THE USE OF MACHINE LEARNING TO ADDRESS FLOODS: A CASE STUDY OF THE MUNICIPALITY OF PELOTAS[1]

Rodrigo Nobre Fernandez
Gabrielito Rauter Menezes
Greike Maia Aguiar
Naurienni Dutra Freitas

Universidade Federal de Pelotas (UFPEL), Pelotas – RS, Brasil

This study evaluates the effectiveness of applying artificial neural networks as a decision-support tool during natural disasters, focusing on the floods that occurred in Pelotas, Rio Grande do Sul, in 2024. Using a machine learning approach, the study analyzes whether the decisions made by the municipal government were conservative or flexible by comparing water level forecasts with the implemented actions. Based on time series data from the São Gonçalo Channel, the results indicate that the model's predictions generally aligned with public policies, though they slightly overestimated water levels. The findings suggest that integrating predictive models based on artificial intelligence can enhance the effectiveness of public policies and risk management during climate emergencies. This study contributes to the literature by demonstrating the potential of data science techniques for public managers, aiding in damage mitigation and the formulation of proactive civil protection strategies.

Keywords: machine learning; artificial neural networks; disaster management; public policy; decision-making.

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O USO DE MACHINE LEARNING PARA O ENFRENTAMENTO DAS ENCHENTES: UM ESTUDO DE CASO PARA O MUNICÍPIO DE PELOTAS

Este estudo avalia a eficácia da aplicação de redes neurais artificiais como ferramenta de suporte à tomada de decisão durante desastres naturais, com foco nas enchentes ocorridas em Pelotas, Rio Grande do Sul, em 2024. Por meio de uma abordagem de aprendizado de máquina, o trabalho analisa se as decisões tomadas pela gestão municipal foram conservadoras ou flexíveis, comparando previsões do nível das águas com as ações implementadas. Utilizando dados de séries temporais do Canal São Gonçalo, os resultados indicam que as previsões do modelo, em geral, alinharam-se às políticas públicas, embora tenham superestimado levemente os níveis de água. Os achados sugerem que a integração de modelos preditivos baseados em inteligência artificial pode melhorar a eficácia das políticas públicas e a gestão de riscos em situações de emergência climática. Este estudo contribui para a literatura ao demonstrar o potencial das técnicas de ciência de dados para gestores públicos, auxiliando na mitigação de danos e na formulação de estratégias proativas de proteção civil.

Palavras-chave: aprendizado de máquina; redes neurais artificiais; gestão de desastres; políticas públicas.

EL USO DE MACHINE LEARNING PARA ENFRENTAR INUNDACIONES: UN ESTUDIO DE CASO EN EL MUNICIPIO DE PELOTAS

Este estudio evalúa la efectividad de la aplicación de redes neuronales artificiales como herramienta de apoyo para la toma de decisiones durante desastres naturales, con un enfoque en las inundaciones ocurridas en Pelotas, Río Grande del Sur, en 2024. A través de un enfoque de aprendizaje automático, el estudio analiza si las decisiones tomadas por el gobierno municipal fueron conservadoras o flexibles, comparando las predicciones de los niveles del agua con las acciones implementadas. Basándose en datos de series temporales del Canal São Gonçalo, los resultados indican que las predicciones del modelo, en general, estuvieron alineadas con las políticas públicas, aunque sobreestimaron ligeramente los niveles de agua. Los hallazgos sugieren que la integración de modelos predictivos basados en inteligencia artificial puede mejorar la efectividad de las políticas públicas y la gestión de riesgos durante emergencias climáticas. Este estudio contribuye a la literatura al demostrar el potencial de las técnicas de ciencia de datos para los gestores públicos, ayudando en la mitigación de daños y en la formulación de estrategias proactivas de protección civil.

Palabras clave: aprendizaje automático; redes neuronales artificiales; gestión de desastres; políticas públicas; toma de decisiones.

1. INTRODUCTION

The Brazilian National Water and Basic Sanitation Agency (ANA) emphasized that the floods which struck the state of Rio Grande do Sul (RS) between April and May 2024 constituted an unprecedented catastrophe, representing the most severe natural disaster in the state's history in terms of both scale and impact (Firenze *et al.*, 2025). The 2024 climate tragedy resulted in substantial human and material losses. The event began on April 27, 2024, with heavy rainfall that persisted for more than ten consecutive days, leading to widespread and devastating flooding.

