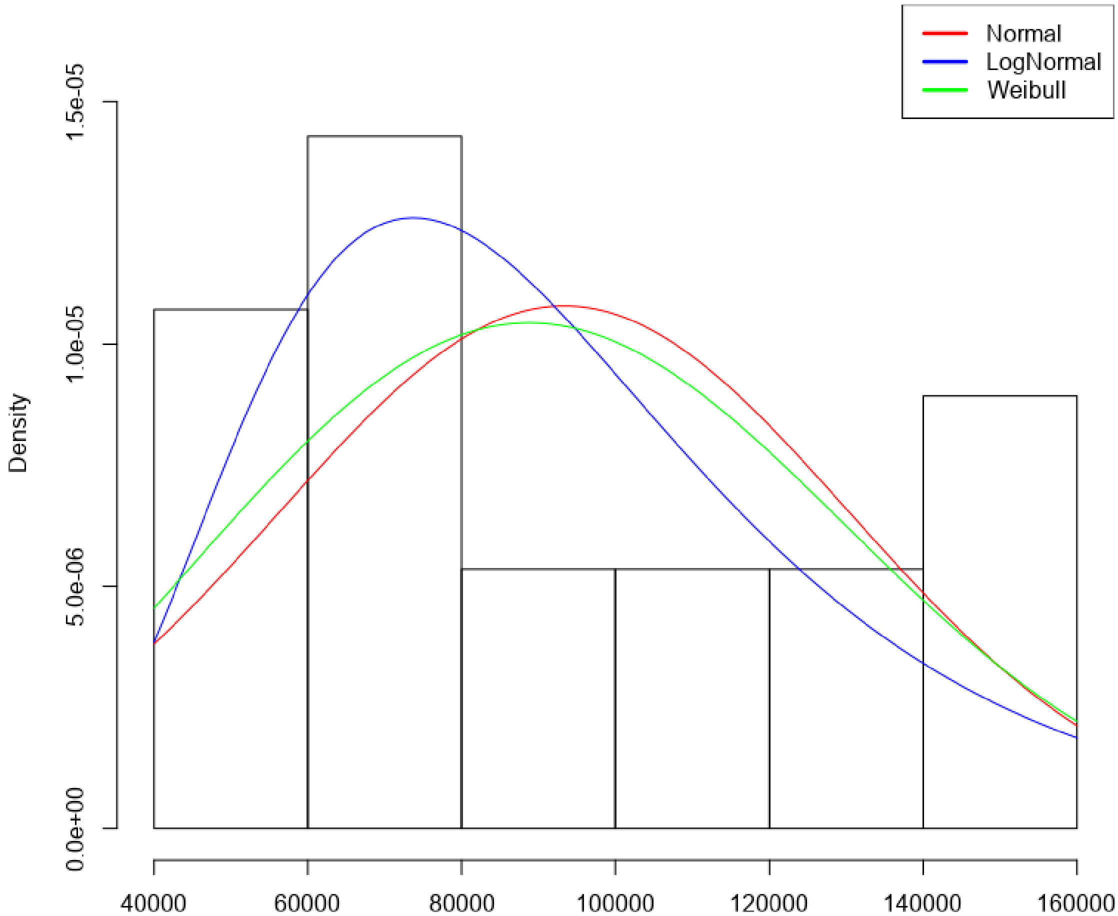
Type	Test	Statistic	Significance
Normal	Chi-Square	6.024	0.1974
LogNormal	Chi-Square	9.162	0.0572
Weibull	Chi-Square	4.203	0.3792

Type	Test	Statistic	Significance
Normal	Cramer-von Mises	0.074	0.2509
LogNormal	Cramer-von Mises	0.116	0.0736
Weibull	Cramer-von Mises	0.040	> 0.25

Type	Test	Statistic	Significance
Normal	Kolmogorov-Smirnov	0.119	> 0.15
LogNormal	Kolmogorov-Smirnov	0.133	> 0.15

Distribution Analysis of A25

Skew	0.46
Number	28.00
Mean	93,340.86
Median	80,008.50
Standard Deviation	37,661.15
Missing Records	0.00

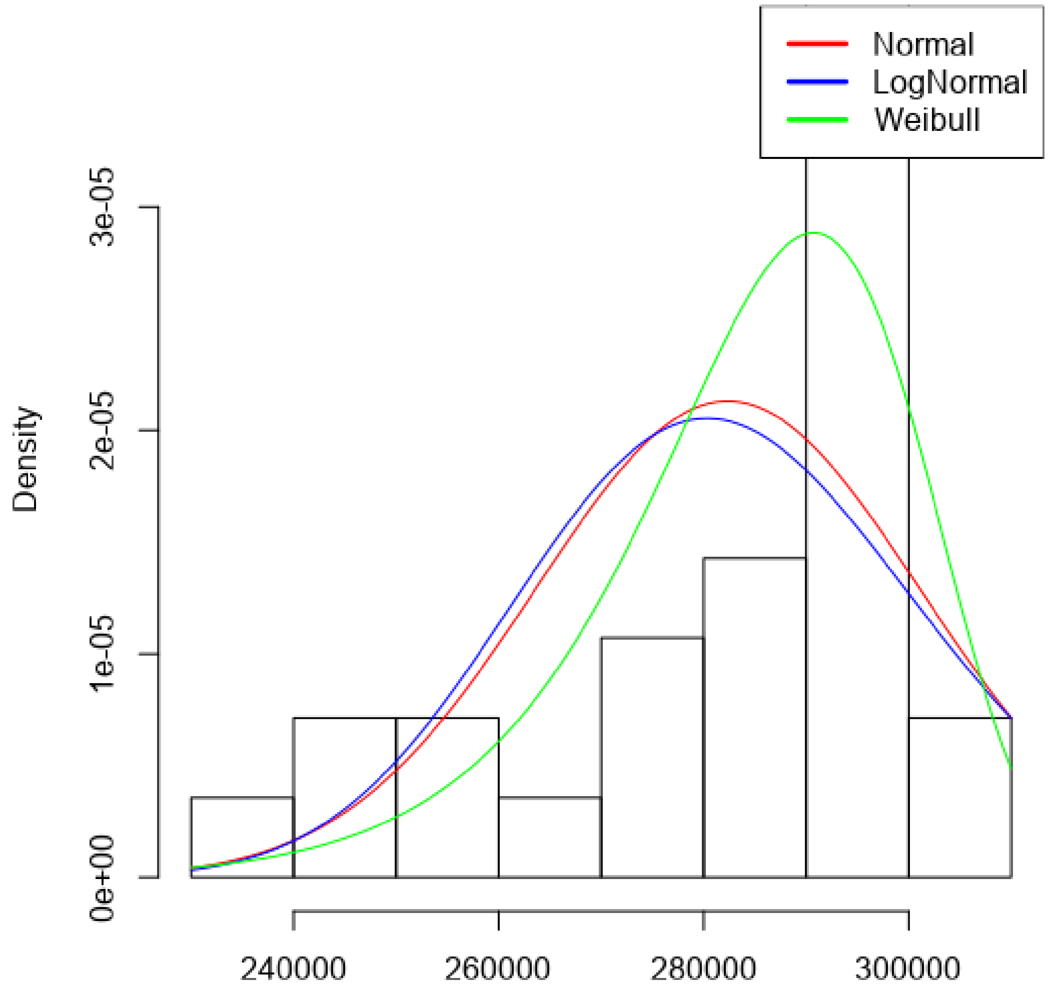


Goodness-of-Fit Statistics

Type	Test	Statistic	Significance
Normal	Anderson-Darling	1.235	< 0.005
LogNormal	Anderson-Darling	1.036	0.01
Weibull	Anderson-Darling	1.047	< 0.01
Type	Test	Statistic	Significance
Normal	Chi-Square	13.162	0.0105
LogNormal	Chi-Square	7.947	0.0935
Weibull	Chi-Square	11.221	0.0242
Type	Test	Statistic	Significance
Normal	Cramer-von Mises	0.205	< 0.005
LogNormal	Cramer-von Mises	0.169	0.0149
Weibull	Cramer-von Mises	0.173	0.0111
Type	Test	Statistic	Significance
Normal	Kolmogorov-Smirnov	0.185	> 0.15
LogNormal	Kolmogorov-Smirnov	0.156	> 0.15

Distribution Analysis of A26

Skew	-1.18
Number	28.00
Mean	282,341.36
Median	290,680.00
Standard Deviation	19,064.48
Missing Records	0.00



Goodness-of-Fit Statistics

Type	Test	Statistic	Significance
Normal	Anderson-Darling	1.714	< 0.005
LogNormal	Anderson-Darling	1.968	< 0.005
Weibull	Anderson-Darling	1.151	< 0.01
Type	**Test**	**Statistic**	**Significance**
Normal	Chi-Square	11.492	0.0216
LogNormal	Chi-Square	13.105	0.0108
Weibull	Chi-Square	7.239	0.1238
Type	**Test**	**Statistic**	**Significance**
Normal	Cramer-von Mises	0.295	< 0.005
LogNormal	Cramer-von Mises	0.336	< 0.005
Weibull	Cramer-von Mises	0.168	0.0137
Type	**Test**	**Statistic**	**Significance**
Normal	Kolmogorov-Smirnov	0.206	> 0.15
LogNormal	Kolmogorov-Smirnov	0.216	> 0.15

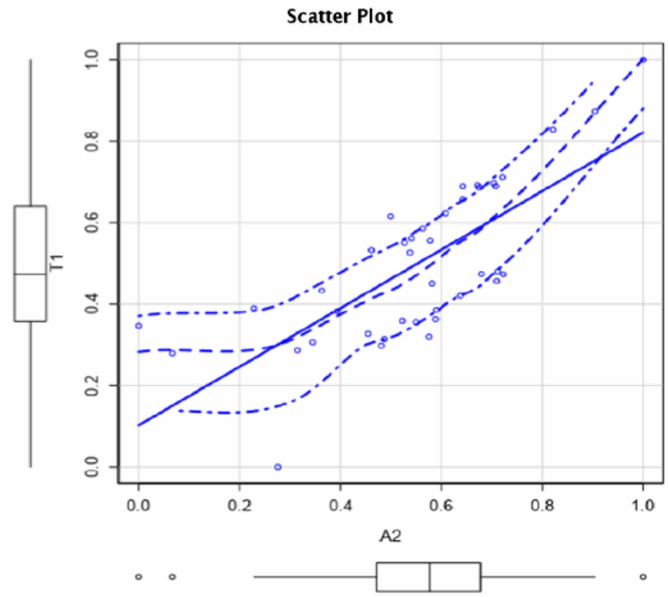
APPENDIX 2 RESEARCH IMPLEMENTATION COMPUTATIONAL ENVIRONMENT

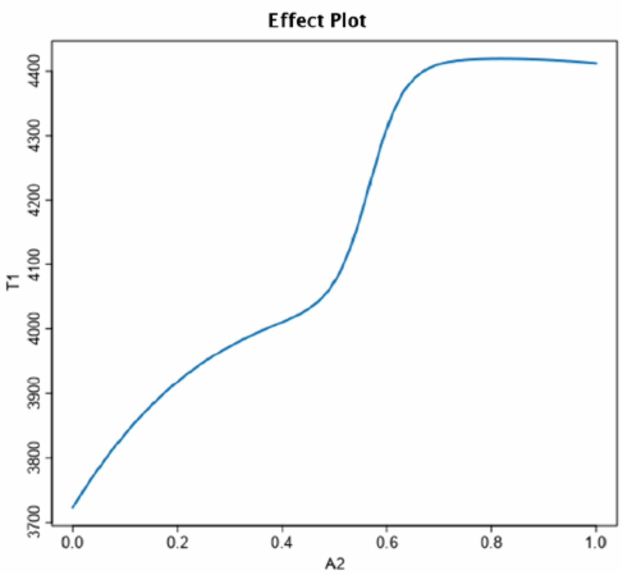
Computational Environment	
OS	Windows 10 64 bits
CPU	Intel i9-9900k @ 3.6 GHz 8 cores - 16 threads
GPU	NVIDIA GeForce RTX 2080 @ 1515 MHz 8 Gb GDDR6 @ 14 Gb/s
RAM	32.0 Gb DDR4 @ 3200 MHz
Storage	2 Tb SATA SSD @ (i/o) 236 Mb/s 8 Tb SATA HD @ (w) 4.74 Mb/s // (i/o) 0.66 Mb/s

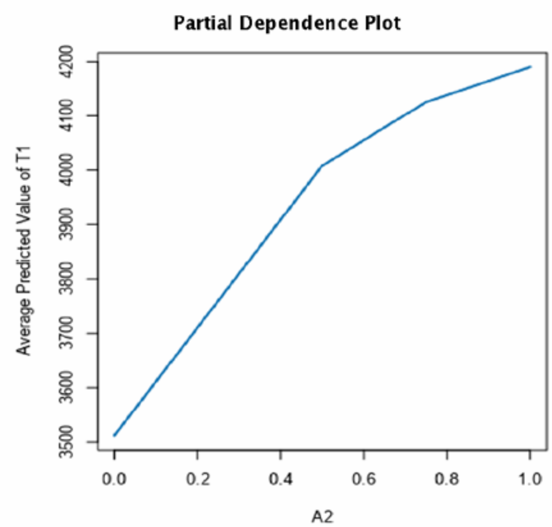
Learning Framework Implementation			
Component	**Language**	**Specification**	
		Package	**Version**
RReliefF	R	Fselector	0.31
Features Space Rearrangement	Python	script	3.6.0
Backward Feature Elimination	Python	script	3.6.0
NN/BP	R	nnet	7.3-13
LIME	R	lime	0.5.1
Partial Dependence Function	R	pdp	0.7.0
SVM	R	e1071	1.7-3
GBM	R	gbm	2.1.5
RF	R	randomForest	4.6-14
Components Interaction (iteration)	Python	script	3.6.0

