The Use of Machine Learning Methods to Determine Risk Zones for Construction Disasters Caused by Wind - A Case Study in Poland

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http://doi.org/10.29227/IM-2024-02-62

Submission date: *17.07.2024.* | Review date: *11.08.2024*

Abstract

The increasing availability and use of artificial intelligence (AI) methods and algorithms have led to their widespread use in analyses aimed at identifying the decisive factors that influence the course of a studied phenomenon or process. AI algorithms include a wide range of methods. They can be used together or separately. The article describes the use of two Machine Learning (ML) methods, PCA and k-means, to identify parameters that may increase or decrease the risk of construction disasters caused by strong winds in Poland. The analysis was conducted using a unique dataset on construction disasters in Europe, sourced from the General Office of Construction Supervision in Poland for the period 1995-2019. The occurrence of disasters was categorised by voivodeship and cause, with information provided on the number of people injured. ML analyses were conducted to determine whether land development, population density, and weather factors, such as wind, have an impact on the number of recorded disasters.

Keywords: *machine learning, PCA, construction disasters, risk zones*

1. Introduction

The development and increasing availability of systems implementing artificial intelligence (AI) algorithms have led to their widespread use in various areas of scientific, engineering, economic, and social activities. The concept of artificial intelligence is not new; the algorithms used today were developed as early as the 1950s. AI is a conglomerate of many data processing algorithms from various scientific fields, primarily statistics. These algorithms can be used both individually and as part of more complex data processing and analysis processes.

Currently, the greatest interest is in complex systems that utilize hundreds or even thousands of processing algorithms, where analyses can be performed using natural language interpreters. Examples of such solutions include ChatGPT, developed by OpenAI, and the Microsoft's Copilot. These systems require enormous computational power and datasets with diverse structures as well as current and reliable information. What characterizes AI algorithms is their need for very large sets of reliable and up-to-date data, which were not available in the past. A breakthrough occurred with the advent of broadband data transmission technology and the widespread access to the Internet.

The era of smartphones and the mass use of various types of sensors in everyday devices, which provided increasing amounts of data through network-connected dataloggers, contributed significantly to this development. Simultaneously, database systems were developed to collect specialized information from various sectors of the economy, at local, national, and global levels. The digitization of the economy that occurred at the end of the 1990s also contributed to the exponential growth of data, which required adequate processing and analysis algorithms. Data collection and processing systems are practically used in every field of the economy and administration. They naturally serve as data sources for various types of analytical systems, including those utilizing AI.

A wider description of the use of AI algorithms in engineering problems was provided by Kamalow [1]. The paper explores the burgeoning influence of AI and machine learning in the field of civil engineering. The introduction emphasizes the transformative potential of AI technologies in improving various civil engineering sectors such as structural, transportation, and geotechnical engineering. These technologies aid in solving complex problems related to damage inspection, safety risk management, and information modeling. However, the integration of AI presents challenges including data collection, defining the human-AI interface, and addressing ethical considerations.

The paper also delves into the application of AI in the optimization of civil engineering structures. AI techniques are being utilized to create optimal structural designs by taking into account factors such as cost, environmental conditions, and material properties. Additionally, AI-based computational tools are promoting sustainable design practices, particularly in seismic impact optimization and environmental sustainability. Despite these advancements, challenges like data availability, model definition, and ethical considerations remain significant. The paper highlights the importance of collaborative partnerships and continued research to overcome these hurdles and fully leverage AI's potential in civil engineering.

Finally, the paper addresses the future prospects of AI in civil engineering. AI technologies, including deep learning, computer vision, and virtual reality, are anticipated to revolutionize urban planning, architectural design, and disaster management. AI-driven robotics and autonomous machines are expected to enhance construction efficiency and safety by automating repetitive tasks and monitoring site conditions. The paper concludes by advocating for ongoing research and development to address ethical issues and maximize the benefits of AI in civil engineering, ultimately improving efficiency, safety, and sustainability in the industry.