The most severely affected areas included the valleys of the Taquari, Caí, Pardo, Jacuí, Sinos, and Gravataí rivers, as well as the Guaíba River in Porto Alegre and the Lagoa dos Patos in the municipalities of Pelotas and Rio Grande. The Serra region also experienced numerous landslides. In total, 169 people lost their lives and more than 629,000 were displaced. Entire cities were submerged, roads became impassable, and bridges were destroyed. The agricultural and industrial sectors suffered heavy losses due to the destruction of crops, infrastructure, and production facilities (Campos & Paradela, 2024; Baggio *et al.*, 2025; Andrades-Filho *et al.*, 2025).

For municipalities in the southern region of the state, considering that water discharge from the Guaíba to the Atlantic Ocean does not occur instantaneously, areas such as Pelotas and Rio Grande had time to prepare and implement preventive measures. These measures included evacuating populations from areas near the banks of Lagoa dos Patos and its tributaries, which are high-risk flood zones. In Pelotas, the municipal government developed a risk map for neighborhoods based on data from the 1940 flood.

As variations in water flow were observed, public authorities adjusted or tightened risk zones accordingly. This study aims to employ a machine learning technique — specifically, artificial neural networks — to assess whether the decisions made by the Pelotas municipal government were conservative or flexible. For this purpose, data on water levels from the São Gonçalo Canal, made available through Pelotas' official social media channels, were utilized.

Using this data, a platform was developed to correlate the dates when the public administration adjusted risk maps with model predictions. This approach allows for comparisons between predictions and actual observations. For instance, if the model predicted a rise in canal water levels and public policy expanded risk zones, but in reality, water levels decreased, this decision would be classified as conservative. Conversely, it would be deemed flexible. The findings suggest that the integration of predictive models based on artificial intelligence can enhance the effectiveness of public policy and risk management during climate emergencies. This study contributes to literature by demonstrating the potential of data science techniques to support public managers in mitigating damages and formulating proactive civil protection strategies.

In Brazil, recent studies have examined the economic impacts of climate emergencies and natural disasters across different regions. Ribeiro *et al.* (2014) analyzed the heavy rains in Santa Catarina in 2008, concluding that monthly industrial production was 5.13% lower until the end of 2010 compared to normal conditions. Lima and Barbosa (2018) highlighted a 7.6% reduction in per capita GDP in municipalities directly affected by the same floods, with most economic sectors recovering within three years, except for agriculture.

Furthermore, Souza and Cerqueira (2019) evaluated the impact of the Mariana dam collapse, identifying significant losses in the agricultural and industrial sectors and reinforcing the need for public policies to mitigate economic damages. In another study, Niquito *et al.* (2021) examined the economic impact of the Fundão dam collapse in Mariana, Minas Gerais, revealing a significant reduction in total GDP (-6.81%) and pronounced negative effects on the agricultural and industrial sectors, though with a 2.69% GDP increase in indirectly affected localities. These findings align with international analyses, such as those by Hallegatte *et al.* (2007), which highlight the economic vulnerability of developing countries to climate disasters and the importance of integrated mitigation strategies.

Studies on artificial intelligence applied to disasters also underscore the relevance of predictive techniques. Goodfellow *et al.* (2016) demonstrate how neural networks can be used to predict complex events, while Mori *et al.* (2020) emphasize the use of machine learning for real-time flood prediction in Japan, with effective applications for evacuating high-risk areas.

While national literature often examines the economic effects of natural disasters, focusing on GDP changes, this study stands out as the first, to the authors' knowledge, to use artificial intelligence — through artificial neural networks and time series — to evaluate public management decisions.

Recent advances in artificial intelligence and numerical modeling have substantially improved the capacity to forecast and analyze hydrometeorological hazards on a global scale. One study developed a deep learning model capable of predicting streamflow and flood events across diverse regions, including both monitored and unmonitored watersheds. Using data from over 2,000 basins in North America and Europe, the model achieved a Nash–Sutcliffe Efficiency coefficient of 0.75, demonstrating superior predictive performance compared to traditional hydrological models and highlighting the power of machine learning in large-scale forecasting (Zhang *et al.*, 2024).

In parallel, researchers proposed a scalable framework for large-scale flood modeling and forecasting, combining satellite observations with AI techniques to enhance early warning capabilities (Xu *et al.*, 2024). Another study focused on the simulation of the chain process of debris flow-induced river blockage at the catchment level, offering valuable insights into sediment dynamics and secondary flood risks (Liu *et al.*, 2024). Collectively, these contributions emphasize the transformative potential of AI-based approaches and numerical simulations for improving disaster risk management, early response, and long-term planning in the context of increasingly frequent extreme climate events.

Broadly speaking, the results indicate that the decisions to either relax or tighten restrictions made by Pelotas' municipal administration were aligned with the model's predictions. It was observed that neural networks tend to slightly overestimate predicted values by a few centimeters; however, the difference compared to actual values is minimal. This demonstrates that data science techniques can serve as valuable tools for public management, contributing to more precise and effective decision-making in emergency situations.

