https://doi.org/10.1590/S1413-415220230085

Scientific Paper

Artificial neural network models to support urban waste management: A technological resource that drives the achievement of Sustainable Development Goals

Modelos de redes neurais artificiais para apoiar a gestão de resíduos urbanos: um recurso tecnológico que impulsiona a concretização dos Objetivos de Desenvolvimento Sustentável

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ABSTRACT

Waste management is crucial to achieving the Sustainable Development Goals (SDGs) established by the United Nations. However, traditional on-site waste characterization techniques require specialized professionals, who are exposed to biological, chemical, and physical risks. In this sense, the use of artificial neural networks (ANN) in models for characterizing municipal solid waste has been discussed, especially after the advent of the COVID-19 pandemic. Predictions made by ANN can be carried out with little or no handling of waste, making the process faster, cleaner, and safer. However, ANN models rely on datasets often provided by third parties, so they require diligent monitoring to ensure that an updated dataset is available at the appropriate regularity. This study presented two standard ANN models that were not available due to a lack of up-to-date datasets and demonstrated that dataset interchangeability may be critical for the long-term use of ANN developed to achieve SDG. Furthermore, interchangeability led to the formulation of a hypothesis about the relevance of the variable associated with basic sanitation in the greater assertiveness of one of the models during the pandemic period, resulting in the identification of abnormal patterns relating to the disposal of textiles and sanitary papers in the years 2020 and 2021. Additionally, this study can be the starting point for the development of more sophisticated interchangeable models developed with alternative datasets, meticulously chosen to reduce the effective error of the desired predictions by reducing the amplitude of the intersection set formed by different models.

Keywords: waste management; artificial intelligence; socioeconomic; population profile; pandemic.

RESUMO

A gestão de resíduos é crucial para atingir os Objetivos de Desenvolvimento Sustentável (ODS) estabelecidos pela Organização das Nações Unidas (ONU). No entanto, as técnicas tradicionais de caracterização de resíduos *in loco* demandam profissionais especializados, expostos a riscos biológicos, químicos e físicos. Nesse contexto, o uso de Redes Neurais Artificiais (RNA) em modelos para caracterização de Resíduos Sólidos Urbanos tem sido discutido, especialmente após o advento da pandemia Covid-19. As previsões feitas por RNA podem ser realizadas com pouco ou nenhum manuseio de resíduos, tornando o processo mais rápido, limpo e seguro. No entanto, os modelos de RNA frequentemente dependem de *datasets* fornecidos por terceiros, exigindo o monitoramento diligente para manutenção da disponibilidade de *datasets* atualizados com a regularidade apropriada. Este estudo apresentou modelos de RNA que estavam indisponíveis devido à falta de *datasets* atualizados, e demonstrou que a intercambialidade de *datasets* pode ser crítica para o uso, a longo prazo, de modelos de RNA desenvolvidos para atingir os ODS. Adicionalmente, a intercambialidade levou à formulação da hipótese sobre a relevância das variáveis de saneamento básico na maior assertividade de previsões relacionadas ao período da pandemia, resultando na identificação de padrões anormais relativos ao descarte de têxteis e papéis sanitários nos anos de 2020 e 2021. Adicionalmente, este trabalho pode ser o ponto de partida para o desenvolvimento de modelos intercambiáveis mais sofisticados, desenvolvidos com *datasets* alternativos, criteriosamente escolhidos para elevar a acurácia das predições desejadas, por meio da redução da amplitude do conjunto intersecção formado por diferentes modelos.

Palavras-chave: gestão de resíduos; inteligência artificial; socioeconômico; perfil populacional; pandemia.

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Conflicts of interest: the authors declare no conflicts of interest.
Funding: none.
Received on: 06/19/2023 – **Accepted on:** 07/08/2024

INTRODUCTION

Waste management plays an essential role in achieving the Sustainable Development Goals (SDGs) established by the United Nations, as depicted in Figure 1. The benefits to society are extensive, including proper waste treatment preventing negative impacts on the environment, and avoiding contamination of air, soil, surface, and groundwater; in terms of public health, appropriate disposal reduces exposure to harmful agents and the spread of diseases, improving the quality of life of the population; and it promotes sustainable patterns of production and consumption, contributing to the circular economy and the preservation of natural resources (UNEP; ISWA, 2024).

SUSTAINABLE DEVELOPMENT GOALS

Goal 1. No poverty: Waste workers in informal economies who have no health or social protections are vulnerable to exploitation and are paid only the material value of the materials they collect. Inclusive municipal waste management policies are most effective for addressing both poverty and pollution.

Goal 2. Zero hunger: While global hunger is increasing, one-third of all the food grown in the world is wasted. Hunger can be reduced by preventing food waste and redistributing excess food. Converting unavoidable food waste into compost can replenish depleted agricultural soils.

Goal 3. Good health and well-being: Communities without adequate municipal waste management services resort to dumping and open burning, both of which have significant negative health consequences, particularly for women and children.

Goal 4. Quality education: Waste management courses in tertiary and higher education are uncommon, resulting in a lack of professional technical capacity and a shortage of workers with appropriate skills and knowledge.