Gevaert et al. [2] describe the application of artificial intelligence (AI) in civil engineering, highlighting how AI can support engineers by providing insights into real-world issues at construction sites, improving work quality, and serving as guidelines for

novice engineers. Various AI methods, such as linear regression, deep neural networks, support vector machines, and decision trees, are described for predicting outcomes and classifying data. AI applications include structural health monitoring, bridge engineering, and performance assessment. Future research directions include image-based interpretations, disaster management, and support on construction sites.

Georgiadou et al. [3] discuss the ethical issues related to the use of AI in disaster risk management (DRM). It emphasizes the importance of fairness, accountability, and transparency in disaster risk models that rely on geospatial data. Concerns about potential biases in algorithms and the need to incorporate local values and socio-cultural context into the development and implementation of these technologies are discussed. Recommendations include integrating FAccT principles into disaster risk model work and striving for greater inclusivity and accountability in this area.

One of the more interesting examples of a data set related to engineering issues, unique on a European and global scale, is the collection of information on construction disasters in Poland[4]. This dataset is a valuable resource for risk assessment analyses of construction disasters in various regions of Poland. A broader analysis of the data contained therein was conducted by Graczyk et al. [4]. The article presents the results of an analysis of building disasters in Poland over the years. An increase in the number of building disasters was observed compared to the initial years of data collection, which may be related to a more effective architectural and construction management system, rather than an actual increase in the number of disasters.

Most frequently, the disasters involved small residential and agricultural buildings with masonry structures. More than half of the disasters involved masonry structures, followed by wooden, steel, and reinforced concrete buildings. In approximately 70% of the cases, the cause of the disasters was random events, with strong winds being the main factor (over 50%). The second most common factor was fires, while other causes such as gas explosions or rainfall occurred in similar numbers.

The majority of disasters involved buildings aged between 11 and 50 years, with the least number of disasters recorded for buildings less than 10 years old. More than 80% of the buildings that experienced disasters belonged to private individuals. The importance of considering the possibility of random events in the design, construction, and use of buildings was emphasized.

Statistical analysis demonstrated a correlation between land use patterns and the total number of disasters. It was confirmed that forested areas and meadows can act as buffers for extreme weather events, reducing the probability of building disasters. It was found that adhering to the principles of sustainable development can reduce the number of building disasters.

The authors emphasize the necessity for further research and the inclusion of the risk of random events in urban planning and building design.

It is evident that the number of building failures can be influenced by various factors such as the building materials [5,6,7,8] used, their technical condition [9,10], and the installations within the buildings [11,12,13]. The current emphasis on maintaining zero emissions in buildings has led to increased complexity in both construction and installation processes. This complexity is further compounded by the emergence of new building materials, both structural and insulating, as well as decorative, which add to the intricacies of construction and, consequently, may lead to a higher number of defects or construction flaws.

These factors must be carefully considered in the risk analysis process for potential building failures caused by various elements or natural phenomena. The quality and suitability of the materials [14,15] used are paramount; using substandard or inappropriate materials can significantly increase the risk of structural failures. Additionally, the technical condition of these materials over time must be monitored and maintained to prevent degradation that could compromise building integrity.

Moreover, the installations within buildings, including electrical, plumbing, and HVAC systems, play a crucial role in overall building safety. Complex and innovative installations, often required to meet modern environmental standards, must be meticulously designed, installed, and maintained to avoid contributing to potential failures. The integration of these systems within the structural framework must be seamless to ensure that they do not undermine the building's stability or safety.

In conclusion, a comprehensive approach to risk analysis in building construction must account for the quality and condition of materials, the complexity of modern construction and installation practices, and the evolving nature of building materials and technologies. This holistic consideration is essential to mitigate the risk of building failures and ensure the safety and sustainability of modern structures.

Reducing the risk of building failures requires a multifaceted approach that encompasses the design, construction, and operation phases of buildings. First and foremost, robust design and planning are essential. Utilizing advanced tools and software for simulation and structural analysis, such as Building Information Modeling (BIM), can help ensure that all aspects of a project are meticulously planned. It is crucial to consider local geological and climatic conditions in the design phase and ensure compliance with existing building standards and regulations.

The quality of building materials plays a significant role in mitigating risks. Selecting certified and tested building materials, conducting regular quality checks on-site, and using materials suitable for specific environmental conditions can greatly enhance the integrity of the construction. Furthermore, ensuring that all construction workers have the appropriate qualifications and certifications is vital. Regular training on new technologies and safety procedures should be provided, encouraging continuous professional development.

