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AI-Powered Early Warning Systems for Economic Crisis Prediction Using Outlier Detection, Time Series Forecasting, and Machine Learning Algorithms

Abstract

The current review addresses the integration of outlier detection, time series forecasting, and machine learning algorithms into the area of Early Warning Systems in the Artificial Intelligence (AI) based economic crisis prediction in the natural and environmental shock. The climate-related losses may have outliers in environmental economics because this type of loss is hard to forecast and appears to be a sudden energy surge or an unexpected pollution spike. The classical methods of statistics analyzed include Mahalanobis Distance and Minimum Covariance Determinant, while advanced methods include Local Outlier Factor, Isolation Forest, and Robust PCA, and their application in working with high-dimensional data. It also stresses machine learning algorithms such as Long Short-Term Memory networks and Random Forests in time series prediction. It puts an emphasis on scalability, robustness, and interpretability, and it shows how artificial intelligence-powered systems can contribute to preparedness, resilience, and policy reaction to risks.

Keywords: Outlier Detection; AI-Powered Early Warning Systems; Economic Crisis Prediction; Machine Learning Algorithms; Time Series Forecasting

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Abstract

The current review addresses the integration of outlier detection, time series forecasting, and machine learning algorithms into the area of Early Warning Systems in the Artificial Intelligence (AI) based economic crisis prediction in the natural and environmental shock. The climate-related losses may have outliers in environmental economics because this type of loss is hard to forecast and appears to be a sudden energy surge or an unexpected pollution spike. The classical methods of statistics analyzed include Mahalanobis Distance and Minimum Covariance Determinant, while advanced methods include Local Outlier Factor, Isolation Forest, and Robust PCA, and their application in working with high-dimensional data. It also stresses machine learning algorithms such as Long Short-Term Memory networks and Random Forests in time series prediction. It puts an emphasis on scalability, robustness, and interpretability, and it shows how artificial intelligence-powered systems can contribute to preparedness, resilience, and policy reaction to risks.

Contents

Keywords: Outlier Detection; AI-Powered Early Warning Systems; Economic Crisis Prediction; Machine Learning Algorithms; Time Series Forecasting

Introduction

The cases that do not correlate with other data are called outliers, and unless they are handled in statistics, they may provide an erroneous analysis. These outliers are common in environmental economics since the extreme events in the ecology, pollution spikes, sudden changes in energy consumption, or economic losses due to a climatic disaster play a key role (Dongre et al., 2025). Such outliers have to be handled effectively in a bid to make satisfactory forecasts and ensure model reliability. The problems of variability of economic data, including in the measures of pollution, energy consumption, and management of ecosystem services, usually have outliers that will be related to the actual data because of an extreme event or measurement error. Unless we take appropriate care, these outliers can have a tremendous impact on economic forecasts and can consist of climatic changes and energy consumption aberrations (Begashaw & Yohannes, 2020).

In the area of environmental economics, economists have to deal with large and sloppy data which is typically due to the presence of outliers (e.g. when monitoring pollution, an abrupt shock of CO 2 breakdown) or energy demands (e.g. when power levels increase due to an unforeseen sudden call by industries) and economic costs of incidents in nature (e.g. exceptional disastrous hurricanes that rarely occur). This, therefore, means that economists have a choice: to handle these outliers through the application of robust statistical models or to transform the data in order not to violate its integrity. This necessity to deal with outliers correctly resulted in the emergence of a specific set of technologies and techniques related to the outlying problems, which includes techniques of Mahalanobis Distance, Robust PCA, and Minimum Covariance Determinant (MCD), which provide a solution in working with multivariate data of very high breakdown points (Cangussu et al., 2024; Zafeirelli & Kavroudakis, 2024).