APPENDIX 3 LEARNING FRAMEWORK GLOBAL EXPLANATION OUTCOMES

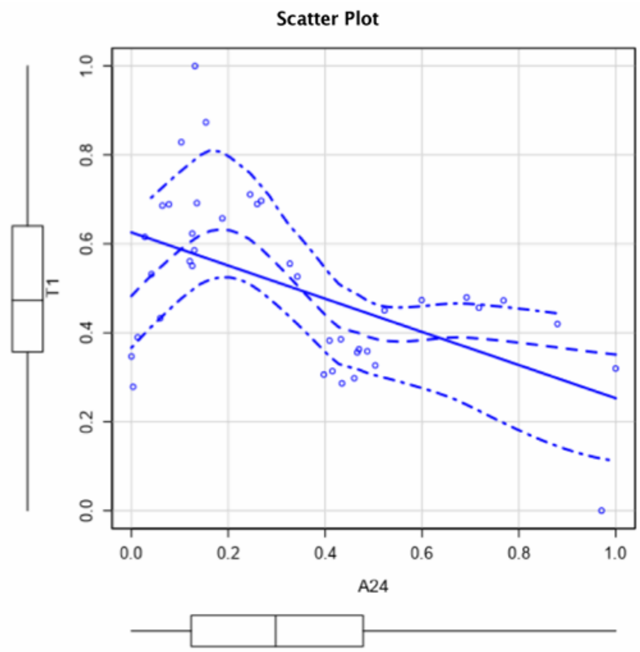
Fossil Fuel Energy Use - Feature A2

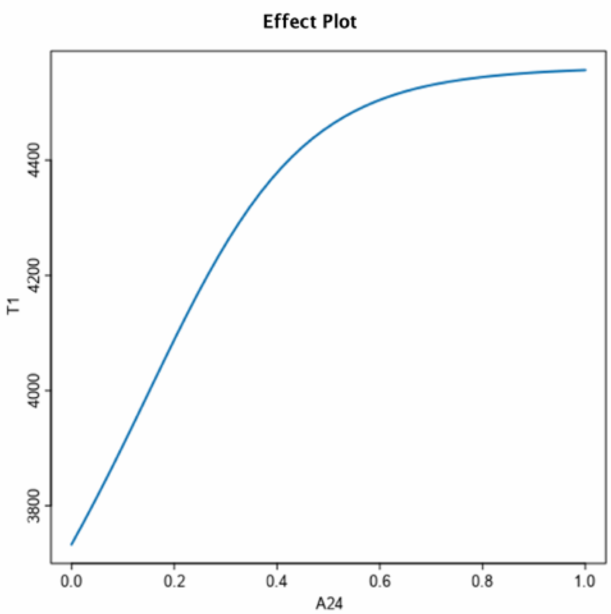


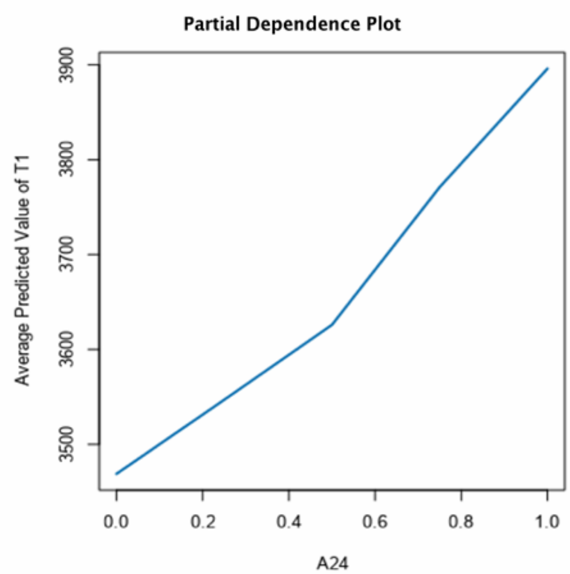




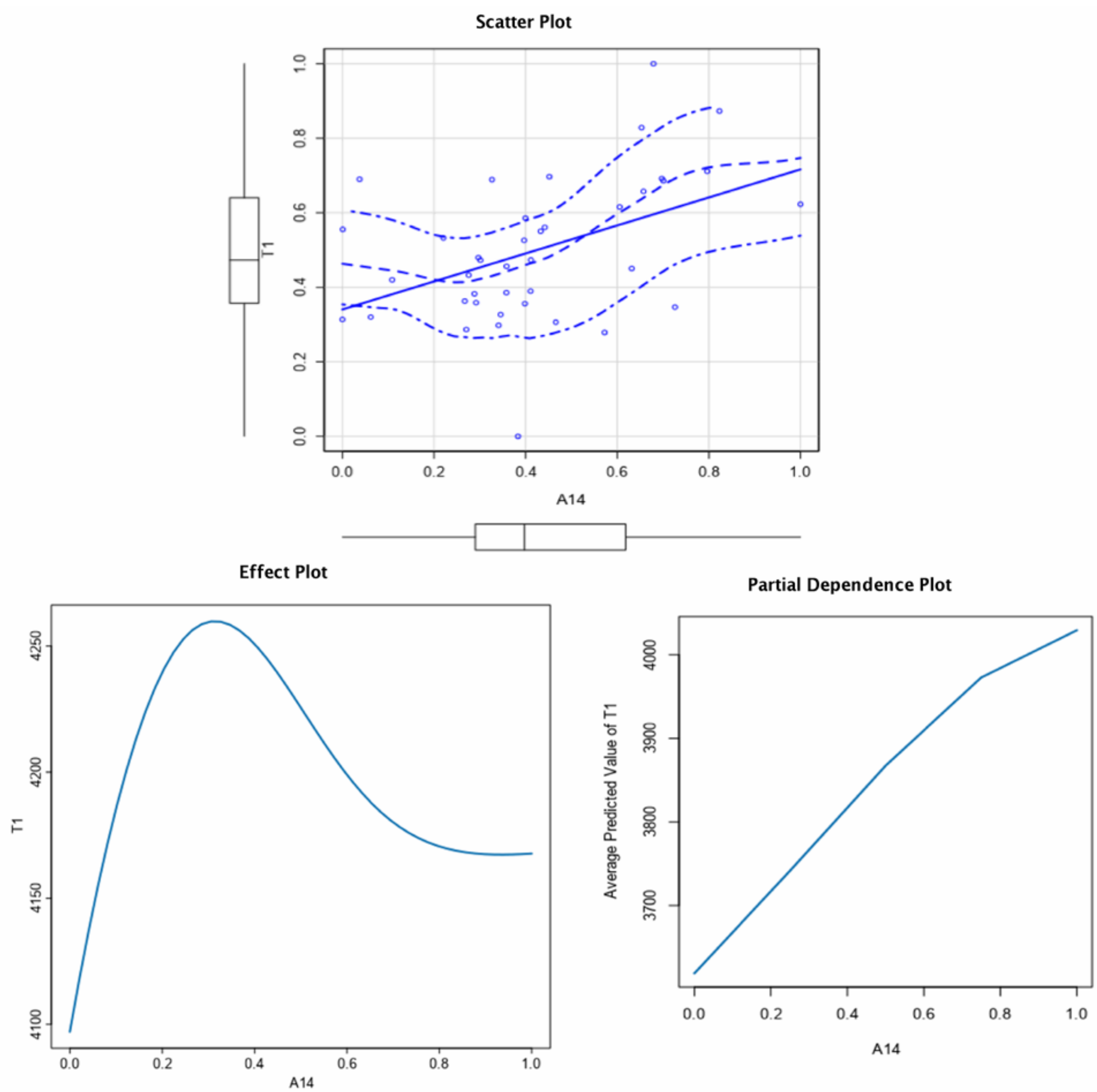
Education Expenditure - Feature A24



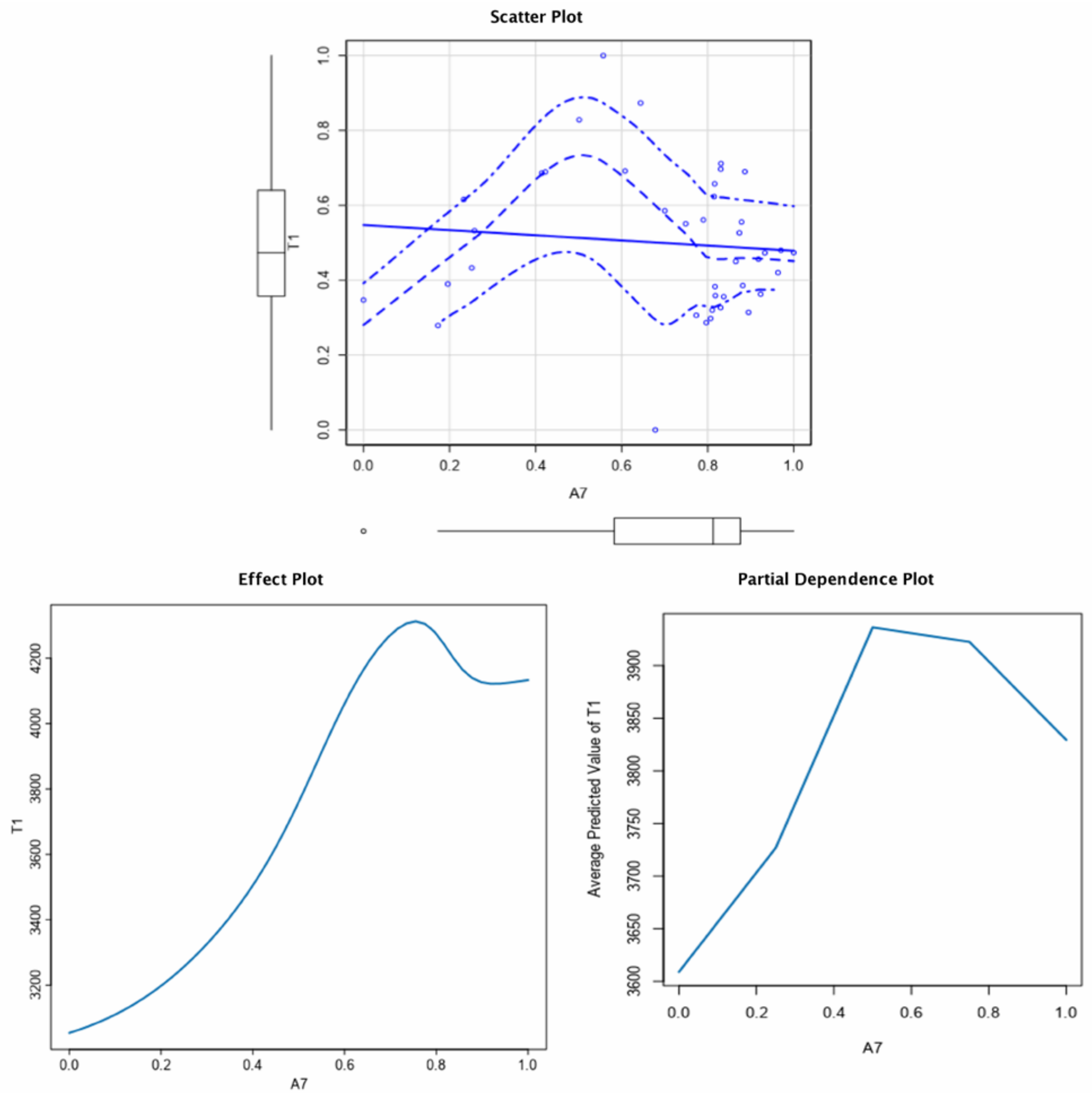




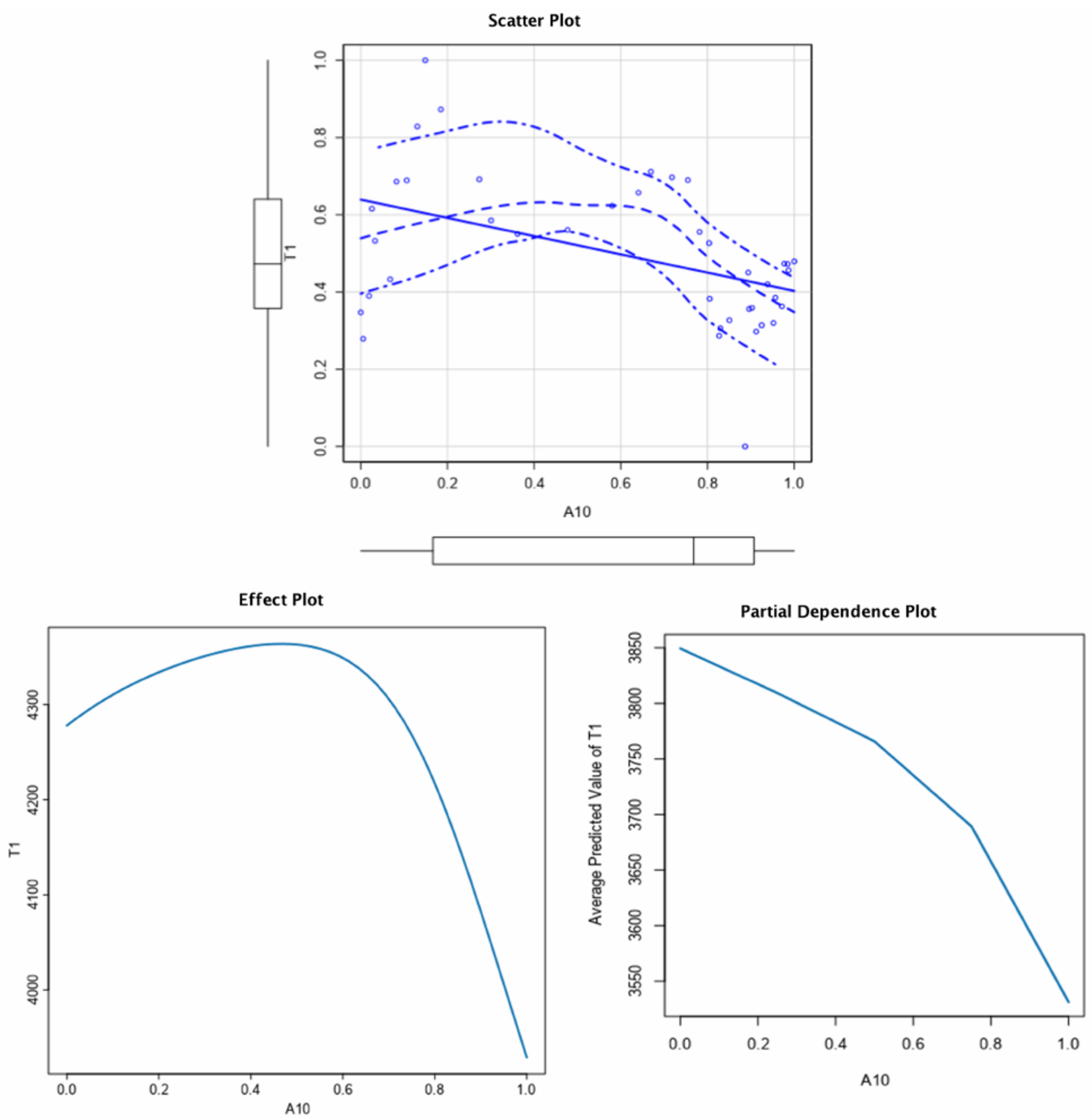
Temperature HDD - Feature A24



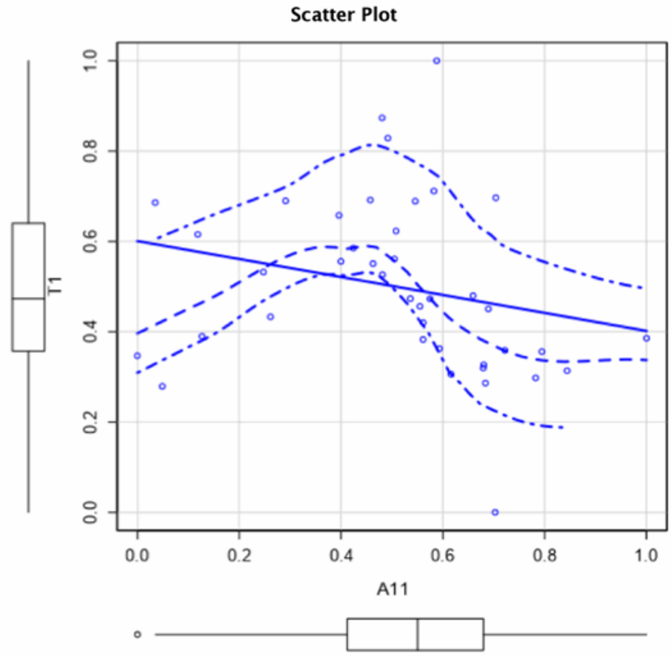
Electricity Production from Coal - Feature A7

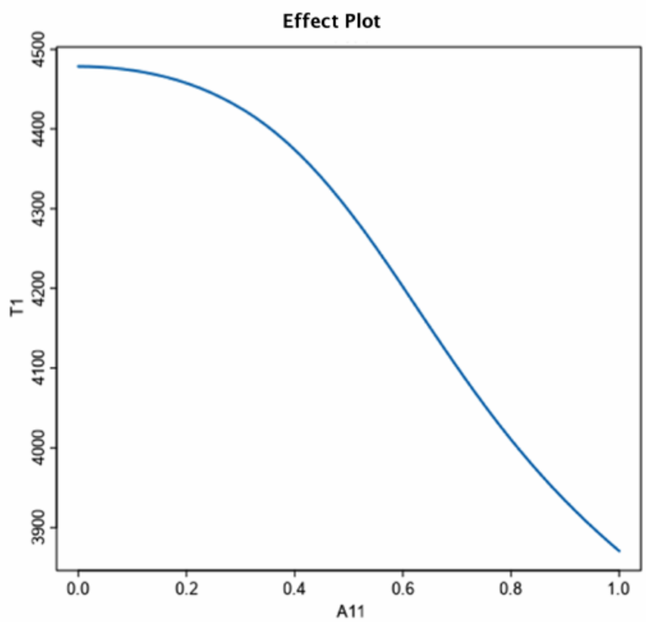


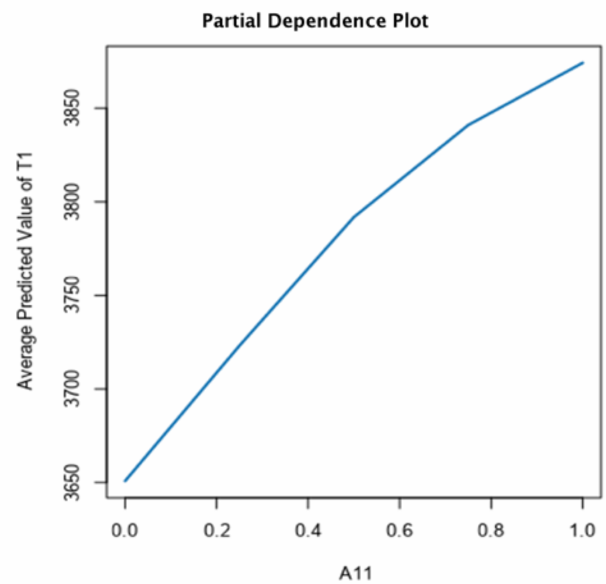
Nuclear Electricity Production - Feature A10



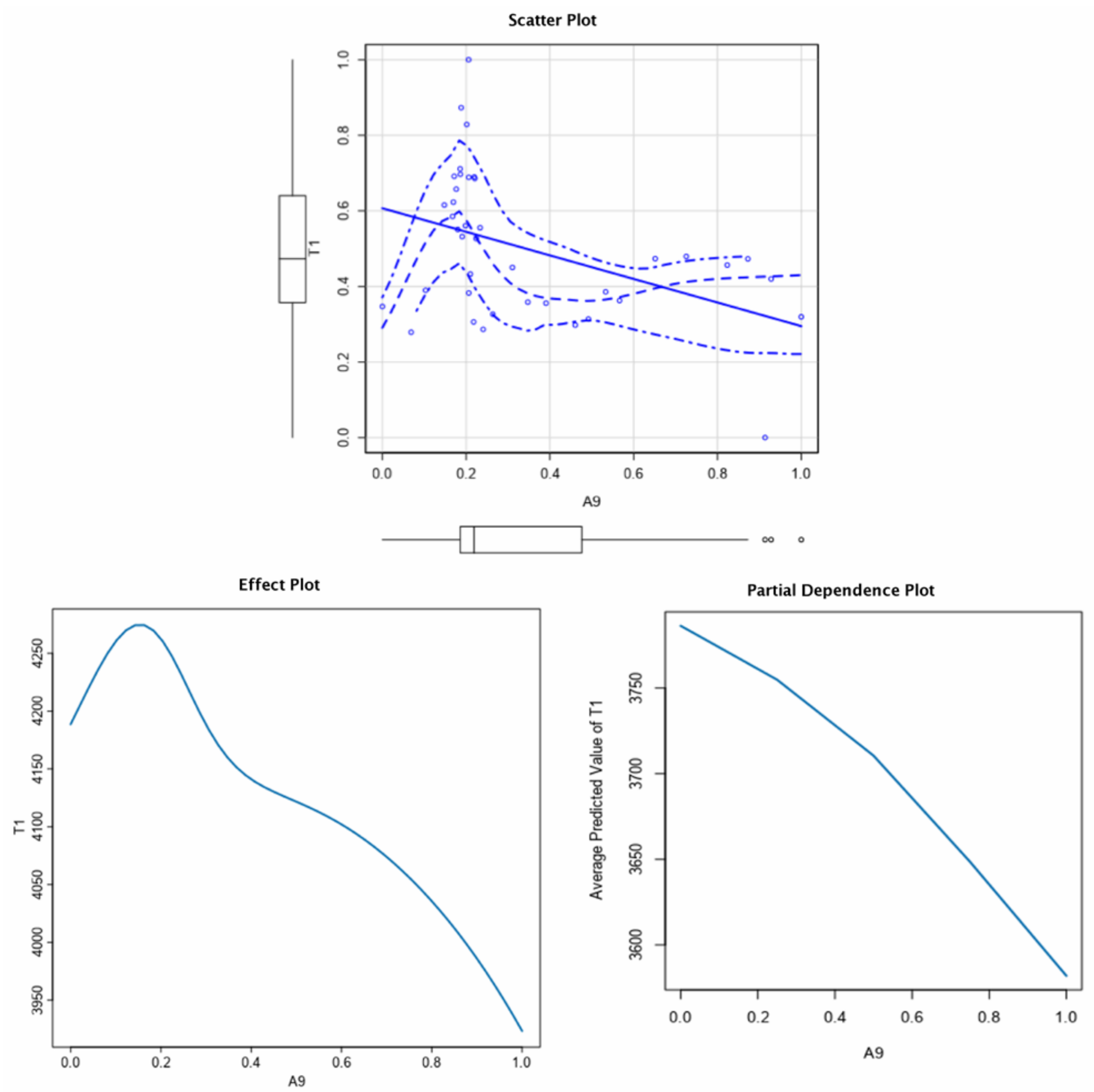
Hydroelectric Energy Production - Feature A11