In summary, this study is structured into five sections, beginning with this brief introduction. The second section provides a brief review of the literature on economics and natural disasters. The third section presents the data and empirical methodology. The fourth section discusses the results, and the fifth provides concluding remarks.

2. LITERATURE REVIEW

Climate change and the increase in extreme weather events have intensified the frequency of natural disasters across various regions worldwide, underscoring the importance of studies that investigate not only their environmental impacts but also their economic and social consequences. Issues related to human and economic development have become a growing focus of research in applied social sciences, as noted by Wink Jr. *et al.* (2023). These studies aim to understand how natural disasters affect economic indicators and the quality of life of populations, with an emphasis on local and institutional conditions that can mitigate or exacerbate such effects.

Classical research, such as that by Horwich (2000), Skidmore and Toya (2002), Benson and Clay (2004), Toya and Skidmore (2007), and Noy (2009), provides a solid foundation for understanding the short- and long-term economic impacts of natural disasters by analyzing indicators such as economic growth, industrial production, and public finances. These studies highlight that local characteristic, such as geography, demographics, and institutional quality, play a crucial role in the resilience of affected regions. In contexts with robust infrastructure and effective institutions, disaster impacts tend to be mitigated, as observed in developed regions (Noy, 2009). Conversely, Ribeiro *et al.* (2014) and Lima and Barbosa (2019) demonstrate that in Brazilian regions, the economic impacts of climate disasters are often exacerbated by pre-existing vulnerabilities, such as low economic diversification and limited institutional capacity.

In addition to broader economic impacts, another set of studies has focused on the socioeconomic effects of disasters, including their influence on human capital, public health, and social inequality. Imberman, Kugler, and Sacerdote (2012) explored how disasters affect human capital formation, while Aguilar and Vicarelli (2022) examined the consequences of these events on poverty and inequality. Oliveira and Quintana-Domeque (2023) reinforce this perspective by highlighting the impacts on the health of vulnerable populations, demonstrating how climate disasters can deepen existing inequalities and worsen precarious living conditions.

Disasters also impose substantial costs on public finances, not only for emergency expenditures but also for infrastructure reconstruction and support for displaced populations. Noy and Nualsri (2011) emphasize that these costs can destabilize government budgets, especially in emerging economies. Additionally, Melecky and Raddatz (2015) argue that natural disasters significantly reduce tax revenues by destroying local economic bases while forcing governments to increase spending on emergency aid and reconstruction. These challenges reinforce the importance of effective public policies for climate mitigation and adaptation. Hsiang and Jina (2014) assert that investments in resilient infrastructure and urban planning are critical to reducing the financial and social impacts of disasters.

In the Brazilian context, recent studies illustrate the vulnerability of different regions to extreme climate events. Ribeiro *et al.* (2014) used the synthetic control method to evaluate the impact of heavy rains in Santa Catarina in 2008, concluding that monthly industrial production was 5.13% lower than it would have been under normal conditions until the end of 2010. Lima and Barbosa (2018) analyzed the direct and indirect effects of the same flood, finding a 7.6% reduction in per capita GDP in directly affected municipalities, with economic recovery in nearly all sectors after three years, except for agriculture. Studies such as those by Souza and Cerqueira (2019) and Niquito *et al.* (2021) deepen this discussion by assessing the economic impacts of the Mariana and Fundão dam collapses, highlighting significant losses in agriculture and industry, along with prolonged difficulties in the recovery of local economies. These works emphasize the need for effective mitigation strategies, not only to address immediate impacts but also to reduce long-term consequences.

International literature also provides relevant insights. Hallegatte *et al.* (2007) explore how economic dynamics influence recovery capacity after extreme climate events, emphasizing the importance of rapid and well-planned interventions. Goodfellow *et al.* (2016) demonstrate the potential of machine learning and artificial neural networks for predicting climate events and managing disasters, while Mori *et al.* (2020) illustrate the application of these technologies in early warning systems in Japan, leading to more efficient responses and reduced damage.

While the reviewed studies present significant advancements, important gaps remain. In Brazil, most research focuses on measuring economic impacts using indicators such as GDP or industrial production. However, there is a lack of studies employing artificial intelligence techniques, such as artificial neural networks, to evaluate the effectiveness of public management decisions during natural disasters. This gap underscores the need to incorporate innovative approaches that combine predictive data and real-time analysis to enhance decision-making and damage mitigation in emergency scenarios.