Effective construction management is another critical aspect. This involves monitoring project progress, budget, and resources efficiently, implementing quality control procedures at every stage of construction, and conducting regular inspections and audits by independent experts. Installing monitoring systems to track the technical condition of buildings, such as vibration or crack sensors, and performing regular maintenance and repairs can prevent material and structural degradation. Establishing emergency management plans that include procedures for detecting and responding to potential hazards is also essential.

Finally, comprehensive risk analysis and crisis management are integral to reducing building failure risks. Conducting thorough risk assessments to identify potential threats and their impacts, developing risk management plans that include preventive and corrective actions, and ensuring that all stakeholders are aware of crisis procedures can significantly enhance the safety and durability of buildings. Implementing these strategies can greatly reduce the risk of building failures, thereby improving user safety and building longevity.

The statistical analyses presented in the article can be further enhanced by incorporating machine learning methods such as Principal Component Analysis (PCA) and K-means clustering.

It is also worth mentioning that the number and type of construction failures will be influenced not only by environmental factors such as wind. The significant diversity of available construction materials, building technologies, infrastructure conditions, and adaptation to climate changes contribute to the heterogeneity of buildings. While structures must meet the requirements specified by regulations and standards, the impact of technical solutions will often condition the likelihood of such events occurring.

2. Materials and Methods

The analyses utilized aggregate data contained in the work [4] of Graczyk et al. (2020). These data are presented in table 1. They were adapted to a format acceptable by the R-Studio system, in which all calculations for the PCA method were performed.

Principal Component Analysis (PCA) is a statistical method developed by Karl Pearson in 1901 and later independently by Harold Hotelling in 1933. PCA is used to reduce the dimensionality of large data sets by transforming the original variables into a new set of uncorrelated variables known as principal components [16]. These principal components are ordered so that the first few retain most of the variation present in the original data set. PCA is widely applied in fields such as genomics, image processing, and finance to simplify data sets while preserving their essential trends and patterns.

One of the primary advantages of PCA is its ability to simplify complex data sets, making them easier to analyze and interpret. By reducing the number of variables, PCA helps mitigate the curse of dimensionality, which can improve the performance of machine learning algorithms. Additionally, PCA can enhance data visualization, enabling researchers to identify patterns and relationships that might be obscured in higher-dimensional spaces. PCA is also a non-parametric method, meaning it does not rely on any assumptions about the underlying distribution of the data, making it a versatile tool for various applications.

However, PCA has some limitations. One significant drawback is that it assumes linearity, which means it may not capture complex, non-linear relationships within the data. Additionally, PCA can be sensitive to outliers, which can disproportionately influence the principal components and distort the results. Another limitation is that PCA requires the mean and variance of the data to be normalized, which can be challenging with data sets that have different scales or units. Despite these drawbacks, PCA remains a fundamental tool in data analysis, especially when dealing with high-dimensional data sets where simplification is crucial for effective analysis and interpretation. [17]

2.1 Tools for PCA Analysis: Python and RStudio

Python and RStudio are two powerful tools for data analysis that enable relatively easy and quick execution of complex statistical analyses, such as Principal Component Analysis (PCA).

Python, with libraries like **scikit-learn**, **pandas**, and **matplotlib**, offers a wide range of tools for data processing, statistical computations, and result visualization. **scikit-learn** is particularly useful for performing PCA, while **matplotlib** is ideal for creating plots, including 3D plots.

RStudio, an integrated development environment for the R language, is equally powerful, offering libraries such as **stats** for performing PCA and **scatterplot3d** and **rgl** for visualizing results in three dimensions. Both Python and RStudio are widely used in academic and business communities, providing many available resources and examples to facilitate learning these tools.

Currently, PCA analysis can be even more accessible thanks to AI-based tools like ChatGPT. ChatGPT can act as an intermediary for individuals unfamiliar with programming in Python or RStudio. Through the ChatGPT interface, users can input data and receive PCA analysis results without needing to engage directly in coding. ChatGPT is capable of understanding user commands and performing the necessary computations, as well as visualizing the results. This approach eliminates technical barriers and makes advanced statistical analyses accessible to a broader audience, enabling more informed decision-making based on data.