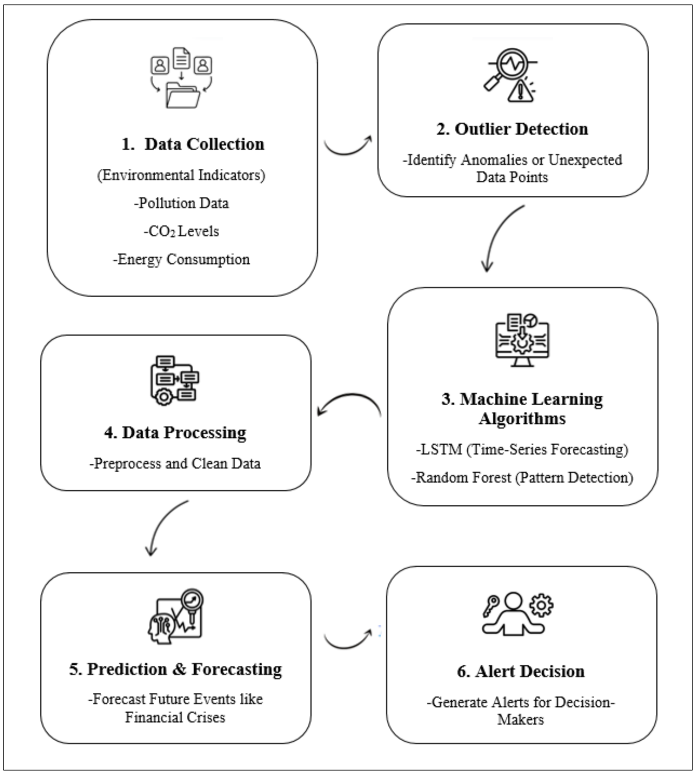
In this pursuit, the paper presents an attempt to describe in detail the different outlier detection systems used in environmental economics with an emphasis on one process that can improve economic crisis forecasting via the application of AI-driven early warning systems. The review appreciates the different types of outlier detection procedures and determines their ability to identify anomalies in environmental data. The review would further examine how Long Short-Term Memory (LSTM) networks and Random Forests machine learning models may be used to make such models even more predictable. Moreover, the paper also describes the implications of enhanced approaches on the upcoming research and policy formulation, which represents the consequences of the encouraging outcomes of AI-based approaches in economic prediction and emergency management, particularly in scenarios connected with environmental outages.

AI-Powered Early Warning Systems for Economic Crisis Prediction

The paradigm shift in predicting both the environmental and other economic crises has been supported by the introduction of the AI-based EWS. New systems incorporating techniques of outlier detection, time series, and machine learning have been developed to work with large-scale sets of multidimensional economic data. These capabilities enable the AI to identify non-linear and complex links between environmental aspects and economic action that are not identified using traditional statistics. Surprisingly, techniques such as LSTM (Long Short Term Memory networks) and Random Forests tend to be more accurate in providing early warnings to destabilization caused by the environment than present means (Dastkhan, 2021). This is the secret behind the power of AI-based solutions, which is a combination of outlier detection processes, cluster-based, and time series forecasting systems/models, such as Prophet. In this way, the systems would not only be able to identify anomalies that may or may not give rise to a precondition of the first steps of an economic crisis, but more strongly, they would also be able to show a higher degree of accuracy in predicting future conditions. In order to highlight these peculiarities of economic indicators, it is possible to use the methods of clustering, such as k-means or DBSCAN. In contrast, time series models get adjusted to the changes propagated by environmental shocks and allow decision-makers to stand in a more favorable position to consider the unpredictability of the markets and plan mitigation mechanisms (Dastkhan, 2021; Chohan et al, 2025).

Figure 1

Flowchart of the AI-Powered Early Warning System.



Moreover, the EWS is a policy writing and company actionable intelligence tool to participate in an ongoing learning process as the companies internalize new information. The benefit of such freedom is that it involves the chance to notice economic risks which pose a threat earlier, and that it would be possible to make improved economic decisions during a period of environmental uncertainty. As the susceptibility of economies in different regions of the world to climate-related events and other disruptive trends increases, the inclusion of outlier detection and an enhanced model of forecasting in the early warning mechanisms will continue to be a practice that is worth considering for stability and preventative responses in predicting riskful events or circumstances (Samitas et al., 2020). Figure 1 demonstrates the mechanism of the early warning developed based on the AI-based technology in detail. It starts with the collection of data concerning the environment, such as the amount of pollution, the extent of CO2, and the energy used. Then it identifies any anomalies or outliers in the data and predicts the future using machine learning software, like LSTM or Random Forest, and through the successive monetary disasters. Finally, they conclude with the development of warnings to decision-makers in order to act preemptively to the emergent environmental and economic risks.

Outlier Detection in Economic Data

Outlier identification is extremely important in identifying extreme data points, which are a very good indicator of an economic crisis. In most cases in environmental economics, the anomalies are natural calamities or financial shocks. It is necessary to identify such outliers as early as possible since they can skew the predictions, generating inaccurate analysis when not accounted for. Several approaches in environmental economics are used to detect outliers, each possessing unique properties and shortcomings in terms of the complexity of ecological data, which is usually high-dimensional, and encompassing all types of outliers: univariate, multivariate, and spatial anomalies (Veselik et al., 2020; Cangussu et al., 2024). There are several popular statistical and machine learning methods for identifying outliers in environmental and economic data. Statistical methods perform such a task with techniques such as the Z-score method and the modified Z-score method that find points that are highly distant compared to the mean.