3. EMPIRICAL METHODOLOGY AND DATA

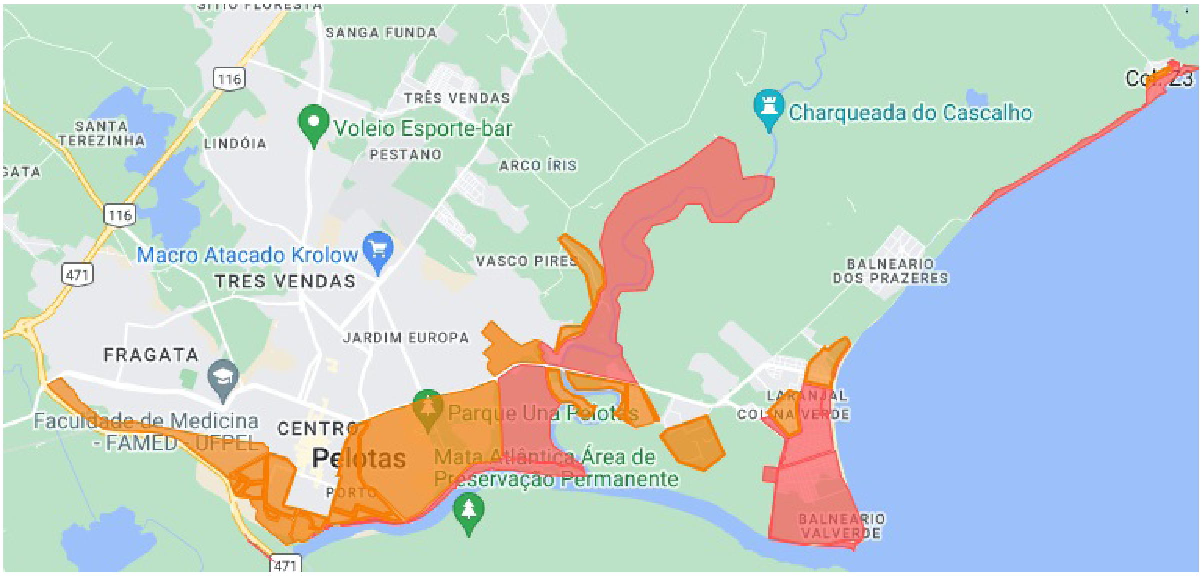
This section is divided into two parts. The first presents the data used, followed by the empirical methodology.

3.1 Database

Starting on May 7, 2024, the municipal government, through its official website and social media channels, published a risk map designed to inform citizens about flood-prone areas due to the discharge of waters flowing from the Guaíba. This risk map accounted for a water level of 40 cm above the highest flood ever recorded in Rio Grande do Sul, where the São Gonçalo Canal, which connects the Lagoa dos Patos to the Lagoa Mirim, reached a level of 2.88 meters.

The geographic information highlighted two categories of regions (neighborhoods) within the municipality using distinct colors. Areas marked in red indicated high risk, requiring immediate evacuation by residents. Areas marked in orange signified alert zones, where inhabitants needed to remain vigilant but did not require evacuation.

Figure 1 – Risk map



Source: Pelotas municipal government (bit.ly/mapaderisco-pelotas).

This initiative by the public administration involved approximately 100,000 inhabitants out of a total municipal population of roughly 326,000, according to IBGE Cidades (IBGE, 2024), representing about 30% of the city's population. Additionally, the municipal government implemented other protective measures, such as constructing dikes with sandbags in areas surrounding the São Gonçalo Canal and the shores of the Lagoa dos Patos.

As the water levels of the São Gonçalo Canal and the Lagoa dos Patos changed due to the flow of waters descending from northern Rio Grande do Sul, the colors on the risk map were adjusted accordingly. Table 1 presents the initial configuration of the risk map based on the publication dated May 7, 2024.

Table 1 – Initial risk map configuration by neighborhood/region

Zone	Risk Flag
Z3	Red
porto	Orange
Pontal da Barra	Red
Santo Antônio	Red
Valverde (Laranjal)	Red
Marina Ilha Verde	Red
Rua das Traíras	Red
Lagoa de São Gonçalo	Red
Parque Uma	Red
Fátima	Red
Navegantes	Orange
Quadrado	Red
Doquinhas	Red
Final da rua Osório	Red
Início do Simões Lopes	Red

Source: Pelotas municipal government.