The PCA results are summarized in terms of the standard deviation of each principal component (PC), the proportion of variance explained by each component, and the cumulative proportion of variance explained.

Tab. 1. Data used for statistical analysis of the impact of land-use, population equivalent and the average wind value on the number of disasters [4]

Voivodeship	**Agricultural land - permanent meadows [-]**	**Forest and wooded land [-]**	**Lakes and rivers [-]**	**Industrial areas [-]**
1.	2	3	4	5
Dolnosląskie	0.0717	0.3109	0.0089	0.0069
Kujawsko-Pomorskie	0.0493	0.2474	0.0263	0.0033
Lubelskie	0.1023	0.2373	0.0078	0.0015
Lubuskie	0.0739	0.5160	0.0177	0.0020
Łódzkie	0.0648	0.2162	0.0061	0.0032
Małopolskie	0.0664	0.3075	0.0144	0.0047
Mazowieckie	0.0800	0.2384	0.0114	0.0030
Opolskie	0.0772	0.2805	0.0131	0.0051
Podkarpackie	0.0671	0.4014	0.0114	0.0027
Podlaskie	0.1041	0.3165	0.0136	0.0012
Pomorskie	0.0645	0.3869	0.0396	0.0028
Śląskie	0.0753	0.3359	0.0150	0.0169
Świętokrzyskie	0.0824	0.2942	0.0075	0.0031
WarminskoMazurskie	0.0731	0.3406	0.0571	0.0012
Wielkopolskie	0.0714	0.2675	0.0142	0.0028
Zachodniopomorskie	0.0702	0.3881	0.0522	0.0034

Tab. 1. Data used for statistical analysis of the impact of land-use, population equivalent and the average wind value on the number of disasters [4]

Voivodeship	Arable land [-]	Built-up and urbanized land - residential areas [-]	Density of population [persons/km^2]	Wind (average value) [m/s]	Number of disasters [No]
1.	6	7	8	9	10
Dolnosląskie	0.4413	0.0102	145.45	3.20	260
Kujawsko-Pomorskie	0.5684	0.0087	115.62	3.40	311
Lubelskie	0.5356	0.0038	84.29	3.00	297
Lubuskie	0.2953	0.0062	72.53	3.10	161
Łódzkie	0.5602	0.0099	135.37	3.70	1265
Małopolskie	0.4435	0.0111	223.98	2.80	437
Mazowieckie	0.4927	0.0113	151.96	3.90	794
Opolskie	0.5247	0.0093	104.82	2.60	466
Podkarpackie	0.3558	0.0070	119.30	3.60	112
Podlaskie	0.3919	0.0043	58.53	2.80	425
Pomorskie	0.3982	0.0097	127.44	3.90	221
Śląskie	0.3816	0.0331	367.59	3.00	565
Świętokrzyskie	0.4801	0.0060	106.02	2.80	206
WarminskoMazurskie	0.3893	0.0051	59.11	3.00	84
Wielkopolskie	0.5330	0.0085	117.14	3.70	699
Zachodniopomorskie	0.3995	0.0048	74.31	3.80	78

3. Calculations and results

For the source data contained in Table 1, the Principal Component Analysis was conducted, and the results were summarized in the table 2 . This table includes the standard deviation, proportion of variance, and cumulative proportion of variance for each of the eight principal components (PCs). These metrics provide insight into how much variance each component captures from the dataset and the cumulative effect of the components when taken together.

Tab. 2. PCA Importance of components

	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8	PC9
Standard deviation	1.795	1.5849	1.2783	0.8485	0.7088	0.51498	0.30238	0.18278	0.1409
Proportion of Variance	0.358	0.2791	0.1815	0.07999	0.05582	0.02947	0.01016	0.00371	0.0022
Cumulative Proportion	0.358	0.6371	0.8186	0.89863	0.95446	0.98392	0.99408	0.9978	1.0000

PCA results offer insights into the variance captured by each principal component and their cumulative contribution to the total variance. The standard deviation of the principal components indicates the spread of the data along each component. The first principal component (PC1) has the highest standard deviation (1.795), followed by PC2 (1.5849) and PC3 (1.2783). This indicates that PC1 captures the largest variation in the data, while PC2 and PC3 also contribute significantly to explaining the variability.