In contrast, machine learning algorithms like isolation forest and local outliers factor (LOF) have dynamic methods that model the data distribution and then find points that are remarkably distinct from their neighbours. Eye-balling procedures like scatter plot and box plot can also help us to identify suspicious data points; however, they are typically enhanced by automated methods when the data set is large (Zafeirelli & Kavroudakis, 2024). The non-parametric smoothing techniques, kernel regression, and residual analysis are only a few of the advanced techniques, along with control charts and Six Sigma methods, which are used in cases involving environmental economics to include outlier parts. The strategies make it possible to distinguish between measurement errors, changes in the standard, and sampling bias, which makes it easier to make the right decision on whether to discard or recreate outliers that are identified. The removal of outliers by proper documentation and justification preserves the transparency and soundness of environmental economic analysis, where the reliability of crisis prediction and action is essential (Huberman, 2019).

Categorization by Technique:

Statistical Methods

Typical classically based outlier detectors used in economic forecasting are based on the Mahalanobis Distance. The algorithm makes assumptions based on the hypothesis that the data will be disseminated in a certain way, and it bets on the distance between the single points' data dispersion and the multivariate centre (Zafeirelli & Kavroudakis, 2024). Nevertheless, classical Mahalanobis Distance might not apply in the case where outliers pollute the data. Stronger measures, such as the Minimum Covariance Determinant (MCD) Estimator, have been developed in order to address this pressing concern. MCD aims to identify a subpopulation of data points with minimal covariance and subsequently estimate the center and dispersion of the data based on this subpopulation. The approach might be used as a central part of environmental economics because the reason behind significant data outliers might be abnormalities, like a sudden rise in pollution or a disaster-related climatic anomaly (Boudt et al., 2020; Groenewald & Van Vuuren, 2024).

Local Outlier Factor (LOF)

Special cases and occurrences where LOF becomes very useful include its application with a non-uniform density dataset to identify local anomalies. The localized anomalies can be characterized by an increase in pollution, as detected in a small part of monitoring locations, environmental metrics, or even the energy sector of a local industry. This process involves determining the local data point density and identifying points that are not similar to their neighbors. The latest studies show that the implication of using LOF to locate the data that are localized on the cluster of data sets can become a beneficial focus in locating localized outliers in sets of environmental data (Almheiri, 2021).

Categorization by Robustness

Based on Robustness, which falls within the domain of outlier detection in ecological economics, methods with high breakdown points are instrumental. A significant breakdown point implies that the method can tolerate a large percentage of polluted data without producing inaccurate outputs. These are intended to be robust to outliers, such as extreme events, which are common in environmental datasets, as indicated by the median or M-estimators. The absence of data on extreme climate events, such as hurricanes or wildfires that cause economic damage, would be incorrect to incorporate into policy predictions as usual. When incorporated incorrectly, it would alter the policies. The robust regression methods allow reducing the effect of anomalies by increasing the insensitivity of the models to outlier data points (Suboh et al., 2023; Zafeirelli & Kavroudakis, 2024). Also, regression models may be made skewed by the concept of leverage points, which is a far-flung observation that has a mean of the predictor. As an example in the model of pollution control efficiency, a plant that has outstanding energy use, yet extremely low emissions, could appear to be efficient, but might be an outlier. In environmental economics, it is essential to detect these outliers and to deal with them accordingly to retain accuracy in economic models (Riechers et al., 2021).

Comparison of Outlier Detection Methods

Table 1 provides a comparative analysis of several methods to detect outliers in the field of environmental data analysis. It compares and analyzes every approach in terms of benefits, drawbacks, environments to use it, and complexity of calculations. These methods are Mahalanobis Distance, which is sensitive to normality assumptions but effective with multivariate data and commonly used in economic forecasting; Local Outlier Factor (LOF), which is useful when attempting to detect local anomalies in heterogeneous data, especially in environmental monitoring, but is sensitive to density assumptions; and Minimum Covariance Determinant (MCD), which is known to be resistant to outliers and also used in environmental economics (although it is computationally intensive). Also listed are other algorithms, such as Z-score and Isolation Forest, which have their advantages and disadvantages in different datasets, making a trade-off in terms of computational performance. The appropriateness of each method is considered within the framework of the requirements of the environmental economic analysis, such as the processing of high-dimensional data and the detection of anomalies in a local area (Zafeirelli & Kavroudakis, 2024).

Table 1

Comparison of Outlier Detection Methods in Environmental Economics.