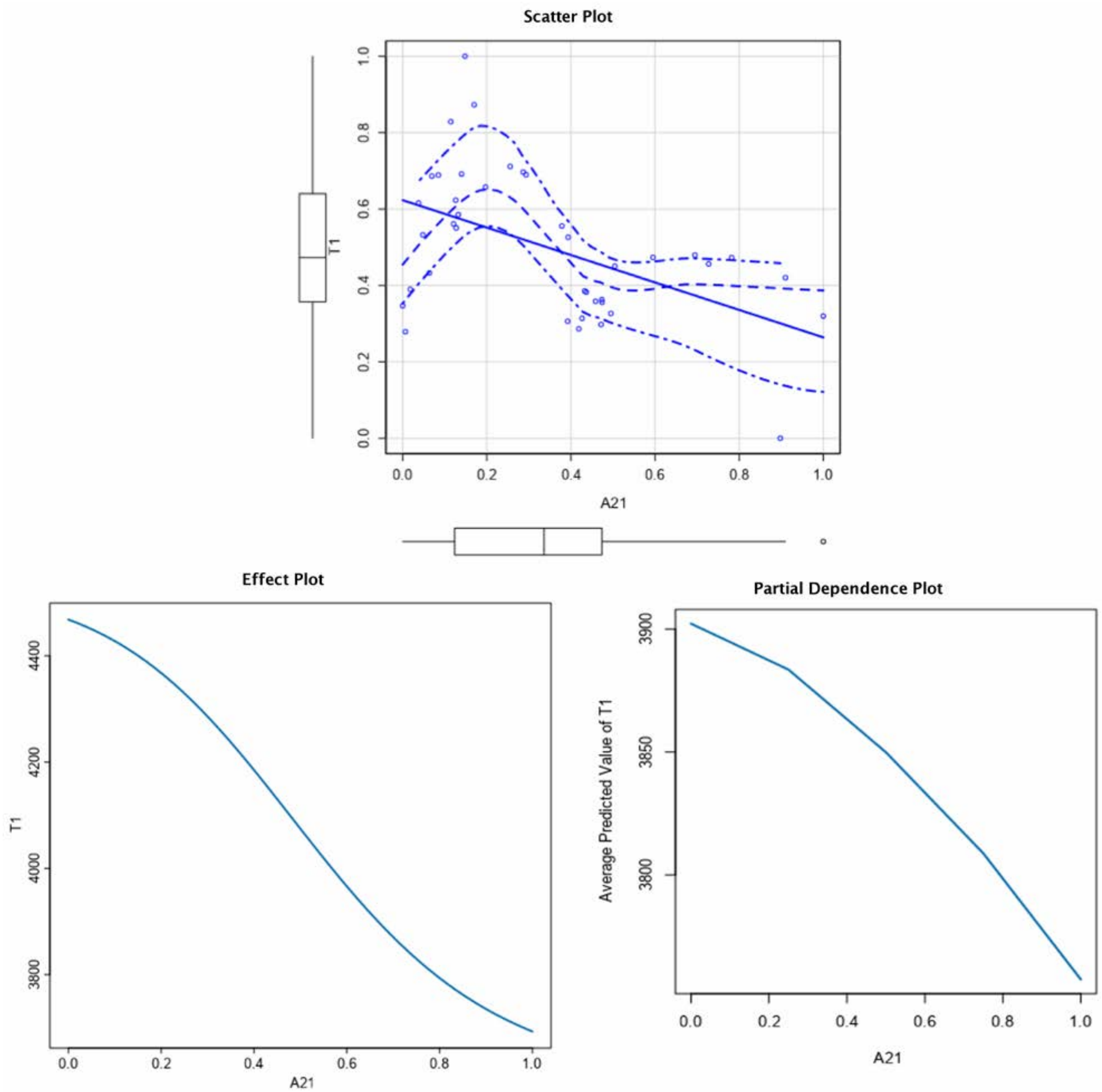




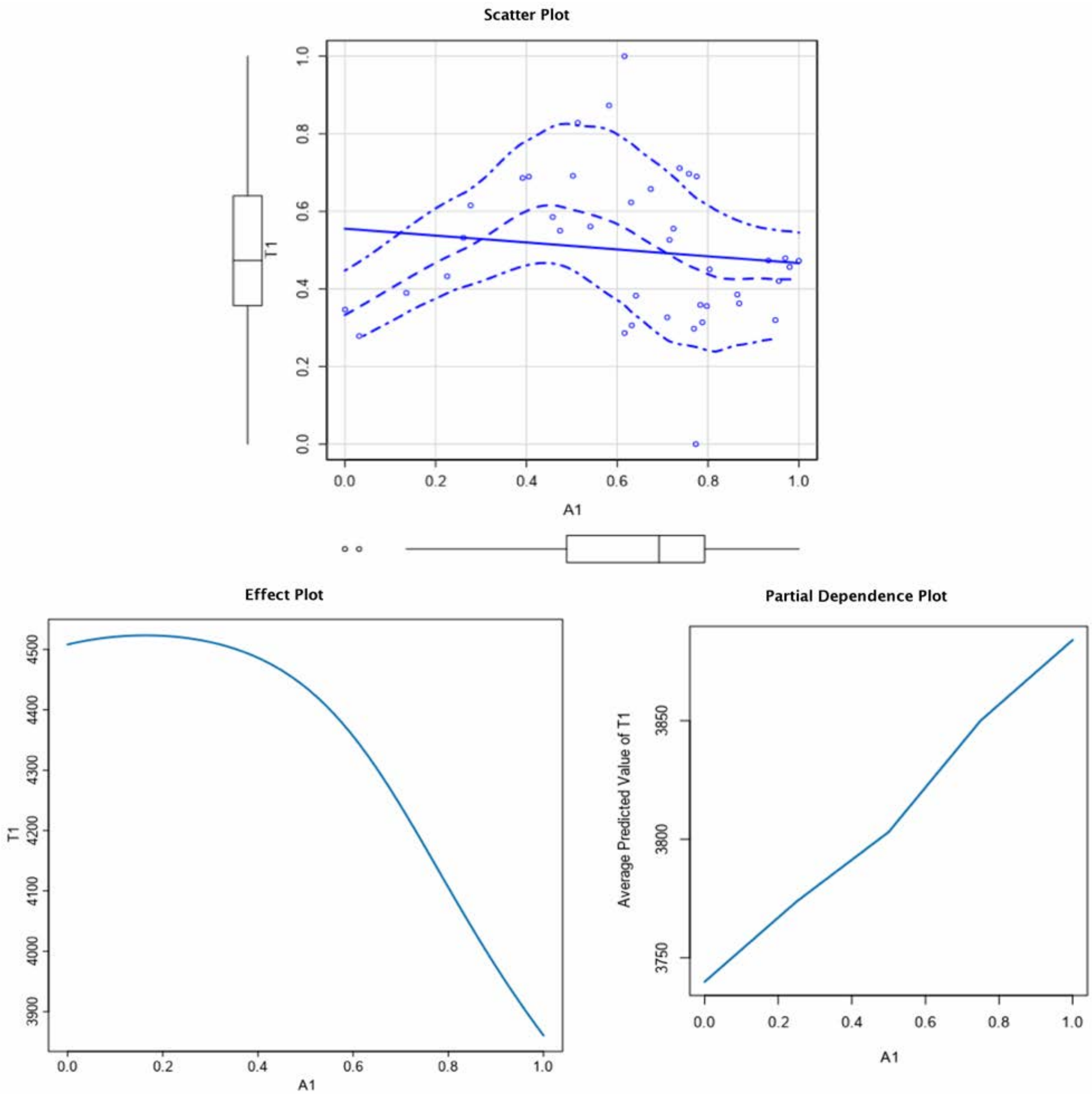
Natural Gas Electricity Production - Feature A9



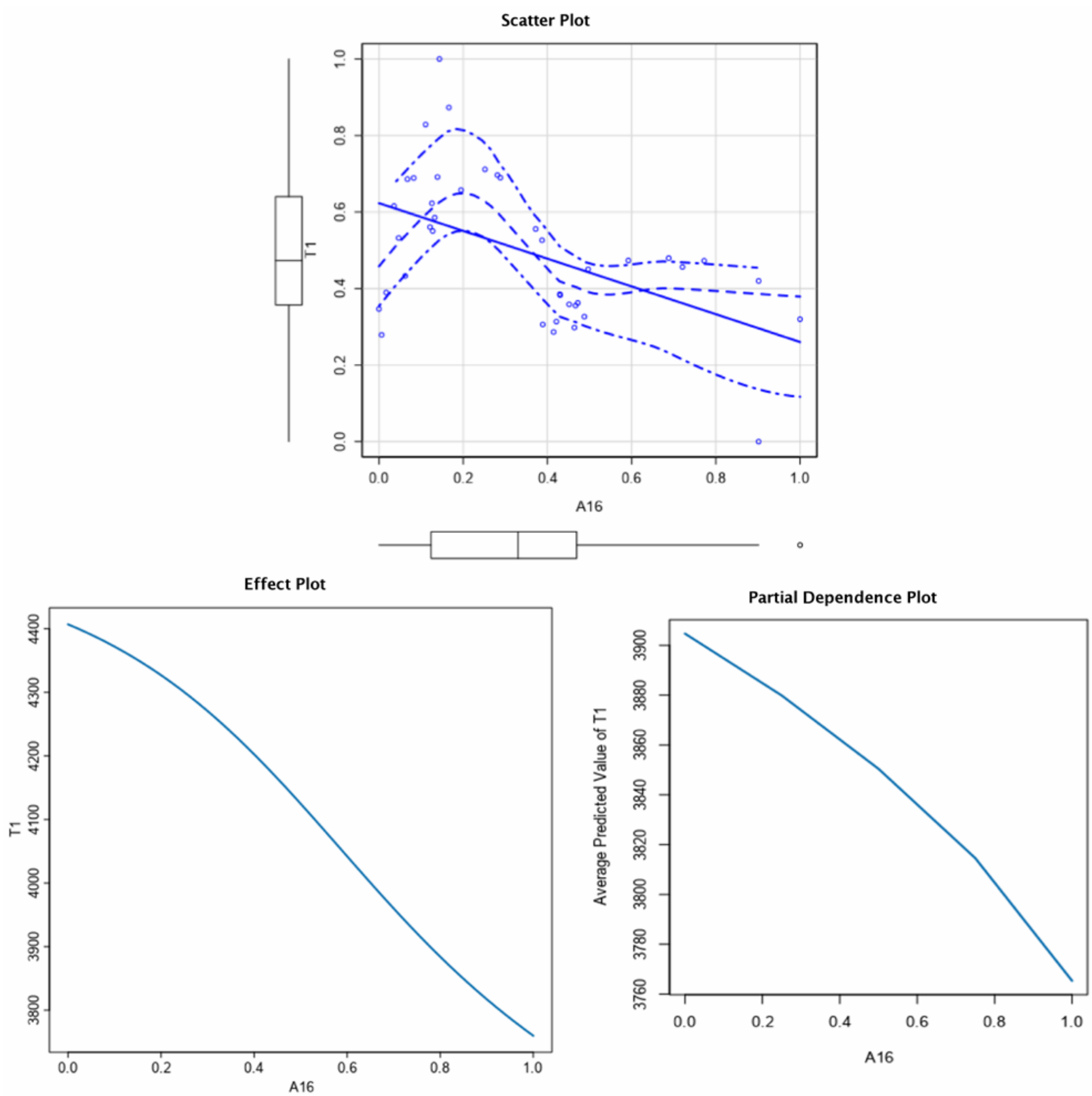
Adjusted Net National Income - Feature A21



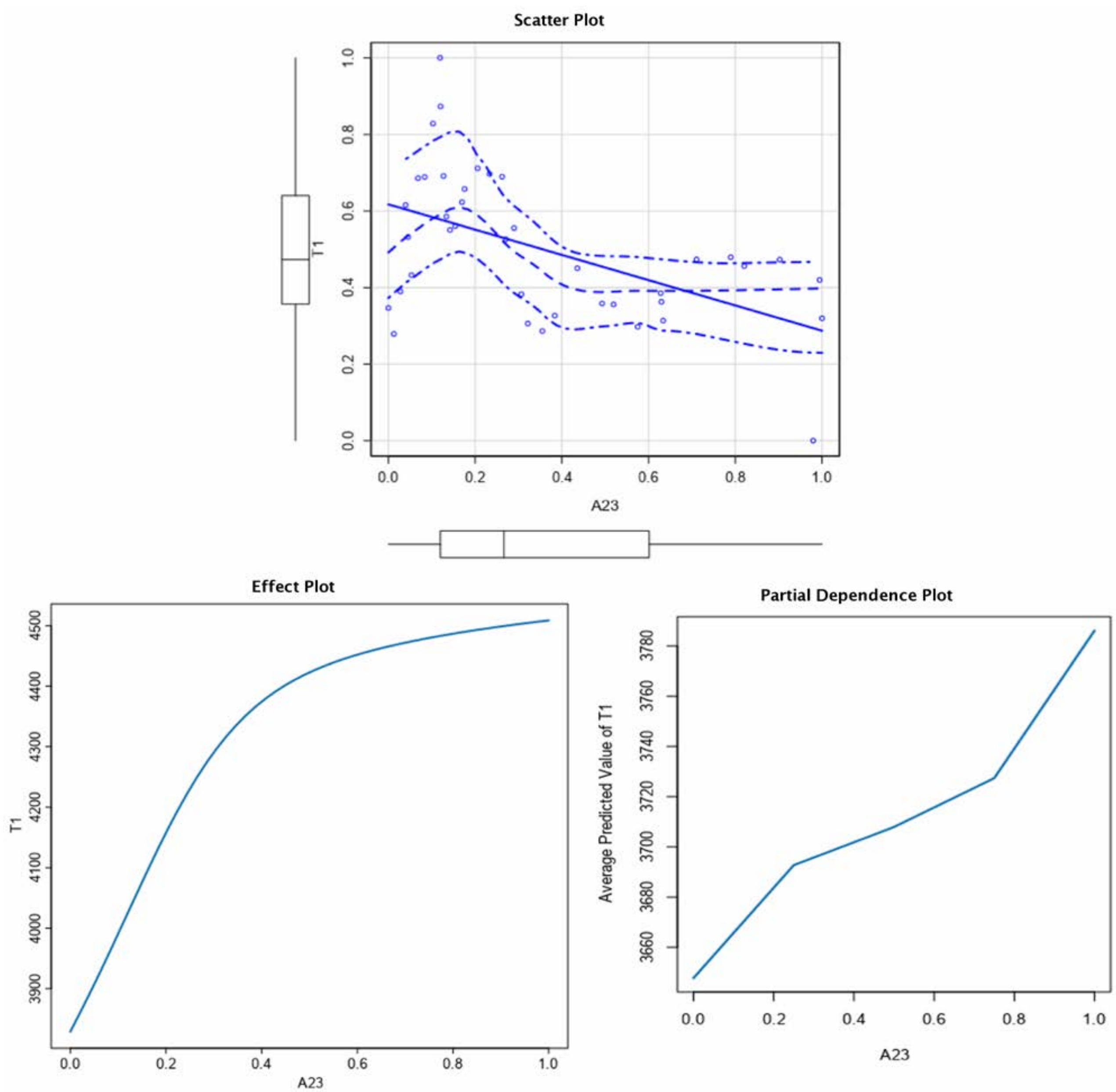
Total Energy Use - Feature A1



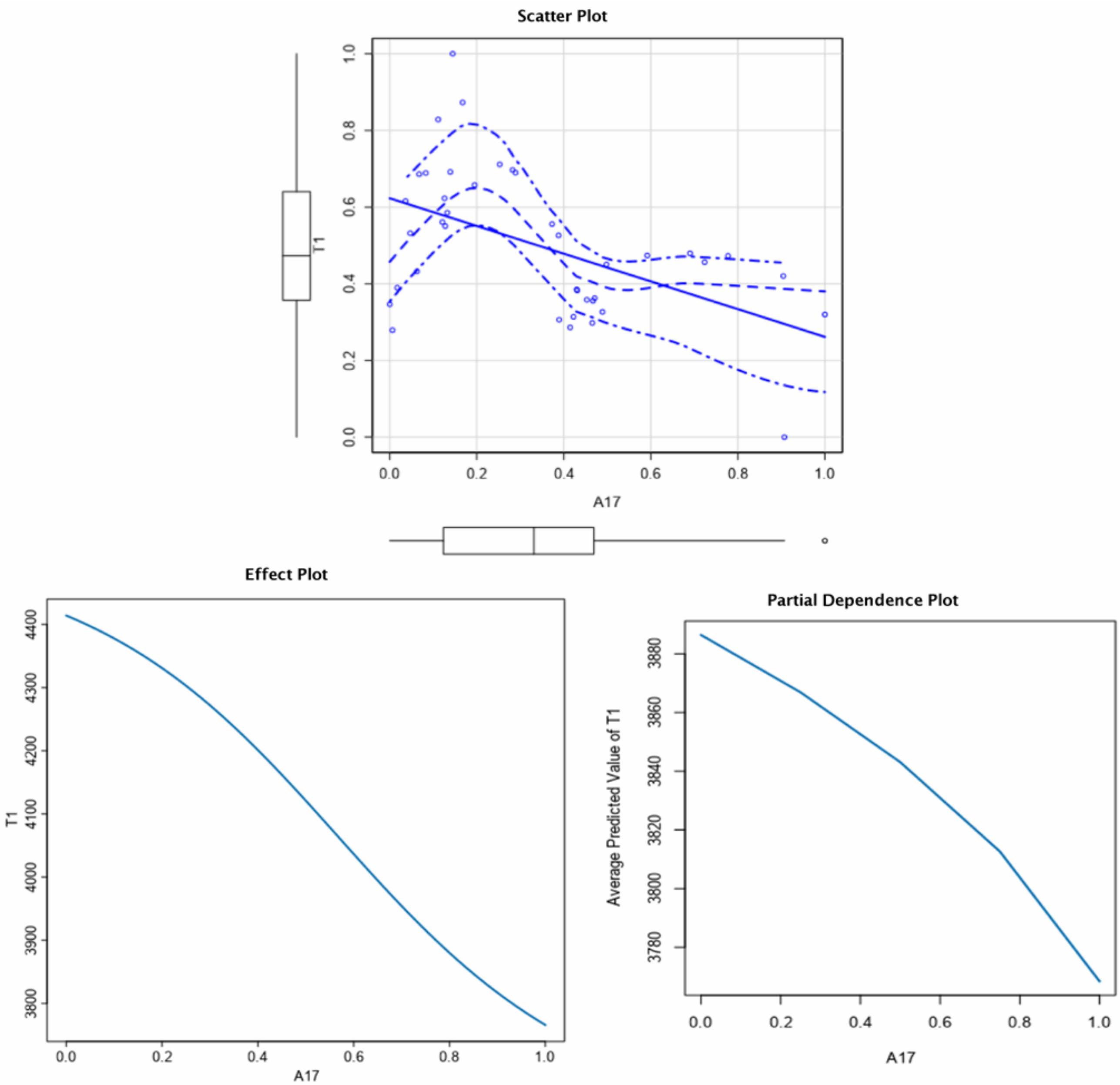
Gross Domestic Product (GDP) - Feature A16