The proportion of variance attributed to each principal component reveals the amount of total variance captured by each component. PC1 explains 35.8% of the total variance, which is substantial, while PC2 accounts for 27.91%. Together, PC1 and PC2 capture 63.71% of the total variance. This suggests that the first two components are effective in summarizing a large portion of the variability in the dataset. The third component, PC3, adds an additional 18.15%, bringing the cumulative proportion of variance explained to 81.86%. This indicates that the first three components together capture a significant majority of the variance in the data.

As we move to higher-order components, the proportion of variance explained by each component decreases. For instance, PC4 contributes 7.999% to the total variance, while PC5 adds 5.582%. By the time we include the sixth component, the cumulative proportion of variance explained reaches 95.446%. The remaining components (PC7 to PC9) contribute very little to the overall variance, with each explaining less than 1% of the total variance. This diminishing contribution suggests that beyond the first few principal components, additional components provide minimal additional explanatory power.

The PCA results indicate that the first three principal components capture over 80% of the total variance in the dataset, making them the most significant contributors to data variability. PC1 alone explains 35.8% of the variance, highlighting its importance. Subsequent components, while still contributing to the overall variance, have a decreasing impact, with PC4 to PC9 together explaining less than 20% of the total variance. This analysis underscores the utility of PCA in reducing dimensionality while retaining most of the information in the original dataset, enabling more efficient data analysis and visualization

3.1 Analysis of PCA Loadings

PCA loadings presented in table 3 provides insight into how each variable contributes to the principal components. The loadings, which are the correlation coefficients between the variables and the principal components (PCs), help us understand which variables are most influential in each principal component. Below is an interpretation based on the provided loadings data.

Principal Component 1 (PC1) appears to be influenced predominantly by variables related to urbanization and industrialization, with significant contributions from industrial areas, density of population, built-up and urbanized land, and disasters. The negative loadings for these variables suggest that higher values in these variables are associated with lower scores on PC1. This component likely represents a contrast between industrial/urban areas and other land types, highlighting regions characterized by high industrial and urban activity.

Tab. 3. PCA loadings

Loadings	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8	PC9
Agricultural land permanent meadows	0.0751	-0.1359	-0.6343	-0.2784	-0.6516	0.1679	-0.0440	-0.1947	0.0587
Forest	0.2568	0.5075	-0.0176	-0.3315	0.2511	-0.1615	-0.3413	-0.5835	0.1425
Lakes_and_rivers	0.2784	0.2557	0.3535	0.4761	-0.6148	-0.3260	0.0289	-0.1036	0.0979
Industrial_areas	-0.4565	0.3212	-0.0633	0.1390	-0.1027	0.1610	-0.5622	0.3483	0.4374
Arable_land	-0.1858	-0.5343	0.1335	0.3864	0.0547	0.2090	-0.3330	-0.5915	0.0738
Built up and urbanized land-residential areas	-0.4853	0.2900	0.0256	0.0086	-0.1685	-0.0263	-0.1211	-0.1525	-0.7827
Density of population	-0.4962	0.2501	0.0146	0.0169	-0.0117	0.1110	0.6551	-0.3407	0.3648
Wind	0.0323	-0.0553	0.6544	-0.5147	-0.2813	0.4700	-0.0434	0.0187	0.0230
Disasters	-0.3538	-0.3468	0.1466	-0.3900	-0.1143	-0.7321	-0.0906	0.0037	0.1538

Principal Component 2 (PC2) seems to capture a combination of forest cover and industrial areas, with significant contributions from forest, industrial areas, arable land, and built-up and urbanized land. The positive loadings for forest and industrial areas, along with the negative loading for arable land, suggest that PC2 differentiates between forested/industrial regions and agricultural areas. This component might represent a gradient from more developed and forested regions to those dominated by agriculture.