Method	Advantages	Disadvantages	Application Context	Computational Complexity	References
Mahalanobis Distance	Effective for multivariate data	Sensitive to normality assumptions	Economic forecasting	Moderate	Rousseeuw et al. (1990)
Local Outlier Factor (LOF)	Detects local anomalies	Sensitive to density assumptions	Environmental monitoring	High	Almheiri (2021)
Minimum Covariance Determinant (MCD)	Robust to outliers	Computationally intensive	Environmental economics, climate data	High	Boudt et al. (2020)
Z-score	Simple and easy to implement	Assumes normal distribution	General statistical analysis	Low	Huberman (2019)
Isolation	Effective for	May not perform	Anomaly	Moderate	Veselík et

Method	Advantages	Disadvantages	Application Context	Computational Complexity	References
Forest	high-dimensional data	well with small datasets	detection in large datasets, fraud detection		al. (2020)
Robust PCA	Reduces dimensionality while preserving outliers	Computationally intensive	Environmental economics, energy consumption analysis	High	Zahariah et al. (2021)

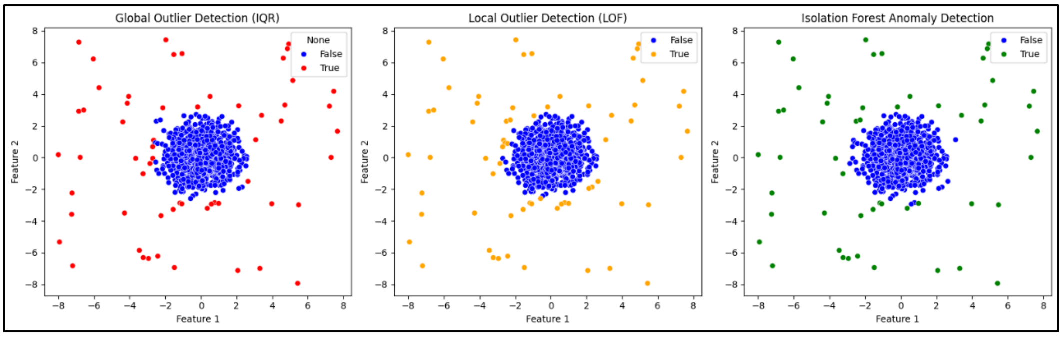
Comparison of Outlier Detection Techniques Using Synthetic Data

In Figure 2, a set of three popular outlier detection tools — Global Outlier Detection (IQR), Local Outlier Factor (LOF), and Isolation Forest — are compared using a synthetic dataset. The visual contrast of those two methods shows how each of them labels data points as normal or anomalous and exemplifies their specifications in data anomaly detection. Although the data involved is synthetic, this comparison can be interpreted as a good example of how these methods operate to find outliers and give a good idea of the strengths and weaknesses of these methods.

As Figure 2 indicates, both approaches designate outliers according to the nature of each approach when applied to the scatter plots. The Global Outlier Detection (IQR) scheme identifies outliers as the data points that are located outside the interquartile range. The Local Outlier Factor (LOF) is sensitive to local anomalies, i.e., to assessing whether the density of the data points in a neighborhood follows this trend, thus applicable to identifying local outliers in regions of changing density. Finally, the Isolation Forest algorithm is based on recursive data partitioning, which makes it relevant to both high-dimensional data and large-scale data. The visual representation of these methods is possible due to the different color coding, and it is easy to compare how each method detects anomalies.

Figure 2, although synthetic, offers insightful information as to the disparities of the way these techniques perform. It serves as a prologue, clarifying the theory of application of these methods before presenting their potential application in economic crisis early warning schemes as one of the proposed AI-driven solutions. These systems utilize outlier detection, time series forecasting, and machine learning algorithms to operate large volumes of data where the anomalies that occur indicate upcoming economic crises (Zafeirelli & Kavroudakis, **2024**). The context offered by the Figure is compatible with the main thesis of the paper, and it shows how these methods can be used as a foundation to build more comprehensive and accurate prediction models of economic crisis, in particular those that are influenced by environmental factors.

Figure 2



Comparative Analysis Approach

An Outlier detection method comparison approach to the environmental setting concerning economic forecasting will entail the utilization of several important criteria in assessing the suitability of several methods to carry out a comparative evaluation of the outlier detection methods.

Robustness

Being able to get the correct estimate of outliers in terms of their most excellent false positive predictability is paramount to an outlier detection method. Additional approaches, including the application of Minimum Covariance Determinant (MCD) or Local Outlier Factor (LOF) methods, are also respected because they are robust in usage in high-dimensional data, which, in the context of environmental economics, are often influenced by aberrant conditions denoted by the spikes in pollution or weather tragedies (Emir et al., 2016). MCD is also effective in identifying multivariate outliers, particularly in breakouts where two subsets of a dataset contain only a few bits and exhibit non-significant covariance, unaffected by anomalous points. Since the LOF assists in the determination of local abnormalities of different densities, it can be applied in the spatial clustering environmental data analysis, where anomalies can be localized on specific monitoring or industrial sites (Heng et al., 2025; Rahman et al., 2025).