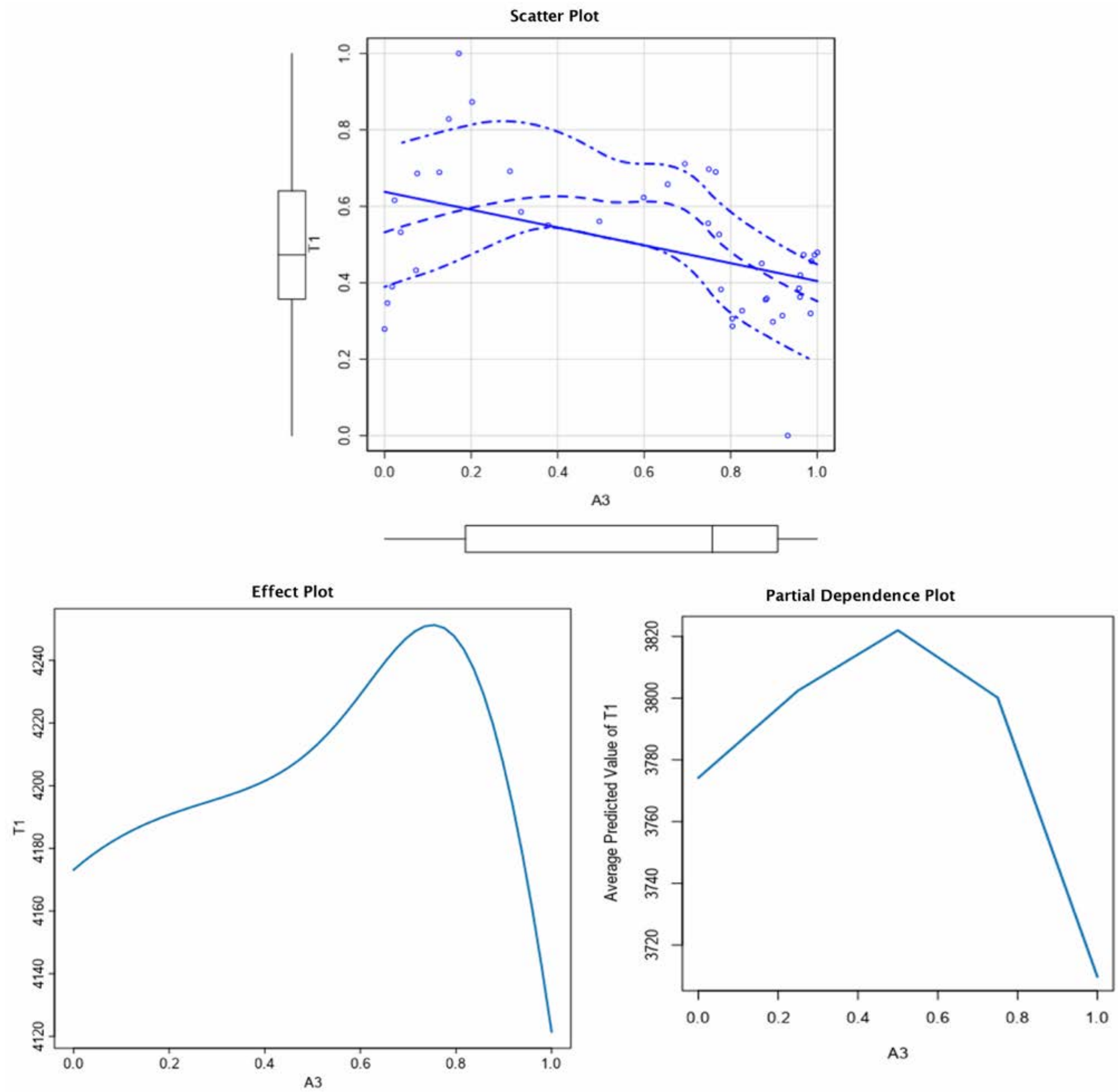
Passengers Air Transport - Feature A23



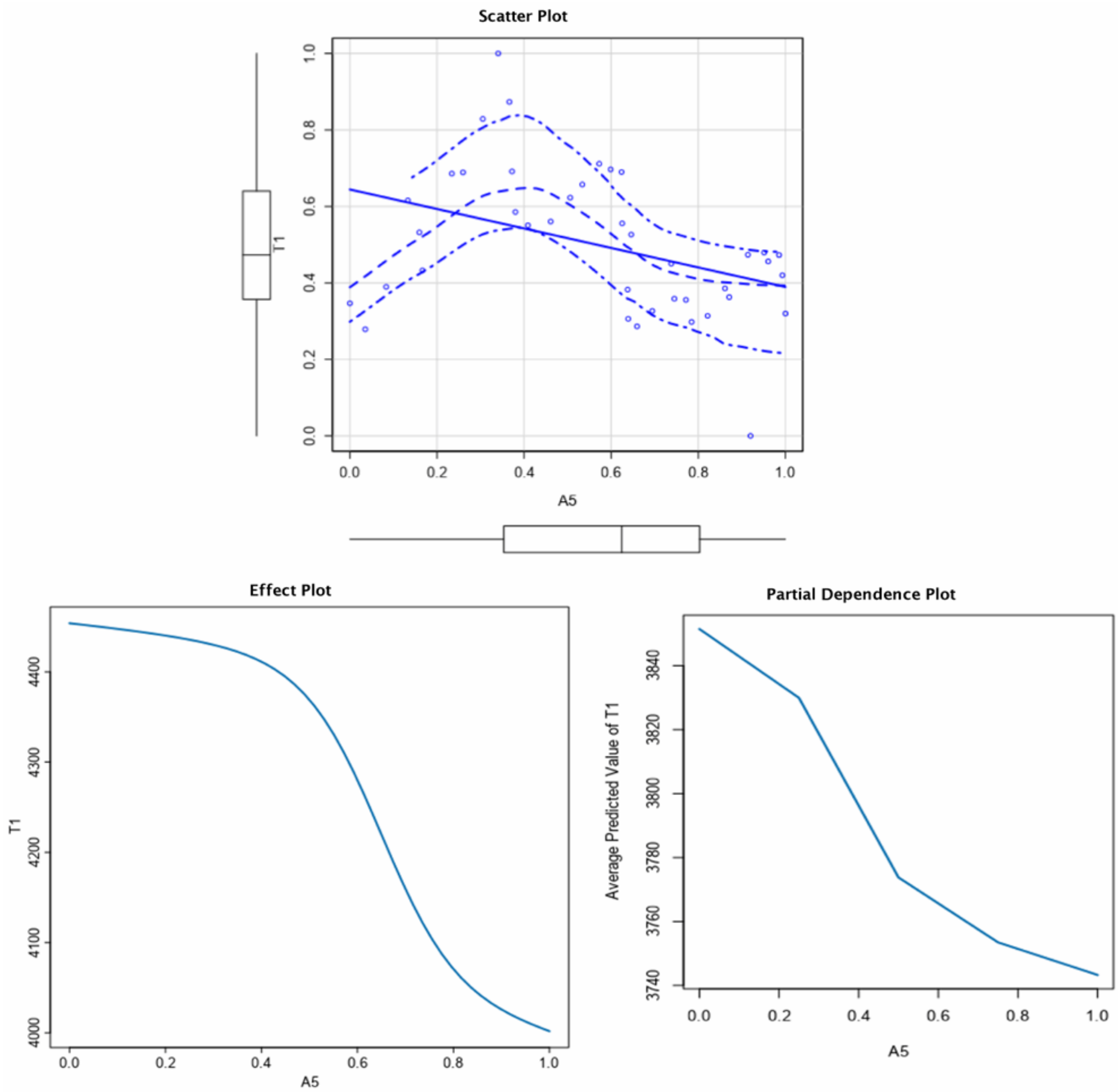
Gross National Income (GNI) - Feature A17



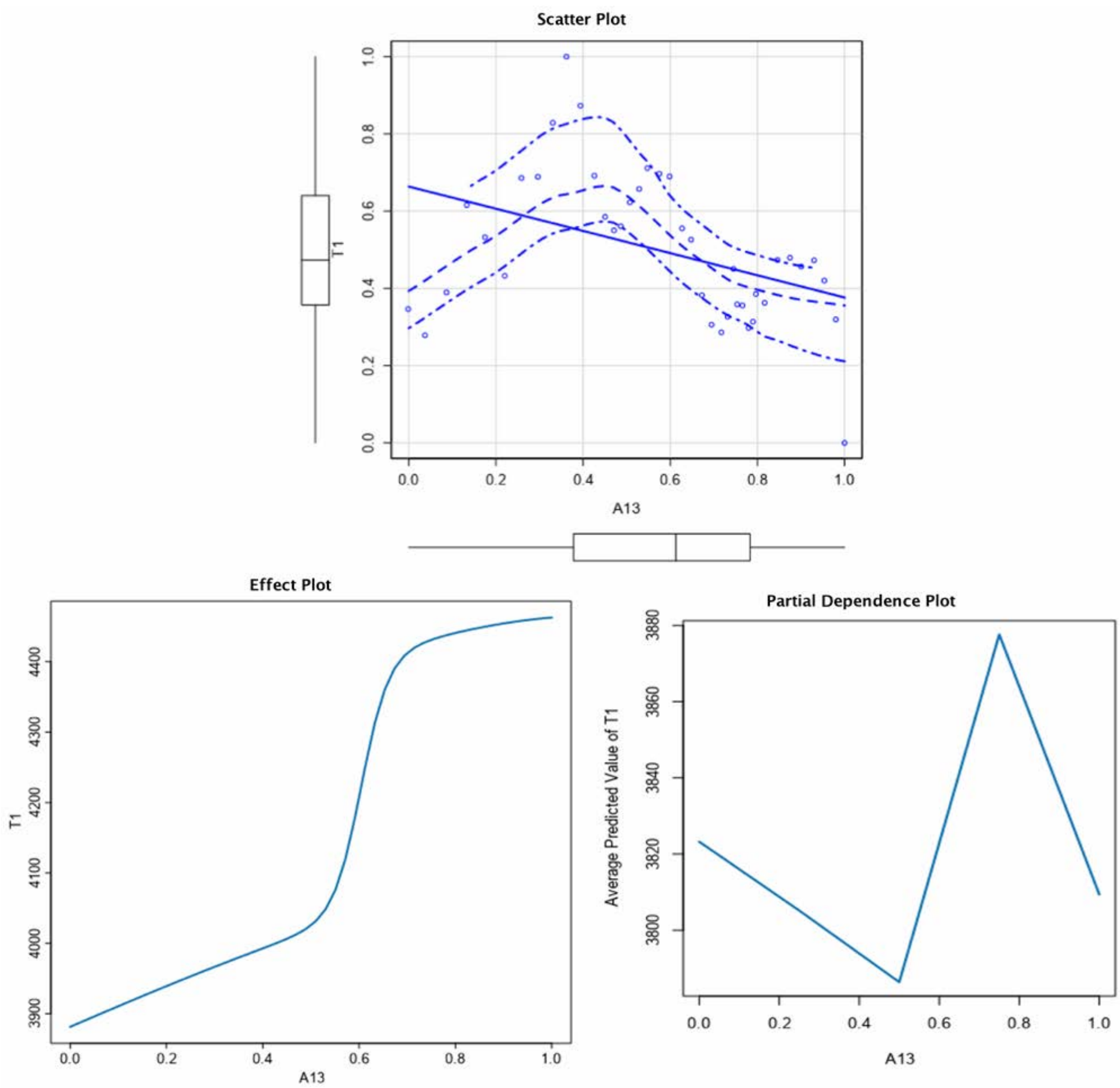
Alternative and Nuclear Energy Use - Feature A3



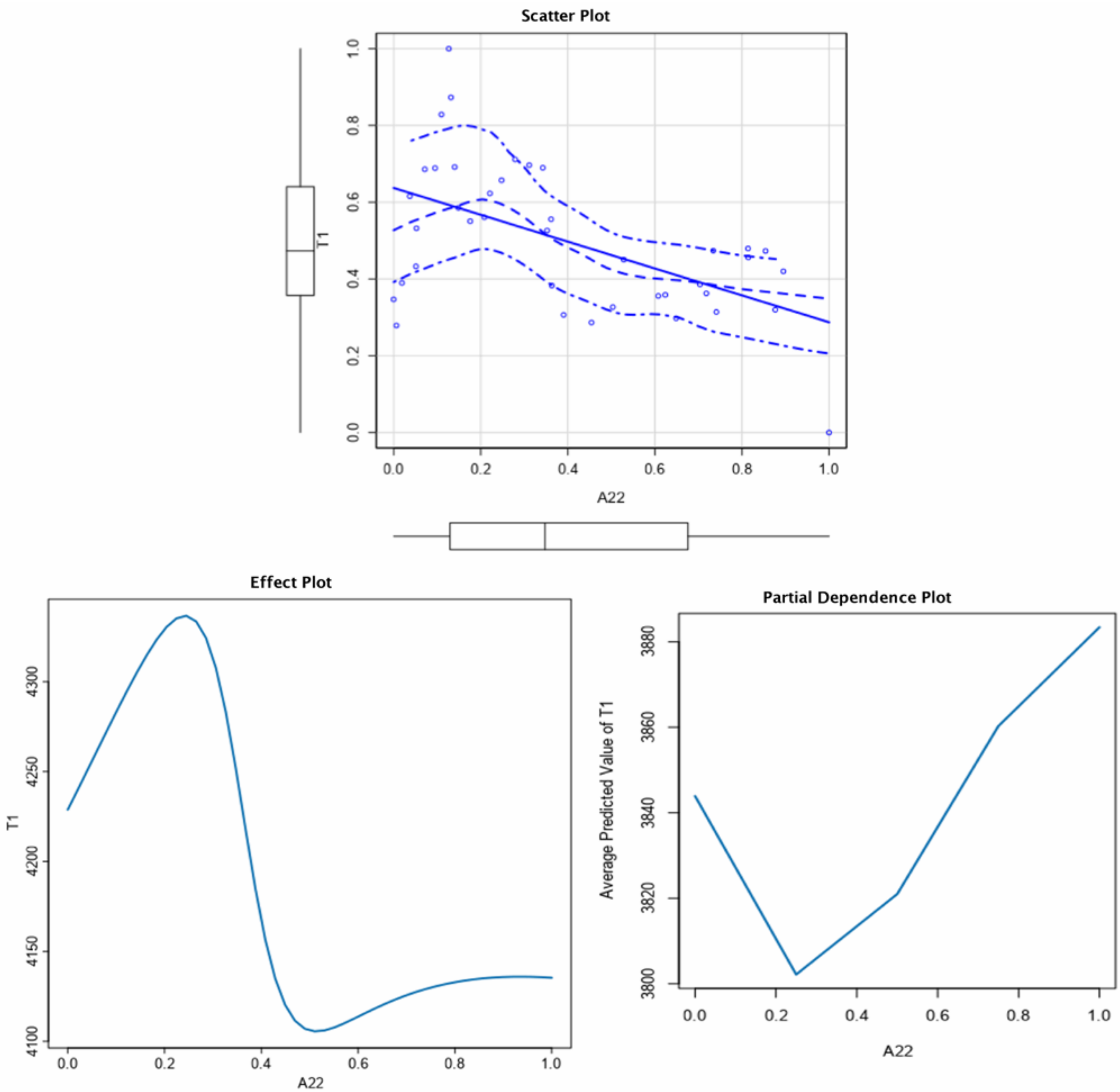
Total Electricity Production - Feature A5