Principal Component 3 (PC3) is heavily influenced by agricultural land, wind, and lakes and rivers. The significant negative loading for agricultural land and the positive loadings for wind and lakes and rivers indicate that PC3 represents regions characterized by significant agricultural activity and wind conditions, possibly reflecting rural areas with natural water bodies. This component highlights the importance of these natural and agricultural features in distinguishing different regions.

Principal Component 4 (PC4) highlights the role of lakes and rivers, arable land, and disasters. The positive loadings for lakes and rivers and arable land, along with the significant negative loading for disasters, suggest that PC4 differentiates regions based on natural water resources and the frequency of disasters. This component underscores the importance of natural features and disaster prevalence in shaping the regional characteristics.

The PCA loadings analysis reveals the underlying structure of the dataset by showing how different land and population characteristics correlate with each principal component. The first few principal components explain the most variance in the data, indicating that urbanization, forest cover, industrial activity, and agricultural land are key factors differentiating the regions in the dataset. By examining these loadings, we can better understand the multidimensional relationships between the variables and identify the primary factors driving the variance in the dataset. This information is crucial for further analyses, such as clustering or regression, and can inform data-driven decision-making in urban planning, environmental management, and disaster mitigation.

The second implication relates to data visualization. By reducing the data to two or three principal components, we can create scatter plots that facilitate the understanding of data structure and the identification of patterns and clusters. Such visualizations are crucial for drawing conclusions about the relationships between variables and for identifying anomalies in the data.

PCA results can also be utilized for cluster analysis. Since the principal components represent the most significant variations in the data, clustering performed on these components can be more effective and accurate. In practice, this means that clustering methods, such as K-means, can be applied to the reduced dimensions, leading to a better understanding of data grouping and the identification of natural clusters within the dataset.

The PCA results conducted on the source data indicate that most of the significant information contained in the data can be effectively represented by the first three principal components. The dimensionality reduction of the data allows for simplified analysis and visualization, which is invaluable in practical research and engineering applications. Additionally, PCA facilitates more accurate cluster analysis, which can lead to a better understanding of the data structure and more effective detection of patterns and anomalies.

The most effective way to present the PCA results is through a 3D scatter plot for the first three principal components (PC1, PC2, and PC3). This visualization method offers several advantages:

A 3D scatter plot of the principal components allows us to observe which columns (variables) in the original dataset are correlated. By analyzing the distribution and orientation of data points in the 3D space, we can identify groups of variables that cluster together, indicating a high degree of correlation. This insight is crucial for understanding the underlying relationships between variables and for simplifying the data by focusing on the most important components.

The 3D plot as presented on Figure 1 also helps in visualizing how different voivodeships (regions) cluster together based on the principal components. By examining the spatial distribution of data points representing different voivodeships, we can detect natural groupings and patterns. This visualization provides a clear and intuitive way to see how similar or different the voivodeships are in terms of the variables analyzed.

In summary, a 3D scatter plot of PC1, PC2, and PC3 is the best way to present PCA results because it effectively highlights correlations between columns and shows how different voivodeships group together. This approach enhances our ability to interpret the data and draw meaningful conclusions from the PCA analysis.

Figure 1 clearly demonstrates a positive correlation between the number of disasters and developed areas, which include arable land and built-up and urbanized residential areas. Urbanized and intensively farmed regions increase the likelihood of building

disasters caused by wind. Conversely, green areas, such as meadows, forests, and lakes, contribute to a reduction in the number of disasters. These types of terrains help mitigate extreme weather events due to their natural buffering capabilities.

It is important to note that the Łódź Voivodeship, which has the smallest proportion of green areas, stands out negatively with a significantly higher number of disasters. During the analyzed period, it recorded the highest number of disasters. This stark contrast highlights the vulnerability of urbanized areas lacking sufficient green space.

Furthermore, there is a noticeable clustering of "green" voivodeships, such as Lubusz, Warmian-Masurian, and Podlaskie, which have the lowest numbers of disasters. These regions, rich in green spaces, demonstrate a reduced frequency of building failures. This suggests that the presence of natural landscapes plays a crucial role in enhancing resilience against wind-related disasters.