Starting from this initial distribution, throughout May, the municipal administration introduced changes to the risk map, taking into account the potential rise or fall in water levels:

Table 2 – Risk map changes

Neighborhood	Coloring	Change Description	Date
End of General Osório	Orange	On 11/05 and 12/05 it was marked as red, then switched to orange	13 May
Beginning of Simões Lopes	Orange	On 11/05 and 12/05 it was marked as red, then switched to orange	13 May
Navegantes	Red	From 07/05 to 10/05 it was marked as orange	11 May
Parque Una	Red	Between 19/05 and 24/05 it was marked as orange	20 and 25 May

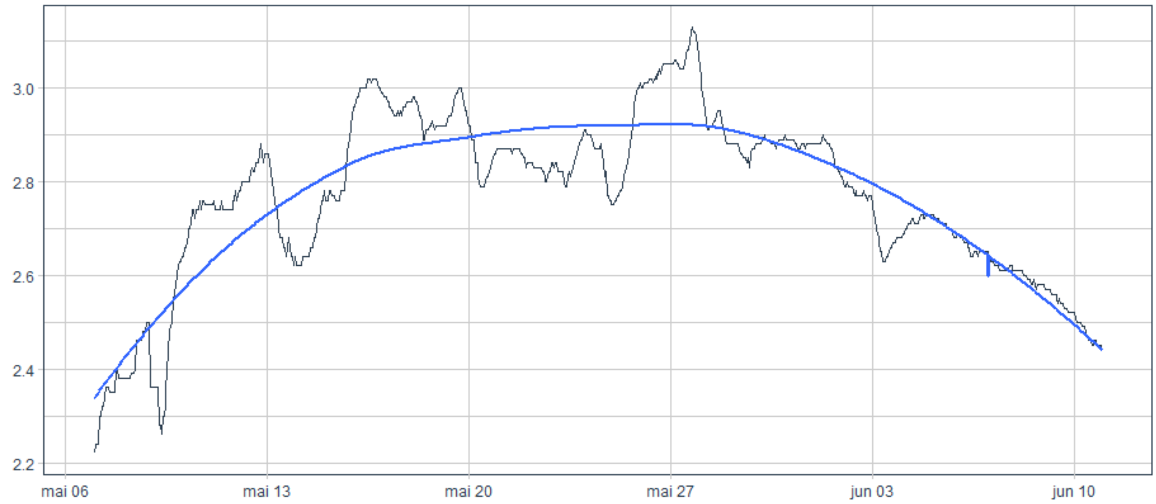
Source: Pelotas municipal government.

The first decision to implement a risk map can be considered conservative or restrictive on the part of the municipal administration. From the subsequent dates, the changes in risk zone coloring softened the initial restrictions. Using the following dates as reference — May 11, 13, 20, and 25 — we assess whether the decisions to restrict (impose the risk map coloring) and relax the restrictions were consistent with the data collected by municipal sensors installed near the São Gonçalo Canal.

For this purpose, an hourly dataset on the water level of the São Gonçalo Channel was collected, covering the period from 7 May to 10 June. These data were initially made publicly available by the Pelotas City Hall through its official social media platforms. Alternatively, this information can be formally requested from SANEP (Pelotas Municipal Water and Sanitation Authority), the municipal authority responsible for water resource management and sewage treatment in the city, in accordance with Brazil's Access to Information Law (Law nº 12.527/2011). In this context, the analysis assesses whether the restrictive or flexible forecasts were consistent with the actual rise or fall in water levels.

Below, the evolution of the time series data for water level measurements at the São Gonçalo Canal is presented:

Figure 2 – Time series graph of São Gonçalo Canal water level



Source: Pelotas municipal government.
Notes: The estimations were performed using version 4.4.2 of the open-source software R. The codes and scripts can be made available upon request by contacting the corresponding author.

It is worth noting that during the flooding period, the municipal government, through its official channels, reported malfunctions in the sensors measuring water levels at the Lagoa dos Patos. For this reason, the time series measurements from the São Gonçalo Canal, which provided a relatively complete set of hourly data, were used. Another important point is that missing observations — those not published by the public entity — were filled using the last available observation as a reference.

Below are the descriptive statistics showing the behavior of the hourly time series over the evaluated period:

Table 3 – Descriptive statistics for São Gonçalo Canal water levels (in meters)

Metric	Minimum	Median	Mean	Maximum	Standard Deviation
São Gonçalo	2.20	2.80	2.77	3.13	0.18

Source: Pelotas Municipal Government

Based on these statistics, it can be observed that during the evaluated period, the water level of the São Gonçalo Canal, a consequence of the Lagoa dos Patos, rose sharply. The peak level reached 3.13 meters, which is 25 cm higher than the historical mark of 2.88 meters recorded during the 1941 flood.