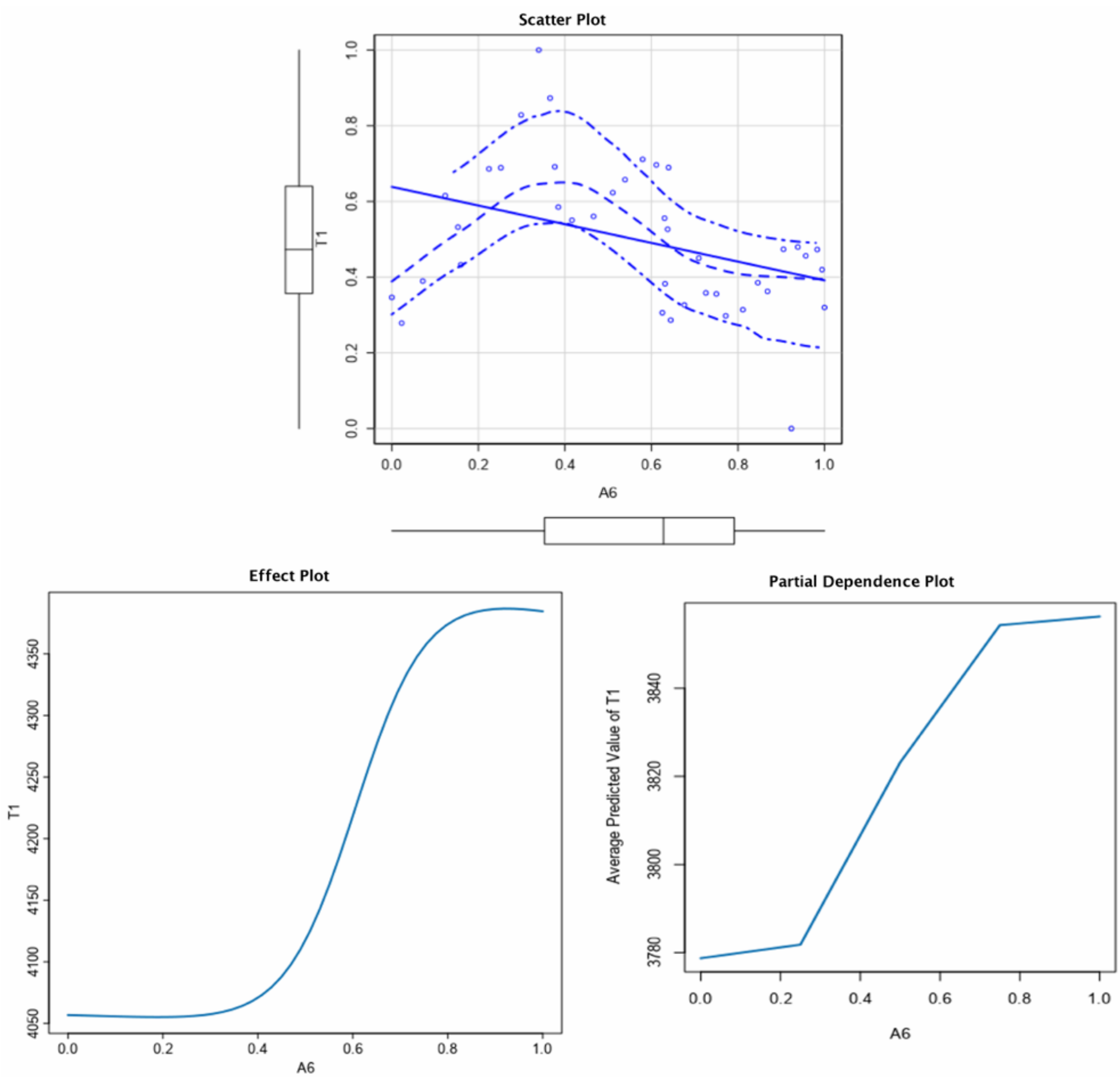
Population - Feature A13



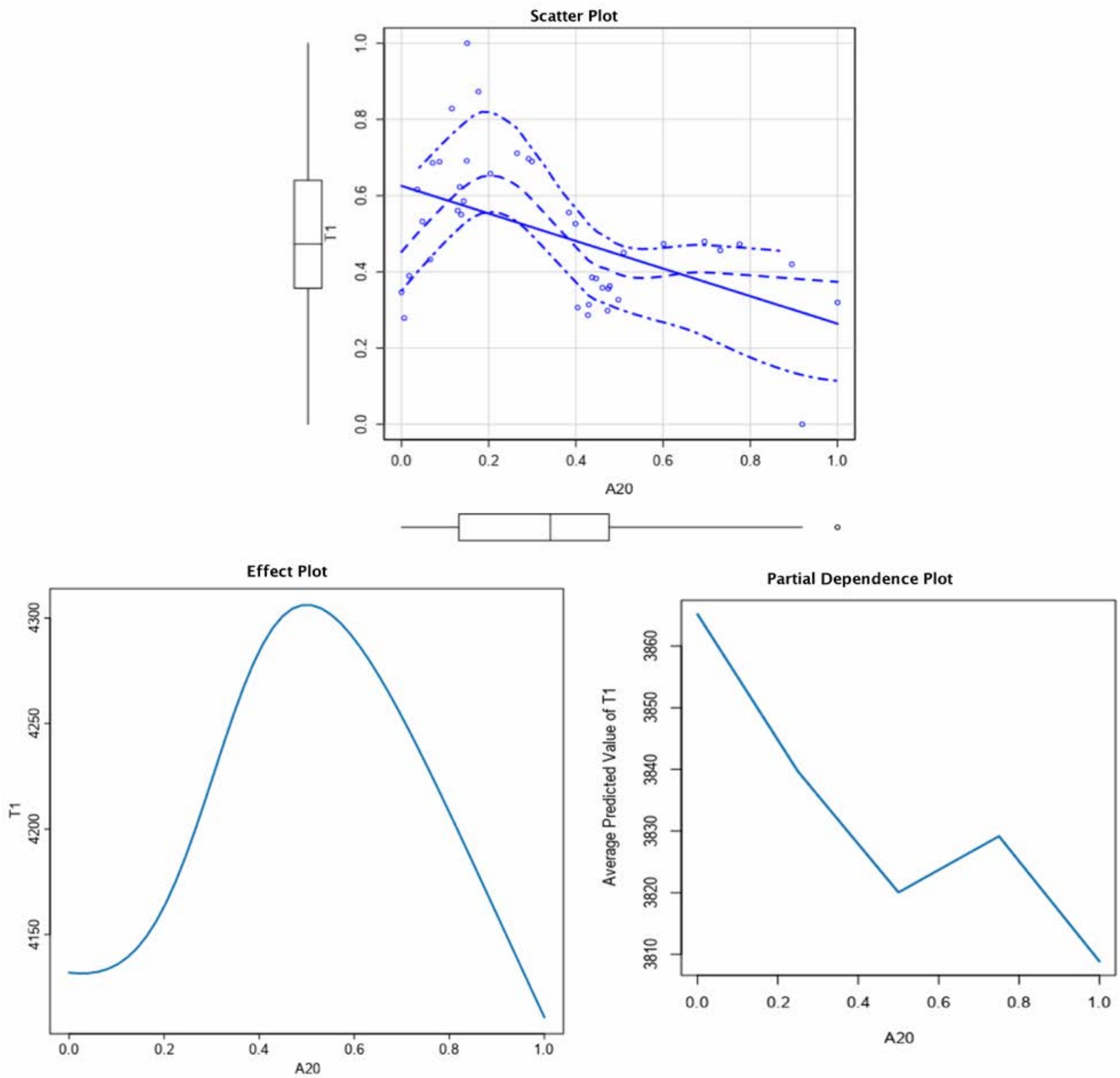
Cargo Air Transport - Feature A22



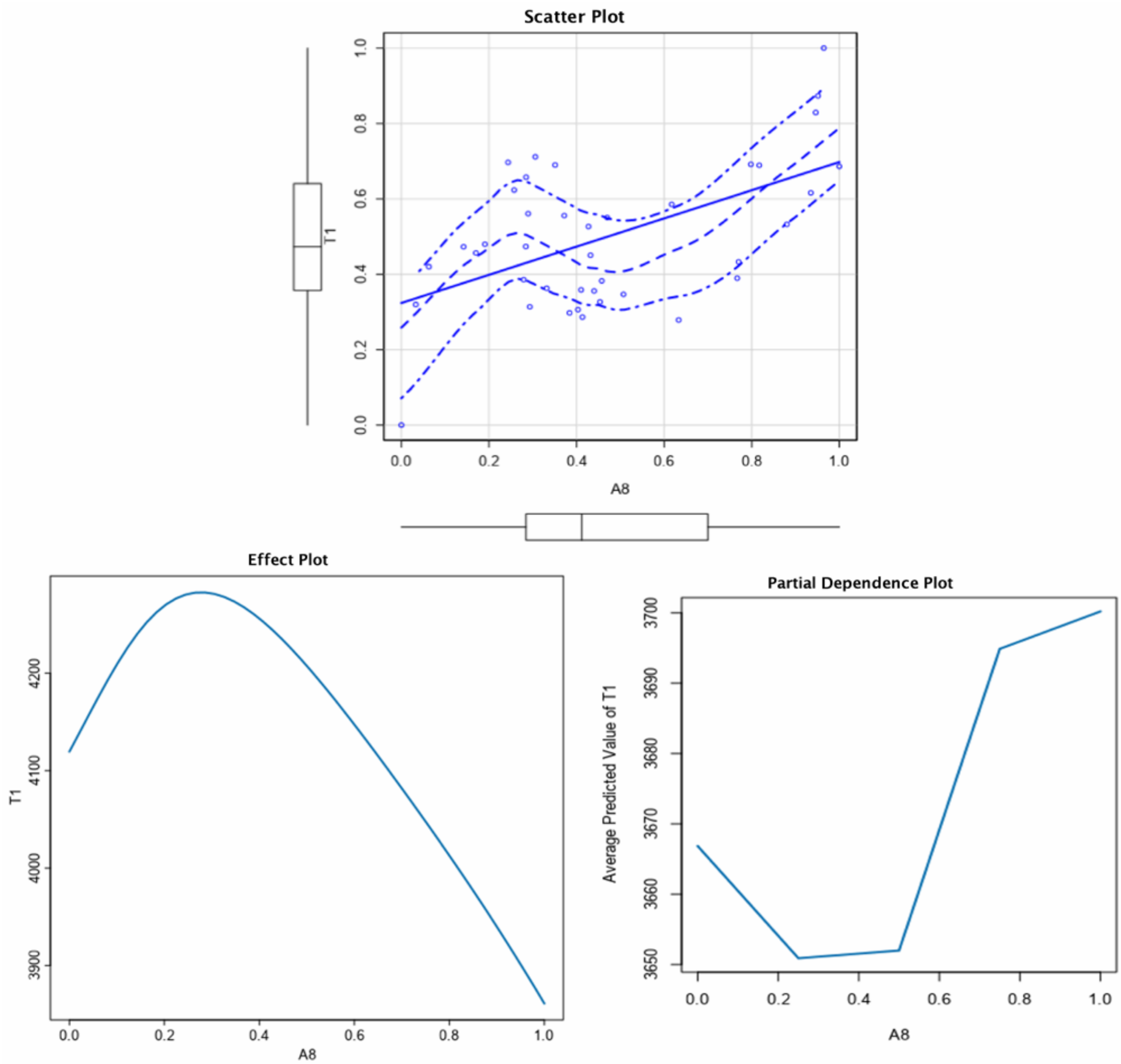
Total Electricity Use - Feature A6



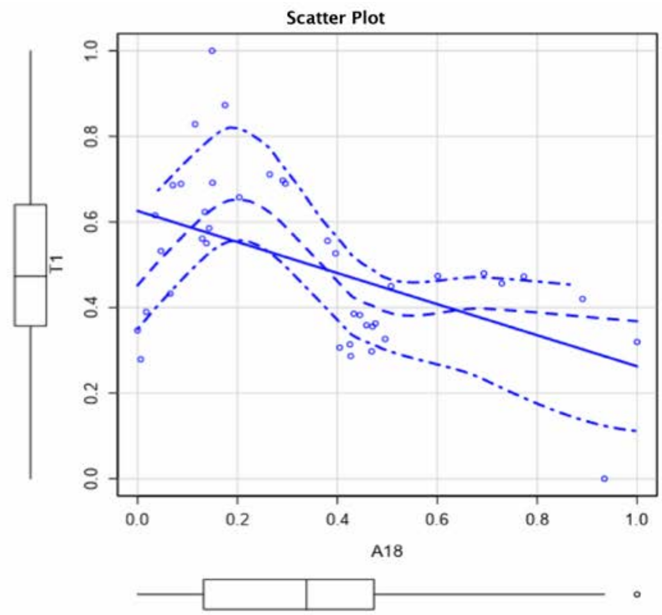
Households Final Consumption Expenditure - Feature A20

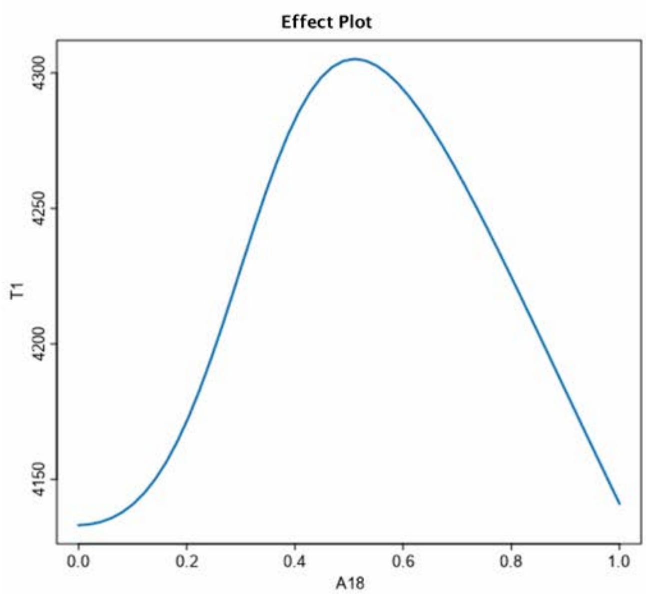


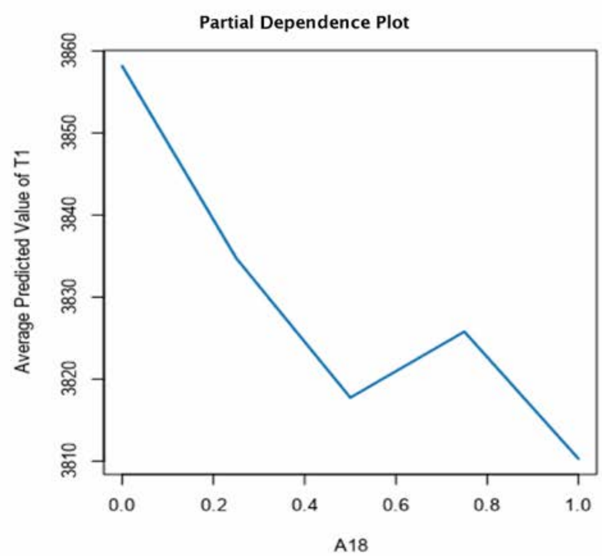
Oil Electricity Production - Feature A8



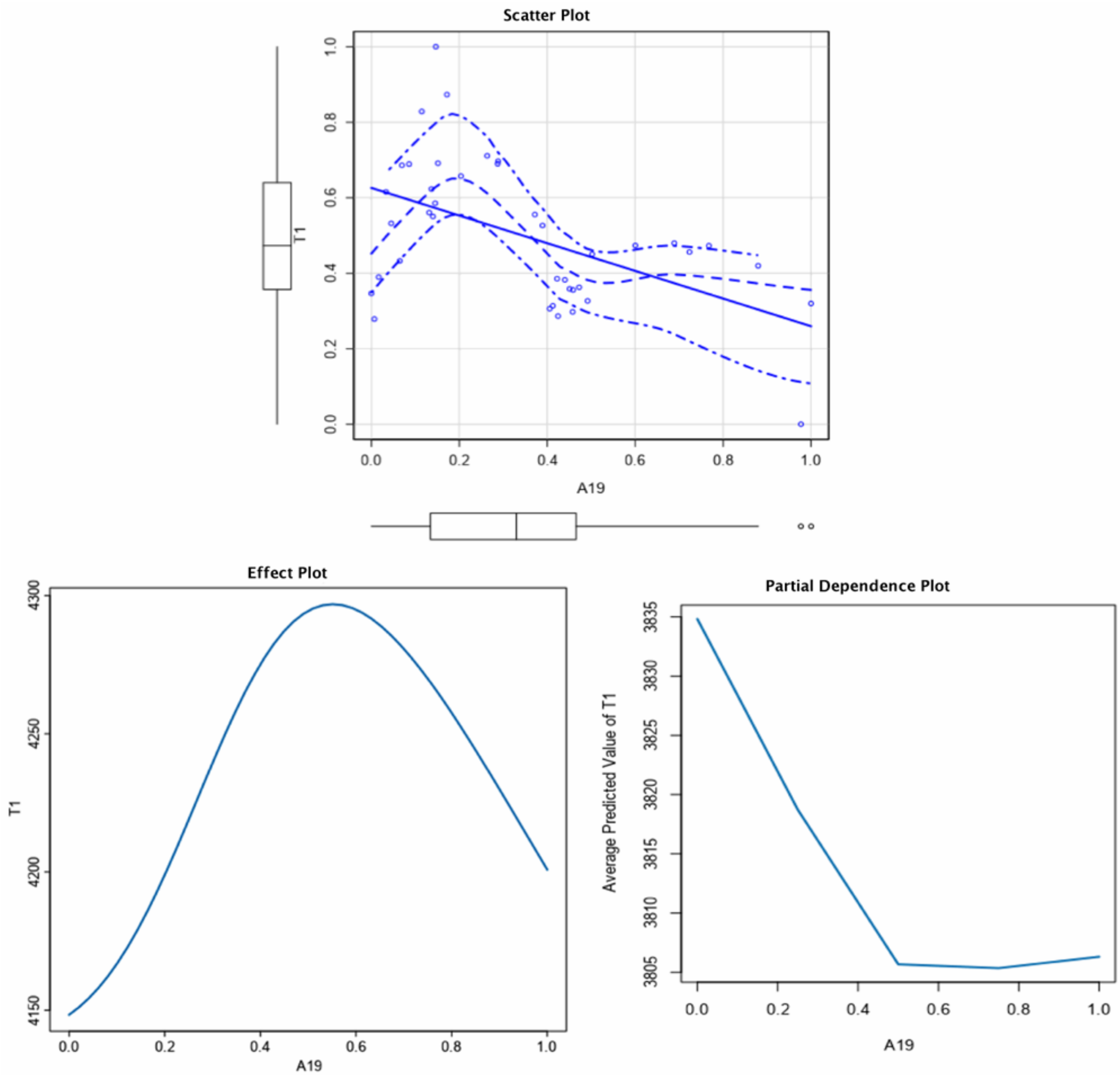
Final Consumption Expenditure - Feature A18