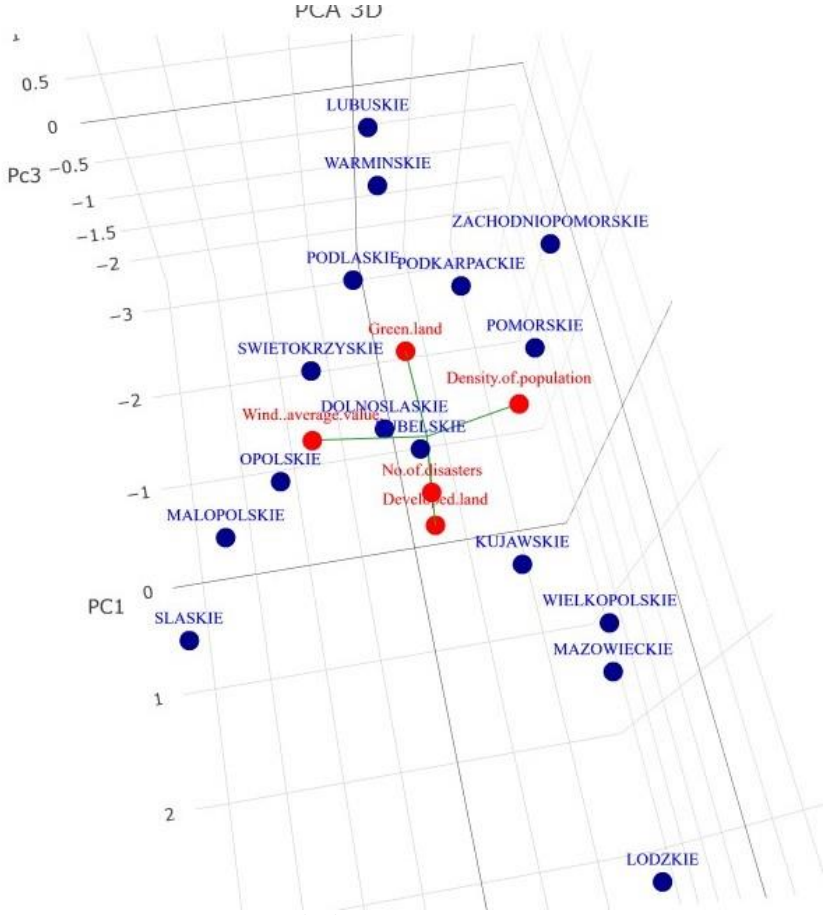

Fig. 1. PCA results for first three principal components

4. Conclusion

This article explores the application of machine learning techniques in the assessment and prediction of building failures, with a particular focus on the use of Principal Component Analysis (PCA). The study utilizes aggregate data from prior research [4] to identify significant factors contributing to building disasters and employs advanced statistical methods to analyze these factors. The primary aim is to enhance the understanding of how various variables, such as construction materials, technical conditions, and environmental influences, affect the likelihood of building failures.

The relationship between land use and disaster frequency underscores the need for urban planning that integrates green spaces. By strategically increasing the presence of forests, meadows, and water bodies within urban and agricultural landscapes, regions can bolster their defenses against extreme weather phenomena. These natural areas act as buffers, absorbing wind energy and reducing the impact on man-made structures.

In addition to mitigating physical impacts, green spaces contribute to overall environmental health, which indirectly supports the stability of built environments. For instance, forests and meadows improve air quality, reduce heat islands, and manage water runoff more effectively than urban surfaces. These benefits further emphasize the importance of incorporating natural elements into urban planning and development strategies.

The data also highlight the need for tailored disaster management practices in regions with different land use characteristics. Urbanized areas with limited green space may require more robust engineering solutions, stricter building codes, and proactive maintenance to withstand wind-related disasters. Conversely, regions with abundant green spaces can focus on preserving these natural buffers to maintain their protective benefits.

In conclusion, the findings support a balanced approach to land use that promotes both development and the conservation of green areas. This balance is crucial for creating resilient communities capable of withstanding the increasing frequency and intensity of extreme weather events. By learning from the contrasting experiences of regions like Łódź and the "green" voivodeships, policymakers can develop more effective strategies to reduce disaster risks and enhance urban sustainability.

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