Scalability

Environmental economic information is rapidly becoming large and very structured, and needs methods that can be effectively scaled as the information becomes large and complex. Both robust PCA and MCD can be reasonably scaled to use high-dimensional data. The powerful PCA technique is useful in eliminating dimensions without losing data about the outliers that may come about when many environmental variables are measured at the same time (e.g., temperature, pollution concentration, energy usage). Computations are not easy; however, algorithmic enhancements can be used to deal with large datasets, and much parameter optimization is required to make MCD a viable approach (Zaharia et al., 2021; Zahariah & Midi, 2023).

Scalability also means the ability to implement algorithms into infrastructures that can dynamically absorb spikes in data from growing environmental and economic systems. Distributed frameworks, such as the ESTemd system created using the Apache Kafka framework, allow for the real-time processing of large volumes of heterogeneous environmental data - a key feature required to provide early warning systems in response to sudden shocks. Moreover, platforms such as PRISM illustrate the possibility of scalable integration of geospatial climate hazard data and socioeconomic indicators in multiple countries to provide actionable monitoring for policymaking in the presence of climate-induced crises. Embedding anomaly detection in these cloud-native or distributed frameworks makes models adaptive, performant, and continuously operational in the face of growing complexity (Zahariah & Midi, 2023).

Interpretability

To policymakers and stakeholders, deciding when specific data points are deemed outliers should always be accompanied by an understanding of the reasons why such outliers have been classified. There is decipherable output in the use of techniques such as LOF and MCD. LOF scores could be used to provide intuitive data on the nature of the identified anomalies since the scores indicate the extent to which the local density of neighbourhoods is not equal to the local density of points. Likewise, data and scattering can be located with high accuracy using MCD, and the analysts can understand how the outliers affect multivariate distributions. Such transparency is required when it comes to risk and uncertainty reporting of environmental economic forecasts (Karasmanoglou et al., 2023).

Interpretability of early warning systems does not only relate to technical transparency, i.e., being interpretable by models. It includes the potential of the models to communicate the findings in a way that policymakers and stakeholders can use. This will include turning complex outputs, such as anomaly scores or LSTM outputs, into informative dashboards, risk maps, or types of alerts that are easily readable and understood. Such techniques as SHAP and LIME provide both local and global explanations of how the model is acting and what environmental or economic factors are driving a forecast. By connecting anomalies to specific and understandable drivers, interpretability inspires trust in AI-powered systems and is conducive to evidence-based intervention in the context of environmental and economic crises (Infant et al., 2025).

Computational Complexity

Although effective, such methods vary in terms of the computational effort. In LOF, the pairwise distance between neighbors is calculated and becomes unstable with massive data sets. Computing subsets of covariation requires combinatorial optimization, which is computationally heavy, especially in high-dimensional spaces (Domingues et al., 2018). This phenomenon is overcome by good PCA and close to optimal MCD algorithms. Nevertheless, the resource availability of the working AI-powered early warning systems must be taken into account, which effectively influences the choice of the right outlier detecting algorithm (Meindl, 2025). In order to reiterate its significance, the robustness, scalability, interpretability, and computational complexity of outlier detection algorithms should be balanced, and the algorithms chosen to predict environmental economic crises. Both MCD and LOF are highly robust and interpretable, and the scalability-insight analysis tradeoff between techniques such as robust PCA provides a viable trade-off (Ouermi et al., 2025). Instead, one is to adjust it to the specifics of data and the limitations of resources to be able to forecast crises and design policies in time and with the necessary amount of accuracy (Emir et al., 2016).

Conclusion

Artificial intelligence can also fundamentally transform the prediction economics model, particularly in the case of environmental disturbances, an area where there will be a warning system. Such systems can make more accurate and prompt predictions by using outlier detection, time series predictive models, and machine learning algorithms, increasing preparedness and response to outlying events. Nevertheless, the possible weaknesses, including the quality of the data and the understandability of the model or processing time, can be overcome and solved to make the most of the possibilities of AI. Such systems will be very helpful in decision-making on environmental economics as the field of AI and data integration evolves. The AI models will also be involved in predicting and preventing the economic effects of what could happen to the environment as they evolve, and will also make the economy more resilient to the potential ills surrounding it.

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