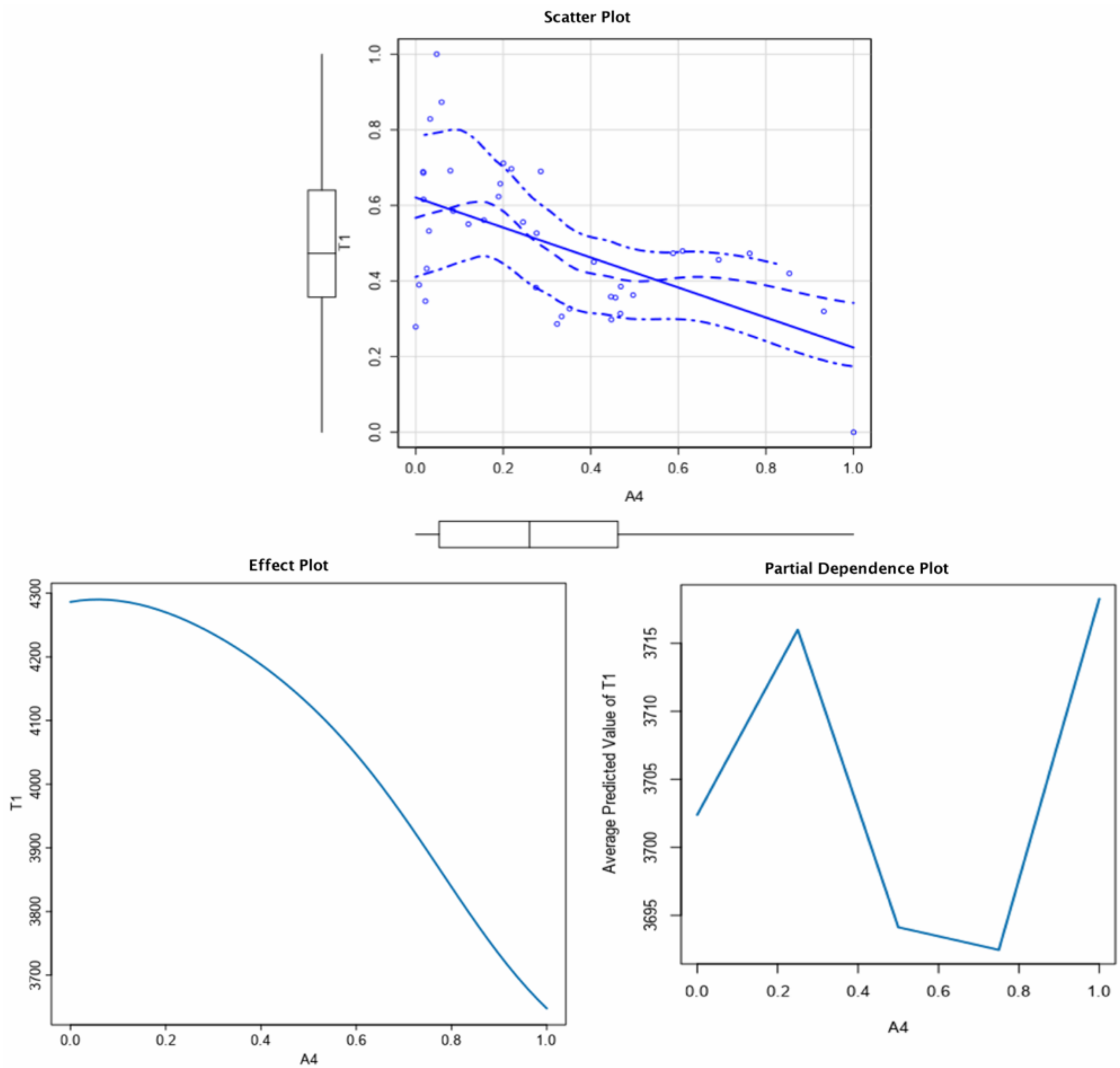




Government Final Consumption Expenditure - Feature A19



Combustible Renewables and Waste Energy - Feature A4



APPENDIX 4 LOCAL EXPLANATIONS - TRAINING DATASET

Local Explanations - 1970 /1971

Year (case)	Surrogate Linear Model R2	Feature	Feature Weight	Influence Interval
1970	0.98729854	A2	67.6089732	A2 <= 0.476
		A14	171.205515	0.612 < A14
		A1	19.8426895	A1 <= 0.495
		A8	-52.461688	0.412 < A8 <= 0.666
		A7	-177.62289	A7 <= 0.595
		A13	49.5038335	A13 <= 0.386
		A24	-126.03585	A24 <= 0.125
		A11	87.9369467	A11 <= 0.418
		A16	25.3024174	A16 <= 0.125
		A20	-23.496403	A20 <= 0.133
		A21	284.335138	A21 <= 0.125
		A4	-104.96502	A4 <= 0.0564
		A18	18.3137292	A18 <= 0.134
		A17	-104.47143	A17 <= 0.125
		A19	114.25752	A19 <= 0.136
		A5	-162.18684	A5 <= 0.360
		A22	118.773311	A22 <= 0.130
		A10	130.664435	A10 <= 0.176
		A6	-337.76289	A6 <= 0.359
		A3	7.43419634	A3 <= 0.195
		A23	-77.958699	A23 <= 0.120
		A9	374.067758	A9 <= 0.186
1971	0.96186395	A2	-45.258907	A2 <= 0.476
		A14	-57.484993	0.397 < A14 <= 0.612
		A1	60.0690592	A1 <= 0.495
		A8	-61.035426	0.412 < A8 <= 0.666
		A7	-44.263718	A7 <= 0.595
		A13	-36.869063	A13 <= 0.386
		A24	-156.16686	A24 <= 0.125
		A11	-68.224292	A11 <= 0.418
		A16	-30.029945	A16 <= 0.125
		A20	-45.000518	A20 <= 0.133
		A21	-35.477661	A21 <= 0.125
		A4	-45.269202	A4 <= 0.0564
		A18	-48.925322	A18 <= 0.134
		A17	-92.463819	A17 <= 0.125
		A19	-27.946709	A19 <= 0.136
		A5	190.806359	A5 <= 0.360
		A22	139.267747	A22 <= 0.130
		A10	208.559053	A10 <= 0.176
		A6	8.66170692	A6 <= 0.359
		A3	85.8769762	A3 <= 0.195
		A23	-46.662262	A23 <= 0.120
		A9	-26.721517	A9 <= 0.186

Local Explanations - 1972 / 1973

Year (case)	Surrogate Linear Model R2	Feature	Feature Weight	Influence Interval
1972	0.91149916	A2	-453.8609	A2 <= 0.476
		A14	41.1705241	0.397 < A14 <= 0.612
		A1	243.946029	A1 <= 0.495
		A8	-36.347288	0.666 < A8
		A7	-353.08972	A7 <= 0.595
		A13	58.7748893	A13 <= 0.386
		A24	-41.483049	A24 <= 0.125
		A11	119.360174	A11 <= 0.418
		A16	192.701959	A16 <= 0.125
		A20	9.86913005	A20 <= 0.133
		A21	224.95808	A21 <= 0.125
		A4	-209.01268	A4 <= 0.0564
		A18	4.53524205	A18 <= 0.134
		A17	-291.45536	A17 <= 0.125
		A19	187.23435	A19 <= 0.136
		A5	120.099998	A5 <= 0.360
		A22	-7.5081943	A22 <= 0.130
		A10	107.062309	A10 <= 0.176
		A6	140.741379	A6 <= 0.359
		A3	47.2537177	A3 <= 0.195
		A23	-158.63063	A23 <= 0.120
		A9	154.103647	A9 <= 0.186
1973	0.96516767	A2	-38.54555	0.476 < A2 <= 0.577
		A14	-26.904479	0.397 < A14 <= 0.612
		A1	14.5527964	A1 <= 0.495
		A8	-13.063516	0.666 < A8
		A7	36.1597082	A7 <= 0.595
		A13	-12.846076	A13 <= 0.386
		A24	-61.008041	A24 <= 0.125
		A11	-45.786939	A11 <= 0.418
		A16	193.147679	A16 <= 0.125
		A20	2.9316376	A20 <= 0.133
		A21	-61.426623	A21 <= 0.125
		A4	-36.095896	A4 <= 0.0564
		A18	-31.677	A18 <= 0.134
		A17	-52.808051	A17 <= 0.125
		A19	-39.59257	A19 <= 0.136
		A5	226.953834	A5 <= 0.360
		A22	-30.732809	A22 <= 0.130
		A10	206.812472	A10 <= 0.176
		A6	0.15056289	A6 <= 0.359
		A3	141.872495	A3 <= 0.195
		A23	-71.841685	A23 <= 0.120
		A9	212.489301	A9 <= 0.186

Local Explanations - 1974 / 1975

Year (case)	Surrogate Linear Model R2	Feature	Feature Weight	Influence Interval
1974	0.99602537	A2	-276.6793	A2 <= 0.476
		A14	-390.7802	A14 <= 0.291
		A1	11.4430702	A1 <= 0.495
		A8	-30.040928	0.666 < A8
		A7	113.91207	A7 <= 0.595
		A13	30.7202534	A13 <= 0.386
		A24	226.632097	A24 <= 0.125
		A11	-100.20062	A11 <= 0.418
		A16	239.704458	A16 <= 0.125
		A20	178.359601	A20 <= 0.133
		A21	104.85316	A21 <= 0.125
		A4	-69.010086	A4 <= 0.0564
		A18	357.903743	A18 <= 0.134
		A17	42.2703923	A17 <= 0.125
		A19	-270.61025	A19 <= 0.136
		A5	-65.884546	A5 <= 0.360
		A22	111.717063	A22 <= 0.130
		A10	427.103446	A10 <= 0.176
		A6	-259.19666	A6 <= 0.359
		A3	-51.825029	A3 <= 0.195
		A23	134.408073	A23 <= 0.120
		A9	-91.522599	0.186 < A9 <= 0.219
1975	0.9998258	A2	-609.59154	A2 <= 0.476
		A14	145.445304	A14 <= 0.291
		A1	25.6469922	A1 <= 0.495
		A8	-74.434285	0.666 < A8
		A7	453.152984	A7 <= 0.595
		A13	145.353419	A13 <= 0.386
		A24	41.11531	A24 <= 0.125
		A11	101.468246	A11 <= 0.418
		A16	259.085553	A16 <= 0.125
		A20	162.197973	A20 <= 0.133
		A21	-188.67687	A21 <= 0.125
		A4	-370.37149	A4 <= 0.0564
		A18	522.996921	A18 <= 0.134
		A17	107.660985	A17 <= 0.125
		A19	103.156642	A19 <= 0.136
		A5	-304.18175	A5 <= 0.360
		A22	-138.60222	A22 <= 0.130
		A10	92.7674198	A10 <= 0.176
		A6	43.1412039	A6 <= 0.359
		A3	350.49462	A3 <= 0.195
		A23	-396.85503	A23 <= 0.120
		A9	-281.79465	0.186 < A9 <= 0.219

Local Explanations - 1976 / 1977

Year (case)	Surrogate Linear Model R2	Feature	Feature Weight	Influence Interval
1976	0.90500207	A2	140.571991	0.577 < A2 <= 0.676
		A14	31.1363839	0.612 < A14
		A1	-329.06073	A1 <= 0.495
		A8	44.0643077	0.666 < A8
		A7	19.9216373	A7 <= 0.595
		A13	159.482303	A13 <= 0.386
		A24	34.6721423	A24 <= 0.125
		A11	-10.858982	A11 <= 0.418
		A16	200.203677	A16 <= 0.125
		A20	-192.7225	A20 <= 0.133
		A21	57.2995819	A21 <= 0.125
		A4	-119.73004	A4 <= 0.0564
		A18	70.242586	A18 <= 0.134
		A17	-43.486502	A17 <= 0.125
		A19	59.7616273	A19 <= 0.136
		A5	90.1160819	A5 <= 0.360
		A22	83.3344438	A22 <= 0.130
		A10	24.081458	A10 <= 0.176
		A6	2.89297006	A6 <= 0.359
		A3	-25.263085	A3 <= 0.195
		A23	-3.5449913	A23 <= 0.120
		A9	17.3365881	0.219 < A9 <= 0.468
1977	0.97758219	A2	130.27246	0.577 < A2 <= 0.676
		A14	-33.773015	0.291 < A14 <= 0.397
		A1	133.535311	A1 <= 0.495
		A8	6.30007819	0.666 < A8
		A7	-24.727852	A7 <= 0.595
		A13	-70.522167	A13 <= 0.386
		A24	-20.50249	A24 <= 0.125
		A11	-9.0203231	0.418 < A11 <= 0.550
		A16	20.8116409	A16 <= 0.125
		A20	-113.06011	A20 <= 0.133
		A21	121.313609	A21 <= 0.125
		A4	-77.671582	A4 <= 0.0564
		A18	175.57255	A18 <= 0.134
		A17	9.03648019	A17 <= 0.125
		A19	52.6807185	A19 <= 0.136
		A5	72.4637487	A5 <= 0.360
		A22	40.9839328	A22 <= 0.130
		A10	329.150674	A10 <= 0.176
		A6	111.437809	A6 <= 0.359
		A3	189.920628	A3 <= 0.195
		A23	-139.6	A23 <= 0.120
		A9	204.770984	0.186 < A9 <= 0.219

Local Explanations - 1978 / 1979

Year (case)	Surrogate Linear Model R2	Feature	Feature Weight	Influence Interval
1978	0.98180433	A2	95.1877008	0.676 < A2
		A14	-200.40157	0.612 < A14
		A1	-105.345	0.495 < A1 <= 0.692
		A8	29.4231422	0.666 < A8
		A7	35.576952	A7 <= 0.595
		A13	23.8409362	A13 <= 0.386
		A24	16.9614433	A24 <= 0.125
		A11	-30.264132	0.418 < A11 <= 0.550
		A16	38.2050882	A16 <= 0.125
		A20	-94.093093	A20 <= 0.133
		A21	188.04279	A21 <= 0.125
		A4	65.8573468	A4 <= 0.0564
		A18	-50.325574	A18 <= 0.134
		A17	21.9987234	A17 <= 0.125
		A19	131.370443	A19 <= 0.136
		A5	164.709381	A5 <= 0.360
		A22	44.1892387	A22 <= 0.130
		A10	252.85771	A10 <= 0.176
		A6	107.963099	A6 <= 0.359
		A3	-1.7819429	A3 <= 0.195
		A23	-41.074491	A23 <= 0.120
		A9	129.437638	0.186 < A9 <= 0.219
1979	0.99936707	A2	121.785381	0.676 < A2
		A14	43.7898043	0.612 < A14
		A1	97.8122661	0.495 < A1 <= 0.692
		A8	1.98194491	0.666 < A8
		A7	-324.65809	A7 <= 0.595
		A13	-38.811377	A13 <= 0.386
		A24	83.4648603	0.125 < A24 <= 0.298
		A11	-349.52208	0.550 < A11 <= 0.680
		A16	97.4817284	0.125 < A16 <= 0.330
		A20	108.378762	0.133 < A20 <= 0.342
		A21	293.210473	0.125 < A21 <= 0.336
		A4	114.493439	A4 <= 0.0564
		A18	327.180732	0.134 < A18 <= 0.338
		A17	31.4228595	0.125 < A17 <= 0.331
		A19	19.3417576	0.136 < A19 <= 0.330
		A5	-74.027299	A5 <= 0.360
		A22	39.4783424	A22 <= 0.130
		A10	67.8170658	A10 <= 0.176
		A6	107.970126	A6 <= 0.359
		A3	94.7653213	A3 <= 0.195
		A23	4.26018472	A23 <= 0.120
		A9	158.947579	0.186 < A9 <= 0.219

Local Explanations - 1980 / 1981

Year (case)	Surrogate Linear Model R2	Feature	Feature Weight	Influence Interval
1980	0.99027041	A2	151.21965	0.676 < A2
		A14	-19.930001	0.612 < A14
		A1	-11.456328	0.495 < A1 <= 0.692
		A8	135.471837	0.666 < A8
		A7	179.291724	0.595 < A7 <= 0.813
		A13	-9.3326684	0.386 < A13 <= 0.613
		A24	192.412421	0.125 < A24 <= 0.298
		A11	-1.0229391	0.418 < A11 <= 0.550
		A16	267.011983	0.125 < A16 <= 0.330
		A20	239.89102	0.133 < A20 <= 0.342
		A21	-122.78498	0.125 < A21 <= 0.336
		A4	-12.630806	0.0564 < A4 <= 0.2600
		A18	35.0757138	0.134 < A18 <= 0.338
		A17	102.679121	0.125 < A17 <= 0.331
		A19	-196.28339	0.136 < A19 <= 0.330
		A5	106.797476	0.360 < A5 <= 0.624
		A22	36.9484237	0.130 < A22 <= 0.348
		A10	182.898933	0.176 < A10 <= 0.768
		A6	-16.295699	0.359 < A6 <= 0.628
		A3	-86.392172	0.195 < A3 <= 0.758
		A23	-17.673732	0.120 < A23 <= 0.266
		A9	14.9442068	0.186 < A9 <= 0.219
1981	0.93223226	A2	11.4269699	0.577 < A2 <= 0.676
		A14	-5.2851996	0.612 < A14
		A1	-37.235797	0.495 < A1 <= 0.692
		A8	-44.886069	0.666 < A8
		A7	2.46960093	0.595 < A7 <= 0.813
		A13	128.689698	0.386 < A13 <= 0.613
		A24	-190.2722	0.125 < A24 <= 0.298
		A11	-175.16472	0.418 < A11 <= 0.550
		A16	-32.77556	0.125 < A16 <= 0.330
		A20	-43.516788	0.133 < A20 <= 0.342
		A21	-13.904269	0.125 < A21 <= 0.336
		A4	18.4637418	0.0564 < A4 <= 0.2600
		A18	68.9586147	0.134 < A18 <= 0.338
		A17	238.654381	0.125 < A17 <= 0.331
		A19	87.6623788	0.136 < A19 <= 0.330
		A5	44.0899274	0.360 < A5 <= 0.624
		A22	-15.052793	0.130 < A22 <= 0.348
		A10	10.1393067	0.176 < A10 <= 0.768
		A6	-86.333258	0.359 < A6 <= 0.628
		A3	314.035647	0.195 < A3 <= 0.758
		A23	-134.10044	0.120 < A23 <= 0.266
		A9	2.13226425	A9 <= 0.186