3.2 Empirical methodology

According to the work of Martinez *et al.* (2022), a Generalized Regression Neural Network (GRNN) is a variant of a Radial Basis Function (RBF) Neural Network, characterized by a single-period training process. A GRNN consists of a hidden layer with neurons equivalent to those in an RBF network. Typically, the hidden layer has as many neurons as there are training examples. The center of a neuron corresponds to its associated training example, and thus its output provides a measure of the proximity of the input vector to the training example. Commonly, a neuron uses the multivariate Gaussian function:

$$G(x, x_i) = exp\left(-\frac{\|x - x_i\|}{2\sigma^2}\right) \tag{1}$$

Where x_i and σ represent, respectively, the center and the smoothing parameter (x is an input data vector). Based on a set consisting of n training patterns—that is, a set of vectors $\{x_1, x_2, \dots, x_n\}$ and their n associated targets, typically scalars $\{y_1, y_2, \dots, y_n\}\}$ —the GRNN output for the input vector x is computed in two steps. First, the hidden layer produces a set of weights that represent the proximity of x to the training pattern:

$$w_i = \frac{exp\left(-\frac{\|x - x_i\|}{2\sigma^2}\right)}{\sum_{j=1}^{n} exp\left(-\frac{\|x - x_j\|}{2\sigma^2}\right)} \tag{2}$$

Note that the weights decrease as the distance from the training pattern increases. The weights sum to 1 and represent the contribution of each training pattern to the result. The GRNN produces an output as follows:

$$\hat{y} = \sum_{i=1}^{n} w_i y_i \tag{3}$$

In this way, a result vector is obtained, weighted by the training patterns, where the weights decay as the distance from the training pattern increases. The smoothing parameter controls how many training targets are considered significant in the weighting process. A time series dataset is introduced, and a training example is defined based on the temporal behavior of the data. Using this training example, the GRNN calculates the weight vector and the outpu $\hat{y}$, which represents the prediction based on the trained time series pattern.

Based on the value of $\hat{y}$, the study aims to evaluate whether the municipal administration's decisions were flexible or conservative. This assessment begins with the first decision to change the color of the Navegantes neighborhood from orange to red, which occurred after being classified as orange from May 7 to May 10. For this purpose, time series data from the window of May 7 to May 10 will be used to generate predictions for the first 12 hours of May 11. Subsequently, the predicted data will be compared with the actual observed data.

If the prediction produced values higher than what actually occurred and the decision was to change the color from orange to red, the measure is considered conservative. Conversely, if the predicted value was lower than the actual observed value and the color change was from red to orange, the measure is classified as flexible.

4. RESULTS

Neural Network models were employed to generate predictions 12 periods ahead, in accordance with the changes in the municipal Risk Map coloring outlined in Table 2. It is important to note that the further into the future the prediction extends, the lower its accuracy tends to be. For this reason, a horizon of only 12 hours was chosen. Taking as the starting point the change in the coloring of the Navegantes neighborhood—which was classified as orange between May 7 and May 10 and then changed to red on May 11—the following results were obtained:

Table 4 – Predictions for navegantes neighborhood on May 11

Time	Observed	Predicted	Difference
01:00	2.75	2.76	-0.01
02:00	2.75	2.77	-0.02
03:00	2.75	2.77	-0.02
04:00	2.75	2.78	-0.03
05:00	2.76	2.78	-0.02
06:00	2.74	2.79	-0.05
07:00	2.74	2.79	-0.05
08:00	2.74	2.80	-0.06
09:00	2.74	2.80	-0.06
10:00	2.74	2.81	-0.07
11:00	2.76	2.81	-0.05
12:00	2.74	2.82	-0.08

Source: prepared by the authors.

As shown in Table 4, the predicted values were slightly higher than the observed measurements for the São Gonçalo Canal on May 11. In the short term, the change in the coloring of this municipal region can therefore be considered a conservative measure. However, observing the trajectory of the time series in Figure 2 reveals that measurements began to rise rapidly starting on May 13. The predictions generated by the model also indicate this upward trend.

Next, the evaluation shifts to the change in coloring for two regions: the end of General Osório Street and the beginning of the Simões Lopes neighborhood, which intersects with the bridge connecting to the municipality of Rio Grande. This bridge was built to enable vehicle passage over the São Gonçalo Canal. Between May 11 and May 12, this region was classified as red, but after May 13, it was reclassified as orange.

Table 5 – Predictions for May 13 for the end of General Osório Street and beginning of Simões Lopes Neighborhood

Time	Observed	Predicted	Difference
01:00	2.86	2.87	-0.01
02:00	2.86	2.87	-0.01
03:00	2.84	2.88	-0.04
04:00	2.82	2.88	-0.06
05:00	2.80	2.89	-0.09
06:00	2.78	2.89	-0.11
07:00	2.76	2.89	-0.13
08:00	2.74	2.90	-0.16
09:00	2.74	2.90	-0.16
10:00	2.74	2.91	-0.17
11:00	2.70	2.91	-0.21
12:00	2.68	2.91	-0.23

Source: prepared by the authors.