Local Explanations - 1982 / 1983

Year (case)	Surrogate Linear Model R2	Feature	Feature Weight	Influence Interval
1982	0.99333614	A2	44.8151755	0.476 < A2 <= 0.577
		A14	40.6344367	0.397 < A14 <= 0.612
		A1	42.8391179	A1 <= 0.495
		A8	-9.008447	0.412 < A8 <= 0.666
		A7	13.7169422	0.595 < A7 <= 0.813
		A13	-77.610347	0.386 < A13 <= 0.613
		A24	-4.3100615	0.125 < A24 <= 0.298
		A11	37.1580056	0.418 < A11 <= 0.550
		A16	216.514961	0.125 < A16 <= 0.330
		A20	52.3059208	0.133 < A20 <= 0.342
		A21	47.0109464	0.125 < A21 <= 0.336
		A4	38.3365725	0.0564 < A4 <= 0.2600
		A18	-54.119149	0.134 < A18 <= 0.338
		A17	36.4997345	0.125 < A17 <= 0.331
		A19	-23.042356	0.136 < A19 <= 0.330
		A5	-12.267207	0.360 < A5 <= 0.624
		A22	-87.331609	0.130 < A22 <= 0.348
		A10	135.992875	0.176 < A10 <= 0.768
		A6	-119.67925	0.359 < A6 <= 0.628
		A3	32.1786233	0.195 < A3 <= 0.758
		A23	10.4030045	0.120 < A23 <= 0.266
		A9	30.5833941	A9 <= 0.186
1983	0.87654485	A2	22.4355221	0.476 < A2 <= 0.577
		A14	65.0447696	0.397 < A14 <= 0.612
		A1	-33.620753	A1 <= 0.495
		A8	27.4786616	0.412 < A8 <= 0.666
		A7	23.1254727	0.595 < A7 <= 0.813
		A13	-117.90845	0.386 < A13 <= 0.613
		A24	18.6060122	0.125 < A24 <= 0.298
		A11	-27.511162	0.418 < A11 <= 0.550
		A16	47.2150949	0.125 < A16 <= 0.330
		A20	47.2259644	0.133 < A20 <= 0.342
		A21	14.1743942	0.125 < A21 <= 0.336
		A4	31.0826973	0.0564 < A4 <= 0.2600
		A18	100.340652	0.134 < A18 <= 0.338
		A17	29.7247331	0.125 < A17 <= 0.331
		A19	20.1614723	0.136 < A19 <= 0.330
		A5	-72.160347	0.360 < A5 <= 0.624
		A22	-103.1723	0.130 < A22 <= 0.348
		A10	16.4732713	0.176 < A10 <= 0.768
		A6	8.71346295	0.359 < A6 <= 0.628
		A3	-36.121175	0.195 < A3 <= 0.758
		A23	-71.258486	0.120 < A23 <= 0.266
		A9	17.39209	A9 <= 0.186

Local Explanations - 1984 / 1985

Year (case)	Surrogate Linear Model R2	Feature	Feature Weight	Influence Interval
1984	0.387693	A2	-15.913733	0.476 < A2 <= 0.577
		A14	2.07489797	0.397 < A14 <= 0.612
		A1	-15.067539	0.495 < A1 <= 0.692
		A8	-0.5190225	0.285 < A8 <= 0.412
		A7	49.4633924	0.595 < A7 <= 0.813
		A13	44.0214518	0.386 < A13 <= 0.613
		A24	-50.31502	A24 <= 0.125
		A11	-5.7279808	0.418 < A11 <= 0.550
		A16	-22.294615	A16 <= 0.125
		A20	108.501978	A20 <= 0.133
		A21	19.1077436	A21 <= 0.125
		A4	-13.08467	0.0564 < A4 <= 0.2600
		A18	26.1148259	A18 <= 0.134
		A17	92.3476818	A17 <= 0.125
		A19	-30.623571	A19 <= 0.136
		A5	-11.916682	0.360 < A5 <= 0.624
		A22	48.1734501	0.130 < A22 <= 0.348
		A10	-10.665675	0.176 < A10 <= 0.768
		A6	-28.480979	0.359 < A6 <= 0.628
		A3	27.2458917	0.195 < A3 <= 0.758
		A23	-17.756101	0.120 < A23 <= 0.266
		A9	1.86891056	0.186 < A9 <= 0.219
1985	0.92029445	A2	67.7465177	0.577 < A2 <= 0.676
		A14	124.410137	0.612 < A14
		A1	65.6767531	0.495 < A1 <= 0.692
		A8	-47.632715	A8 <= 0.285
		A7	100.88587	0.813 < A7 <= 0.875
		A13	41.510427	0.386 < A13 <= 0.613
		A24	63.4326532	0.125 < A24 <= 0.298
		A11	249.549676	0.418 < A11 <= 0.550
		A16	-12.971871	0.125 < A16 <= 0.330
		A20	5.28123692	0.133 < A20 <= 0.342
		A21	22.1287132	0.125 < A21 <= 0.336
		A4	-37.024399	0.0564 < A4 <= 0.2600
		A18	-111.70093	0.134 < A18 <= 0.338
		A17	47.1644355	0.125 < A17 <= 0.331
		A19	-40.509549	0.136 < A19 <= 0.330
		A5	-31.641285	0.360 < A5 <= 0.624
		A22	6.8513064	0.130 < A22 <= 0.348
		A10	-70.184226	0.176 < A10 <= 0.768
		A6	-39.575	0.359 < A6 <= 0.628
		A3	-85.978512	0.195 < A3 <= 0.758
		A23	-144.28728	0.120 < A23 <= 0.266
		A9	87.9003756	A9 <= 0.186

Local Explanations - 1986 / 1987

Year (case)	Surrogate Linear Model R2	Feature	Feature Weight	Influence Interval
1986	0.9381312	A2	278.715143	0.577 < A2 <= 0.676
		A14	-17.726555	0.612 < A14
		A1	-251.39637	0.495 < A1 <= 0.692
		A8	-267.09132	0.285 < A8 <= 0.412
		A7	-2.3409149	0.813 < A7 <= 0.875
		A13	-124.78129	0.386 < A13 <= 0.613
		A24	-32.20214	0.125 < A24 <= 0.298
		A11	-129.06869	A11 <= 0.418
		A16	86.4719776	0.125 < A16 <= 0.330
		A20	-18.575456	0.133 < A20 <= 0.342
		A21	-40.999256	0.125 < A21 <= 0.336
		A4	161.121079	0.0564 < A4 <= 0.2600
		A18	16.5487164	0.134 < A18 <= 0.338
		A17	110.20829	0.125 < A17 <= 0.331
		A19	-29.843142	0.136 < A19 <= 0.330
		A5	-4.5638583	0.360 < A5 <= 0.624
		A22	-63.278924	0.130 < A22 <= 0.348
		A10	-50.128812	0.176 < A10 <= 0.768
		A6	-89.258434	0.359 < A6 <= 0.628
		A3	293.077853	0.195 < A3 <= 0.758
		A23	-111.84628	0.120 < A23 <= 0.266
		A9	241.874283	A9 <= 0.186
1987	0.82818321	A2	79.8943225	0.676 < A2
		A14	-19.936592	0.612 < A14
		A1	-68.032698	0.692 < A1 <= 0.790
		A8	35.6843083	0.285 < A8 <= 0.412
		A7	-1.3334533	0.813 < A7 <= 0.875
		A13	-36.602618	0.386 < A13 <= 0.613
		A24	61.5333326	0.125 < A24 <= 0.298
		A11	-1.7836002	0.550 < A11 <= 0.680
		A16	-12.155699	0.125 < A16 <= 0.330
		A20	-40.001012	0.133 < A20 <= 0.342
		A21	-134.93453	0.125 < A21 <= 0.336
		A4	153.390229	0.0564 < A4 <= 0.2600
		A18	-5.1013329	0.134 < A18 <= 0.338
		A17	-31.756152	0.125 < A17 <= 0.331
		A19	0.67705204	0.136 < A19 <= 0.330
		A5	-4.9787324	0.360 < A5 <= 0.624
		A22	-16.65559	0.130 < A22 <= 0.348
		A10	57.795019	0.176 < A10 <= 0.768
		A6	59.2256556	0.359 < A6 <= 0.628
		A3	-21.389402	0.195 < A3 <= 0.758
		A23	-49.497705	0.120 < A23 <= 0.266
		A9	197.043385	A9 <= 0.186

Local Explanations - 1988 / 1989

Year (case)	Surrogate Linear Model R2	Feature	Feature Weight	Influence Interval
1988	0.99820581	A2	67.5470465	0.676 < A2
		A14	56.364371	0.397 < A14 <= 0.612
		A1	58.2107211	0.692 < A1 <= 0.790
		A8	236.64206	A8 <= 0.285
		A7	-83.505471	0.813 < A7 <= 0.875
		A13	-58.49431	0.386 < A13 <= 0.613
		A24	-113.96332	0.125 < A24 <= 0.298
		A11	82.9634206	0.680 < A11
		A16	161.981103	0.125 < A16 <= 0.330
		A20	-114.28431	0.133 < A20 <= 0.342
		A21	55.3186049	0.125 < A21 <= 0.336
		A4	44.4649029	0.0564 < A4 <= 0.2600
		A18	298.240022	0.134 < A18 <= 0.338
		A17	29.8889371	0.125 < A17 <= 0.331
		A19	-37.916531	0.136 < A19 <= 0.330
		A5	52.9185242	0.360 < A5 <= 0.624
		A22	-40.889285	0.130 < A22 <= 0.348
		A10	-48.541027	0.176 < A10 <= 0.768
		A6	51.3151911	0.359 < A6 <= 0.628
		A3	112.024359	0.195 < A3 <= 0.758
		A23	-212.85006	0.120 < A23 <= 0.266
		A9	-30.574989	0.186 < A9 <= 0.219
1989	0.99003414	A2	148.646647	0.676 < A2
		A14	-338.82533	A14 <= 0.291
		A1	107.264858	0.692 < A1 <= 0.790
		A8	91.9672694	0.285 < A8 <= 0.412
		A7	349.726321	0.875 < A7
		A13	25.118107	0.386 < A13 <= 0.613
		A24	-182.51463	0.125 < A24 <= 0.298
		A11	116.133733	A11 <= 0.418
		A16	-258.52169	0.125 < A16 <= 0.330
		A20	-149.82526	0.133 < A20 <= 0.342
		A21	214.987621	0.125 < A21 <= 0.336
		A4	119.67379	0.2600 < A4 <= 0.4593
		A18	161.219733	0.134 < A18 <= 0.338
		A17	123.011286	0.125 < A17 <= 0.331
		A19	-9.8991699	0.136 < A19 <= 0.330
		A5	71.4493654	0.360 < A5 <= 0.624
		A22	67.8030456	0.130 < A22 <= 0.348
		A10	73.1499317	0.176 < A10 <= 0.768
		A6	-158.29059	0.628 < A6 <= 0.782
		A3	81.5591508	0.758 < A3 <= 0.903
		A23	-46.340086	0.120 < A23 <= 0.266
		A9	70.2198644	0.219 < A9 <= 0.468

Local Explanations - 1990 / 1991

Year (case)	Surrogate Linear Model R2	Feature	Feature Weight	Influence Interval
1990	0.79520138	A2	-54.719601	0.577 < A2 <= 0.676
		A14	-57.894191	A14 <= 0.291
		A1	86.4860489	0.692 < A1 <= 0.790
		A8	-4.8175301	0.285 < A8 <= 0.412
		A7	32.4085162	0.875 < A7
		A13	108.091838	0.613 < A13 <= 0.781
		A24	20.0687252	0.298 < A24 <= 0.474
		A11	123.583349	A11 <= 0.418
		A16	80.7824501	0.330 < A16 <= 0.468
		A20	-154.02122	0.342 < A20 <= 0.475
		A21	-3.4235414	0.336 < A21 <= 0.474
		A4	35.2293853	0.0564 < A4 <= 0.2600
		A18	-3.9295008	0.338 < A18 <= 0.472
		A17	105.368257	0.331 < A17 <= 0.468
		A19	34.6385903	0.330 < A19 <= 0.462
		A5	-22.263747	0.624 < A5 <= 0.794
		A22	-173.02751	0.348 < A22 <= 0.662
		A10	39.9858998	0.768 < A10 <= 0.905
		A6	16.9307468	0.628 < A6 <= 0.782
		A3	-71.039674	0.195 < A3 <= 0.758
		A23	-65.460185	0.266 < A23 <= 0.588
		A9	-56.517214	0.219 < A9 <= 0.468
1991	0.89249637	A2	121.937443	0.476 < A2 <= 0.577
		A14	94.1827389	0.291 < A14 <= 0.397
		A1	-3.1447576	0.692 < A1 <= 0.790
		A8	187.558245	0.412 < A8 <= 0.666
		A7	292.830641	0.813 < A7 <= 0.875
		A13	117.539072	0.613 < A13 <= 0.781
		A24	134.255518	0.298 < A24 <= 0.474
		A11	52.1810069	0.418 < A11 <= 0.550
		A16	97.3867225	0.330 < A16 <= 0.468
		A20	107.781842	0.342 < A20 <= 0.475
		A21	-236.25901	0.336 < A21 <= 0.474
		A4	-15.924714	0.2600 < A4 <= 0.4593
		A18	149.872505	0.338 < A18 <= 0.472
		A17	-135.1674	0.331 < A17 <= 0.468
		A19	-113.22362	0.330 < A19 <= 0.462
		A5	-194.6661	0.624 < A5 <= 0.794
		A22	-149.11183	0.348 < A22 <= 0.662
		A10	30.5618543	0.768 < A10 <= 0.905
		A6	270.542267	0.628 < A6 <= 0.782
		A3	-131.02899	0.758 < A3 <= 0.903
		A23	69.7174917	0.266 < A23 <= 0.588
		A9	-171.22318	0.219 < A9 <= 0.468

Local Explanations - 1992 / 1993

Year (case)	Surrogate Linear Model R2	Feature	Feature Weight	Influence Interval
1992	0.84505001	A2	-86.671998	A2 <= 0.476
		A14	-163.89518	A14 <= 0.291
		A1	58.5476021	0.495 < A1 <= 0.692
		A8	111.703304	0.412 < A8 <= 0.666
		A7	-37.703906	0.813 < A7 <= 0.875
		A13	105.221873	0.613 < A13 <= 0.781
		A24	48.7313272	0.298 < A24 <= 0.474
		A11	7.26743266	0.550 < A11 <= 0.680
		A16	19.3389843	0.330 < A16 <= 0.468
		A20	177.589855	0.342 < A20 <= 0.475
		A21	-33.15453	0.336 < A21 <= 0.474
		A4	-3.4078878	0.2600 < A4 <= 0.4593
		A18	-111.523	0.338 < A18 <= 0.472
		A17	164.221785	0.331 < A17 <= 0.468
		A19	-94.23444	0.330 < A19 <= 0.462
		A5	40.3466526	0.624 < A5 <= 0.794
		A22	50.7466725	0.348 < A22 <= 0.662
		A10	-15.184192	0.768 < A10 <= 0.905
		A6	-20.886133	0.628 < A6 <= 0.782
		A3	31.1847444	0.758 < A3 <= 0.903
		A23	154.258378	0.266 < A23 <= 0.588
		A9	52.9842704	0.186 < A9 <= 0.219
1993	0.99686377	A2	-269.24078	A2 <= 0.476
		A14	50.8057101	0.397 < A14 <= 0.612
		A1	15.7677716	0.495 < A1 <= 0.692
		A8	79.0804068	0.285 < A8 <= 0.412
		A7	61.9040926	0.595 < A7 <= 0.813
		A13	51.4037614	0.613 < A13 <= 0.781
		A24	50.9121465	0.298 < A24 <= 0.474
		A11	-54.195194	0.550 < A11 <= 0.680
		A16	152.404894	0.330 < A16 <= 0.468
		A20	40.4976135	0.342 < A20 <= 0.475
		A21	135.32324	0.336 < A21 <= 0.474
		A4	321.493039	0.2600 < A4 <= 0.4593
		A18	174.356926	0.338 < A18 <= 0.472
		A17	51.9652135	0.331 < A17 <= 0.468
		A19	37.4646603	0.330 < A19 <= 0.462
		A5	-203.89941	0.624 < A5 <= 0.794
		A22	55.5400073	0.348 < A22 <= 0.662
		A10	-533.25009	0.768 < A10 <= 0.905
		A6	-140.33264	0.359 < A6 <= 0.628
		A3	-138.78513	0.758 < A3 <= 0.903
		A23	86.7144774	0.266 < A23 <= 0.588
		A9	282.720036	0.186 < A9 <= 0.219