Based on the previous behavior of the time series, the neural network model predicted a rise in water levels, which did not occur. It is important to note that other factors, such as wind direction and tide levels, can influence the retention or drainage of water into the Atlantic Ocean. The observed decrease in canal levels aligns with the public entity's decision to relax restrictions.

As a final estimate, the analysis focuses on the relaxation implemented for the Parque Una neighborhood, which was classified as orange from May 19 to May 24. Before and after this period, it was classified as red, indicating the evacuation of residents in this area.

Table 6 – Predictions for May 19 for the Parque Una Neighborhood

Time	Observed	Predicted	Difference
01:00	2.92	2.87	0.05
02:00	2.92	2.87	0.05
03:00	2.92	2.88	0.04
04:00	2.92	2.88	0.04
05:00	2.92	2.89	0.03
06:00	2.92	2.89	0.03
07:00	2.93	2.89	0.04
08:00	2.94	2.90	0.04
09:00	2.94	2.90	0.04
10:00	2.94	2.91	0.03
11:00	2.95	2.91	0.04
12:00	2.97	2.91	0.06

Source: prepared by the authors.

As observed, the prediction model indicated a sharper drop in water levels compared to what was actually measured. From May 20 to May 25, the canal levels ranged between 2.8 and 2.9 meters, suggesting that the relaxation during this period may have been appropriate. However, starting on May 25, this neighborhood was once again classified as red, coinciding with a significant rise in canal levels.

Table 7 – Predictions for May 25 for the Parque Una Neighborhood

Time	Observed	Predicted	Difference
01:00	2.91	2.90	0.01
02:00	2.91	2.90	0.01
03:00	2.90	2.91	-0.01
04:00	2.90	2.91	-0.01
05:00	2.90	2.91	-0.01
06:00	2.90	2.91	-0.01
07:00	2.90	2.91	-0.01
08:00	2.89	2.91	-0.02
09:00	2.88	2.91	-0.03
10:00	2.87	2.92	-0.05
11:00	2.87	2.92	-0.05
12:00	2.87	2.92	-0.05

Source: prepared by the authors.

The predictive neural network model provided a slightly conservative estimate compared to the observed data. This tendency toward overestimation, although minor, suggests that the model predicts water levels slightly higher than those actually measured. However, this caution can be viewed as an advantage in disaster management contexts, where ensuring public safety is the priority.

The observed upward trend in water levels within the time series reinforces the appropriateness of decisions to classify certain areas as red zones, especially considering the potential risks associated with underestimating flood hazards. Moreover, the decision to classify certain regions as high-risk zones, reflected by the red coloring on the map, while restrictive, aligned with the trends observed in the time series.

This alignment between the model's predictions and the municipal administration's decisions highlights the potential of artificial neural networks as a robust and effective tool for decision-making during emergencies. Such models not only contribute to more informed and proactive management but also aid in damage mitigation, providing critical support during crisis scenarios.

5. DISCUSSION

The results obtained in this study reinforce the utility of Generalized Regression Neural Networks (GRNN) as predictive tools in climate emergency scenarios, demonstrating their ability to accurately forecast water levels in the São Gonçalo Canal during the 2024 floods in Pelotas. Overall, the predictions exhibited high accuracy, with minimal deviations from observed values, particularly during periods of extreme variation when uncertainty complicates decision-making. However, the robustness of these results depends on the quality of data input, and reliance on real-time measurements exposes the model to risks related to collection errors or inconsistencies in records. Additionally, while the model's parameters were optimized through cross-validation, constant adjustments may be required to maintain efficacy in dynamic scenarios, as emphasized by Greene (2012), Gujarati and Porter (2022) and Wooldridge (2010) in their discussions on model specification and sensitivity in the context of cross-sectional and panel data.

The alignment between the model's predictions and the decisions made by Pelotas' municipal administration highlights the practical potential of this approach. The flexibility offered by GRNNs allowed the model to track changes in water behavior, providing valuable support for defining and adjusting risk maps. This adaptability is crucial for municipalities vulnerable to recurrent disasters, such as Pelotas, where swift responses can significantly mitigate economic and social impacts. However, the practical application of predictive technologies requires investments in technological infrastructure and capacity-building for the teams responsible for their operation, especially in resource-limited locations.