Local Explanations - 1994 / 1995

Year (case)	Surrogate Linear Model R2	Feature	Feature Weight	Influence Interval
1994	0.99417807	A2	-531.28761	A2 <= 0.476
		A14	124.926217	A14 <= 0.291
		A1	197.432426	0.495 < A1 <= 0.692
		A8	51.8138985	0.412 < A8 <= 0.666
		A7	231.257424	0.595 < A7 <= 0.813
		A13	-200.84445	0.613 < A13 <= 0.781
		A24	-223.91023	0.298 < A24 <= 0.474
		A11	152.511319	0.680 < A11
		A16	-202.66079	0.330 < A16 <= 0.468
		A20	92.5885403	0.342 < A20 <= 0.475
		A21	-39.268357	0.336 < A21 <= 0.474
		A4	139.881061	0.2600 < A4 <= 0.4593
		A18	-69.674662	0.338 < A18 <= 0.472
		A17	-301.54038	0.331 < A17 <= 0.468
		A19	-74.088792	0.330 < A19 <= 0.462
		A5	24.6162728	0.624 < A5 <= 0.794
		A22	149.307326	0.348 < A22 <= 0.662
		A10	-114.15307	0.768 < A10 <= 0.905
		A6	76.1210672	0.628 < A6 <= 0.782
		A3	213.351006	0.758 < A3 <= 0.903
		A23	116.39274	0.266 < A23 <= 0.588
		A9	191.739599	0.219 < A9 <= 0.468
1995	0.98243178	A2	-75.783479	A2 <= 0.476
		A14	264.432789	0.291 < A14 <= 0.397
		A1	129.484499	0.692 < A1 <= 0.790
		A8	-43.996818	0.412 < A8 <= 0.666
		A7	67.4275475	0.813 < A7 <= 0.875
		A13	-44.78266	0.613 < A13 <= 0.781
		A24	274.441705	0.474 < A24
		A11	-80.597591	0.680 < A11
		A16	-129.02328	0.468 < A16
		A20	-8.140098	0.475 < A20
		A21	-96.822383	0.474 < A21
		A4	155.415575	0.2600 < A4 <= 0.4593
		A18	45.3299199	0.472 < A18
		A17	-91.167677	0.468 < A17
		A19	-99.683585	0.462 < A19
		A5	20.1102333	0.624 < A5 <= 0.794
		A22	292.759539	0.348 < A22 <= 0.662
		A10	-53.69106	0.768 < A10 <= 0.905
		A6	-276.00472	0.628 < A6 <= 0.782
		A3	80.1788007	0.758 < A3 <= 0.903
		A23	-104.78508	0.266 < A23 <= 0.588
		A9	-62.314994	0.219 < A9 <= 0.468

Local Explanations - 1996 / 1997

Year (case)	Surrogate Linear Model R2	Feature	Feature Weight	Influence Interval
1996	0.90352485	A2	157.427657	0.577 < A2 <= 0.676
		A14	197.051575	0.612 < A14
		A1	-30.813503	0.790 < A1
		A8	172.289929	0.412 < A8 <= 0.666
		A7	21.2021187	0.813 < A7 <= 0.875
		A13	122.013512	0.613 < A13 <= 0.781
		A24	112.385332	0.474 < A24
		A11	-24.057141	0.680 < A11
		A16	-35.176658	0.468 < A16
		A20	220.837035	0.475 < A20
		A21	-89.175144	0.474 < A21
		A4	-8.3048934	0.2600 < A4 <= 0.4593
		A18	87.2176942	0.472 < A18
		A17	-15.606141	0.468 < A17
		A19	-264.59511	0.462 < A19
		A5	44.8312536	0.624 < A5 <= 0.794
		A22	-5.5260776	0.348 < A22 <= 0.662
		A10	-196.30182	0.768 < A10 <= 0.905
		A6	133.835772	0.628 < A6 <= 0.782
		A3	-40.302007	0.758 < A3 <= 0.903
		A23	47.4011686	0.266 < A23 <= 0.588
		A9	-29.476633	0.219 < A9 <= 0.468
1997	0.9847716	A2	-271.65019	0.476 < A2 <= 0.577
		A14	-45.048969	0.291 < A14 <= 0.397
		A1	213.170687	0.692 < A1 <= 0.790
		A8	-17.893416	0.285 < A8 <= 0.412
		A7	-62.616636	0.813 < A7 <= 0.875
		A13	135.55294	0.613 < A13 <= 0.781
		A24	206.050665	0.474 < A24
		A11	114.10669	0.680 < A11
		A16	-242.22068	0.330 < A16 <= 0.468
		A20	37.5742471	0.342 < A20 <= 0.475
		A21	109.206949	0.336 < A21 <= 0.474
		A4	23.2345968	0.2600 < A4 <= 0.4593
		A18	-4.1728795	0.338 < A18 <= 0.472
		A17	-2.8970235	0.331 < A17 <= 0.468
		A19	93.7548146	0.330 < A19 <= 0.462
		A5	-272.60455	0.624 < A5 <= 0.794
		A22	430.280574	0.348 < A22 <= 0.662
		A10	-243.8461	0.768 < A10 <= 0.905
		A6	61.106499	0.628 < A6 <= 0.782
		A3	-105.55666	0.758 < A3 <= 0.903
		A23	138.983753	0.266 < A23 <= 0.588
		A9	62.9080204	0.219 < A9 <= 0.468

Local Explanations - 1998 / 1999

Year (case)	Surrogate Linear Model R2	Feature	Feature Weight	Influence Interval
1998	0.99880943	A2	-75.580711	0.476 < A2 <= 0.577
		A14	143.179683	0.397 < A14 <= 0.612
		A1	138.576297	0.790 < A1
		A8	232.904363	0.412 < A8 <= 0.666
		A7	-197.2834	0.813 < A7 <= 0.875
		A13	83.543775	0.613 < A13 <= 0.781
		A24	29.9170106	0.298 < A24 <= 0.474
		A11	107.411744	0.680 < A11
		A16	291.94552	0.330 < A16 <= 0.468
		A20	76.1592162	0.342 < A20 <= 0.475
		A21	-80.433533	0.474 < A21
		A4	-204.12025	0.2600 < A4 <= 0.4593
		A18	-294.83901	0.338 < A18 <= 0.472
		A17	130.157499	0.331 < A17 <= 0.468
		A19	-85.474026	0.330 < A19 <= 0.462
		A5	-144.16601	0.624 < A5 <= 0.794
		A22	119.30406	0.348 < A22 <= 0.662
		A10	-498.67147	0.768 < A10 <= 0.905
		A6	106.383921	0.628 < A6 <= 0.782
		A3	-95.598057	0.758 < A3 <= 0.903
		A23	124.655236	0.266 < A23 <= 0.588
		A9	132.994104	0.219 < A9 <= 0.468
1999	0.83219334	A2	17.8193171	0.476 < A2 <= 0.577
		A14	12.2654334	0.291 < A14 <= 0.397
		A1	-110.68916	0.692 < A1 <= 0.790
		A8	70.2571501	0.285 < A8 <= 0.412
		A7	-13.389148	0.595 < A7 <= 0.813
		A13	-9.2906232	0.613 < A13 <= 0.781
		A24	154.659296	0.298 < A24 <= 0.474
		A11	27.1156095	0.680 < A11
		A16	15.8874842	0.330 < A16 <= 0.468
		A20	-67.402105	0.342 < A20 <= 0.475
		A21	63.9400738	0.336 < A21 <= 0.474
		A4	94.1939265	0.2600 < A4 <= 0.4593
		A18	-79.044508	0.338 < A18 <= 0.472
		A17	149.358488	0.331 < A17 <= 0.468
		A19	-82.235961	0.330 < A19 <= 0.462
		A5	131.750235	0.624 < A5 <= 0.794
		A22	-48.282919	0.348 < A22 <= 0.662
		A10	-111.7338	0.905 < A10
		A6	-40.355543	0.628 < A6 <= 0.782
		A3	-134.6856	0.758 < A3 <= 0.903
		A23	84.5411888	0.266 < A23 <= 0.588
		A9	-83.960453	0.219 < A9 <= 0.468

Local Explanations - 2000 / 2001

Year (case)	Surrogate Linear Model R2	Feature	Feature Weight	Influence Interval
2000	0.84724601	A2	-102.84359	0.476 < A2 <= 0.577
		A14	3.82939242	A14 <= 0.291
		A1	16.4079434	0.692 < A1 <= 0.790
		A8	67.4965067	0.285 < A8 <= 0.412
		A7	26.9364298	0.875 < A7
		A13	-6.5594725	0.781 < A13
		A24	89.6061255	0.298 < A24 <= 0.474
		A11	197.366749	0.680 < A11
		A16	10.8245126	0.330 < A16 <= 0.468
		A20	-17.521564	0.342 < A20 <= 0.475
		A21	-7.692202	0.336 < A21 <= 0.474
		A4	-92.573561	0.4593 < A4
		A18	-111.57018	0.338 < A18 <= 0.472
		A17	14.0586898	0.331 < A17 <= 0.468
		A19	-36.746749	0.330 < A19 <= 0.462
		A5	10.5834219	0.794 < A5
		A22	118.920689	0.662 < A22
		A10	-104.26439	0.905 < A10
		A6	29.2436911	0.782 < A6
		A3	-4.7939643	0.903 < A3
		A23	2.25750485	0.588 < A23
		A9	-1.4590415	0.468 < A9
2001	0.88725786	A2	7.43550603	0.577 < A2 <= 0.676
		A14	-82.57602	0.291 < A14 <= 0.397
		A1	-4.6303623	0.790 < A1
		A8	-33.329626	A8 <= 0.285
		A7	208.492366	0.875 < A7
		A13	13.9409695	0.781 < A13
		A24	38.3949245	0.298 < A24 <= 0.474
		A11	4.9069996	0.680 < A11
		A16	-2.497574	0.330 < A16 <= 0.468
		A20	56.5077289	0.342 < A20 <= 0.475
		A21	41.9148457	0.336 < A21 <= 0.474
		A4	-3.8461265	0.4593 < A4
		A18	199.349141	0.338 < A18 <= 0.472
		A17	13.9462659	0.331 < A17 <= 0.468
		A19	4.30094699	0.330 < A19 <= 0.462
		A5	1.70010997	0.794 < A5
		A22	-30.434038	0.662 < A22
		A10	22.9200434	0.905 < A10
		A6	30.3924505	0.782 < A6
		A3	-11.055241	0.903 < A3
		A23	4.77026338	0.588 < A23
		A9	112.341349	0.468 < A9

Local Explanations - 2002 / 2003

Year (case)	Surrogate Linear Model R2	Feature	Feature Weight	Influence Interval
2002	0.91294745	A2	-136.24799	0.577 < A2 <= 0.676
		A14	218.108699	A14 <= 0.291
		A1	-3.0573776	0.790 < A1
		A8	-40.486617	0.285 < A8 <= 0.412
		A7	1.12913952	0.875 < A7
		A13	63.4168157	0.781 < A13
		A24	0.76492689	0.298 < A24 <= 0.474
		A11	-2.4965428	0.550 < A11 <= 0.680
		A16	11.1991767	0.468 < A16
		A20	-5.7826119	0.475 < A20
		A21	93.2828239	0.336 < A21 <= 0.474
		A4	23.3528857	0.4593 < A4
		A18	-3.8799751	0.472 < A18
		A17	20.9720665	0.468 < A17
		A19	175.307956	0.462 < A19
		A5	-65.342089	0.794 < A5
		A22	163.121559	0.662 < A22
		A10	-150.8255	0.905 < A10
		A6	-60.45397	0.782 < A6
		A3	-123.73681	0.903 < A3
		A23	286.756257	0.588 < A23
		A9	-23.984198	0.468 < A9
2003	0.98465317	A2	28.6488463	0.676 < A2
		A14	156.717238	0.397 < A14 <= 0.612
		A1	-44.021012	0.790 < A1
		A8	242.827925	A8 <= 0.285
		A7	-674.65239	0.875 < A7
		A13	294.918057	0.781 < A13
		A24	68.273674	0.474 < A24
		A11	102.381512	0.418 < A11 <= 0.550
		A16	-184.15522	0.468 < A16
		A20	-165.45521	0.475 < A20
		A21	-11.709762	0.474 < A21
		A4	-113.67786	0.4593 < A4
		A18	-100.92828	0.472 < A18
		A17	-262.48882	0.468 < A17
		A19	215.355971	0.462 < A19
		A5	283.109492	0.794 < A5
		A22	-101.63906	0.662 < A22
		A10	-54.645385	0.905 < A10
		A6	-46.092452	0.782 < A6
		A3	332.58897	0.903 < A3
		A23	32.3476436	0.588 < A23
		A9	23.9368145	0.468 < A9

Local Explanations - 2004 / 2005

Year (case)	Surrogate Linear Model R2	Feature	Feature Weight	Influence Interval
2004	0.73080161	A2	99.8905915	0.676 < A2
		A14	143.535988	0.291 < A14 <= 0.397
		A1	-80.569099	0.790 < A1
		A8	-68.152534	A8 <= 0.285
		A7	16.7097334	0.875 < A7
		A13	105.697337	0.781 < A13
		A24	12.079433	0.474 < A24
		A11	4.31176873	0.550 < A11 <= 0.680
		A16	-48.528445	0.468 < A16
		A20	-37.487335	0.475 < A20
		A21	11.3595897	0.474 < A21
		A4	-8.6572007	0.4593 < A4
		A18	122.491593	0.472 < A18
		A17	-75.798802	0.468 < A17
		A19	-67.5681	0.462 < A19
		A5	-151.80663	0.794 < A5
		A22	35.1629556	0.662 < A22
		A10	-52.968667	0.905 < A10
		A6	-84.890639	0.782 < A6
		A3	-24.961093	0.903 < A3
		A23	189.037396	0.588 < A23
		A9	45.5197162	0.468 < A9
2005	0.97746009	A2	58.0784889	0.676 < A2
		A14	41.5039152	0.291 < A14 <= 0.397
		A1	7.39644173	0.790 < A1
		A8	344.825504	A8 <= 0.285
		A7	-9.809737	0.875 < A7
		A13	50.0152107	0.781 < A13
		A24	58.6471384	0.474 < A24
		A11	36.0009661	0.550 < A11 <= 0.680
		A16	-18.013913	0.468 < A16
		A20	-0.6939068	0.475 < A20
		A21	26.5923222	0.474 < A21
		A4	45.9573353	0.4593 < A4
		A18	-10.329676	0.472 < A18
		A17	-39.812193	0.468 < A17
		A19	-10.923056	0.462 < A19
		A5	60.3223188	0.794 < A5
		A22	-78.600084	0.662 < A22
		A10	-58.606839	0.905 < A10
		A6	-58.969198	0.782 < A6
		A3	-136.83737	0.903 < A3
		A23	126.256674	0.588 < A23
		A9	-117.5907	0.468 < A9

Local Explanations - 2006 / 2007

Year (case)	Surrogate Linear Model R2	Feature	Feature Weight	Influence Interval
2006	0.6786353	A2	139.896468	0.676 < A2
		A14	27.3157085	0.291 < A14 <= 0.397
		A1	169.244016	0.790 < A1
		A8	-34.294121	A8 <= 0.285
		A7	25.0170389	0.875 < A7
		A13	-54.93281	0.781 < A13
		A24	204.856287	0.474 < A24
		A11	-40.490245	0.550 < A11 <= 0.680
		A16	-21.110312	0.468 < A16
		A20	79.9221913	0.475 < A20
		A21	-28.38399	0.474 < A21
		A4	-83.325023	0.4593 < A4
		A18	40.5604472	0.472 < A18
		A17	23.4045759	0.468 < A17
		A19	22.7445131	0.462 < A19
		A5	-126.32899	0.794 < A5
		A22	-4.1518806	0.662 < A22
		A10	8.80827506	0.905 < A10
		A6	-47.127772	0.782 < A6
		A3	-66.123182	0.903 < A3
		A23	56.7171645	0.588 < A23
		A9	49.1225354	0.468 < A9
2007	0.97168409	A2	88.9248993	0.577 < A2 <= 0.676
		A14	14.1279785	A14 <= 0.291
		A1	-126.3973	0.790 < A1
		A8	-122.74527	A8 <= 0.285
		A7	-95.056476	0.875 < A7
		A13	-86.267495	0.781 < A13
		A24	426.967135	0.474 < A24
		A11	240.539336	0.550 < A11 <= 0.680
		A16	-76.151847	0.468 < A16
		A20	-43.136572	0.475 < A20
		A21	-42.959048	0.474 < A21
		A4	-176.05137	0.4593 < A4
		A18	-38.395895	0.472 < A18
		A17	-95.441862	0.468 < A17
		A19	-145.21523	0.462 < A19
		A5	166.504288	0.794 < A5
		A22	0.46714192	0.662 < A22
		A10	-71.504672	0.905 < A10
		A6	314.14286	0.782 < A6
		A3	-16.796491	0.903 < A3
		A23	207.184622	0.588 < A23
		A9	-87.013686	0.468 < A9

Local Explanations - 2008 / 2009

Year (case)	Surrogate Linear Model R2	Feature	Feature Weight	Influence Interval
2008	0.83941087	A2	70.1075544	0.476 < A2 <= 0.577
		A14	-197.7202	A14 <= 0.291
		A1	-132.58162	0.790 < A1
		A8	-128.34842	A8 <= 0.285
		A7	97.5166047	0.595 < A7 <= 0.813
		A13	157.99947	0.781 < A13
		A24	100.842864	0.474 < A24
		A11	-15.736737	0.550 < A11 <= 0.680
		A16	70.1533532	0.468 < A16
		A20	48.6078067	0.475 < A20
		A21	31.3307846	0.474 < A21
		A4	104.281338	0.4593 < A4
		A18	-1.9352818	0.472 < A18
		A17	20.6149691	0.468 < A17
		A19	-33.612441	0.462 < A19
		A5	92.961096	0.794 < A5
		A22	-126.0427	0.662 < A22
		A10	-100.84357	0.905 < A10
		A6	-31.90256	0.782 < A6
		A3	177.838847	0.903 < A3
		A23	151.12272	0.588 < A23
		A9	-42.801655	0.468 < A9
2009	0.97912484	A2	-728.41418	A2 <= 0.476
		A14	-101.0112	0.291 < A14 <= 0.397
		A1	-16.377552	0.692 < A1 <= 0.790
		A8	62.0129541	A8 <= 0.285
		A7	-51.064901	0.595 < A7 <= 0.813
		A13	154.083839	0.781 < A13
		A24	107.41985	0.474 < A24
		A11	98.8048477	0.680 < A11
		A16	-473.71505	0.468 < A16
		A20	100.90129	0.475 < A20
		A21	-17.297446	0.474 < A21
		A4	205.030824	0.4593 < A4
		A18	-34.066944	0.472 < A18
		A17	55.9726053	0.468 < A17
		A19	-20.569894	0.462 < A19
		A5	114.726596	0.794 < A5
		A22	-21.107717	0.662 < A22
		A10	-22.052875	0.768 < A10 <= 0.905
		A6	322.699268	0.782 < A6
		A3	-12.21738	0.903 < A3
		A23	183.286603	0.588 < A23
		A9	-18.326189	0.468 < A9