The findings of this study align with international literature, such as the works of Mori *et al.* (2020), which demonstrated the effectiveness of machine learning models in flood prediction in Japan, and Hallegatte *et al.* (2007), which highlighted the importance of data-driven interventions to enhance the resilience of vulnerable regions. In the Brazilian context, the results complement studies that have analyzed the economic impacts of natural disasters, such as Ribeiro *et al.* (2014) and Lima and Barbosa (2018). However, this study advances the field by exploring the use of neural networks as a tool to support public decision-making, offering an innovative perspective on environmental crisis management.

Furthermore, the practical implications of the results underscore the need for public policies that promote the integration of predictive technologies into early warning systems. This integration not only allows for more efficient resource allocation but also enables more agile and effective responses, especially during emergencies. However, it is essential that such initiatives be accompanied by strengthened local institutional capacities to ensure that the technologies are used efficiently and that the benefits are broadly distributed.

Finally, the results of this study highlight the importance of advancing the application of predictive methodologies in public management. Incorporating additional variables, such as long-term socioeconomic and climatic indicators, could enrich analyses and provide a more comprehensive view of the factors influencing decision-making in emergency scenarios. Additionally, replicating this methodology in other vulnerable regions of Brazil would validate its applicability across different geographic and social contexts, expanding the potential of neural networks as a tool for disaster management.

6. FINAL REMARKS

This study demonstrated the feasibility of using machine learning techniques, particularly artificial neural networks, as valuable tools to support decision-making in natural disaster scenarios. By applying these techniques to evaluate the decisions made by Pelotas' public administration during the 2024 floods, it was found that the predictions generated by the model were largely consistent with the actions implemented. Despite a slight tendency to overestimate water levels, the observed discrepancies were minimal, reaffirming the potential of neural networks as an effective tool for public managers in mitigating damage and implementing civil protection measures.

The results highlight the importance of integrating AI-based predictive models into public policies for disaster management. The high accuracy of the models, even in short-term forecasts, suggests that decisions related to relaxing or tightening risk zones could be further refined through the continuous and enhanced use of these technologies. Such integration would enable more precise forecasting of adverse events and more efficient responses to climate emergencies, reducing both economic and social impacts.

Moreover, the study demonstrates that, in the context of natural disasters, adopting advanced technological tools goes beyond complementing traditional response efforts, offering a more dynamic and adaptive approach to crisis management. The model's cautious overestimation can be viewed as an advantage in situations where protecting human lives is the priority. Thus, this work contributes to the literature by demonstrating that data- and evidence-driven public policies are fundamental to strengthening urban resilience against extreme climate events.

Based on the results, it is recommended that public managers prioritize the integration of these technologies into their risk planning and mitigation strategies, especially in regions highly vulnerable to hydrological disasters, such as Rio Grande do Sul. By combining artificial intelligence with the practical expertise of decision-makers, public policies can become more robust, proactive, and effective in anticipating adverse scenarios, minimizing the socioeconomic consequences of natural disasters.

The incorporation of advanced machine learning techniques into the decision-making process has the potential not only to save lives but also to significantly reduce post-disaster recovery costs. Furthermore, it contributes to safer and more sustainable urban development, fostering cities that are better prepared and more resilient to climate change and the challenges it imposes.

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Rodrigo Nobre Fernandez
https://orcid.org/0000-0001-8596-2898
PhD in Economics (emphasis: Applied Economics) from the Federal University of Rio Grande do Sul (UFRGS). Professor in the Department of Economics at the Federal University of Pelotas (UFPel) and faculty member of the Graduate Program in Organizations and Markets (Master's/PhD in Applied Economics).
rodrigonobrefernandez@gmail.com

Gabrielito Rauter Menezes
https://orcid.org/0000-0001-7649-5132
PhD in Applied Economics from the Federal University of Rio Grande do Sul (UFRGS). Assistant Professor and Leader of the LabReg research group at the Federal University of Pelotas (UFPel).
gabrielitorm@gmail.com

Greike Maia Aguiar
https://orcid.org/0009-0009-7605-4850
PhD Candidate in the Graduate Program in Economics (PPGOM) at the Federal University of Pelotas (UFPel). Bachelor's degree in Information Systems from Faculdade Santa Maria de Recife (FSM). MBA in Database Administration from the Associação de Docentes da Universidade Estácio de Sá (ADESA). Researcher at LabReg (Regional Economics Laboratory).
greike.aguiar@gmail.com

Naurienni Dutra Freitas
https://orcid.org/0000-0002-9170-9669
PhD candidate in the Graduate Program in Materials Science and Engineering and MSc in Architecture and Urbanism at the Federal University of Pelotas (UFPel). BSc in Civil Engineering from the Catholic University of Pelotas (UCPel).
naurienni@gmail.com