Goal 5. Gender equality: People's experience with waste and its management is gender-differentiated: e.g. household purchasing and domestic waste-generating activities, and levels of influence over community decision-making regarding waste collection services.

Goal 6. Clean water and sanitation: Pollutants leaching from dumpsites can contaminate freshwater sources and associated food chains. Meanwhile, combining municipal solid waste and container-based sanitation services can achieve economies of scale that make both services more attractive to investors.

Goal 7. Affordable and clean energy: Unavoidable food waste can be used to make biogas, a clean-burning renewable fuel that could be used to tackle energy poverty, including in off-grid communities.

Goal 8. Decent work and economic growth: The waste management and recycling sector is uniquely positioned to improve global resource efficiency, decouple economic growth from environmental degradation, and provide safe and decent work opportunities for all.

Goal 9. Industry, innovation and infrastructure: Decentralised waste management systems can attract private sector investment, encouraging innovation, entrepreneurship, domestic technology development, greater resource efficiency and increased employment opportunities, and reduce financial risks for governments and municipalities.

Goal 10. Reduced inequalities: Intragenerational and intergenerational inequalities must be addressed through developing waste and resource management systems; attention is required from all stakeholders because the transition to a more circular economy will not occur by default.

Goal 11. Sustainable cities and communities: Solid waste management is a basic utility service without which air quality and living conditions become degraded, leading to poor health and social discontent. To make cities and communities inclusive, safe, resilient and sustainable, universal access to municipal waste management services is essential.

Goal 12. Responsible consumption and production: Production and consumption patterns directly impact municipal waste generation. To reduce waste and prevent pollution, efforts are needed by companies, governments and citizens.

Goal 13. Climate action: Poorly managed waste generates a wide range of emissions that contribute to climate change, most significantly methane from landfills and dumpsites, and black carbon and a range of other emissions from the widespread practice of the open burning of waste.

Goal 14. Life below water: Understanding why and how land-based waste reaches the sea, and introducing mitigation measures, is essential. Urgent action is particularly required in the case of Small Island Developing States, which face a complex set of waste management challenges.

Goal 15. Life on land: The terrestrial environment continues to be the primary sink for waste, while rural communities face complex waste management challenges that if left unmanaged can significantly impact ecosystems and dependent livelihoods.

Goal 16. Peace, justice and strong institutions: The increasingly global nature of waste management calls for heightened international cooperation to build national capacity for the safe management of hazardous waste and to prevent its illegal trafficking.

Goal 17. Partnerships for the Sustainable Development Goals: Current investments in waste management are insufficient. Far higher investments will be needed in the future to cope with increasing waste generation and the accumulation of legacy waste. The return on investment for waste management needs to be realised to catalyse increased finance.

Source: UNEP and ISWA (2024).

Figure 1 – Waste management and its links to the SDGs.

To ensure adequate treatment and disposal, municipal solid waste (MSW) must be characterized, as physical characteristics, such as gravimetric composition, which are very relevant for the good planning of urban cleaning. However, traditional methods of monitoring MSW properties may not be available in many circumstances. To exemplify, during the COVID-19 pandemic, the collection and characterization of waste underwent several changes due to accessibility restrictions, quarantine, social distancing, and the implementation of sanitary protocols (Valizadeh *et al.*, 2021; Thomaz; Mahler; Calôba, 2023).

In the Brazilian context, the restrictive measures imposed by the federal and municipal governments, such as quarantines — so valuable to protect society — resulted in gaps in the continuous monitoring of solid waste in some municipalities, as can be exemplified by the excerpt from a document official from the Municipality of Rio de Janeiro (COMLURB, 2023):

"Due to the pandemic, the complete characterization of waste was not carried out for the year 2020, therefore the information was not broken down by Planning Area" (translated from Portuguese to English).

Fortunately, it is pertinent to emphasize that the evolution of technology has allowed sophisticated computational resources to expand the scope beyond the conventional limits of environmental research, benefiting both a sustainable economy and society. Artificial intelligence can be of great support to governments, policymakers, municipalities, and private waste management organizations to increase recycling, reduce manual labor, reduce costs, maximize efficiency, and transform the way to deal with waste management (Andeobu; Wibowo; Grandhi, 2022; Sánchez, 2024).

According to UNEP and ISWA (2024), artificial intelligence is being increasingly adopted for several waste management applications: predicting urban waste composition (Thomaz; Mahler; Calôba, 2023); identifying and sorting waste materials (Moore, 2023); reducing food waste and food loss in various stages of the supply chain (Onyeaka *et al.*, 2023; Said *et al.*, 2023); and predicting pollution hotspots in marine environments related to waste (Fazri *et al.*, 2023; Seyyedi *et al.*, 2023).

Within the spectrum of artificial intelligence solutions, artificial neural networks (ANN) emerge as a powerful alternative. The extensive application of ANN in addressing a wide range of environmental challenges can be attributed to their superior self-learning capabilities and their exceptional precision in solving complex non-linear interactions without complicated mathematical rules (Shekoohiyan *et al.*, 2023).

In the context of the waste management area, it is possible to use ANN to estimate the gravimetric composition of MSW from socioeconomic data based on the predictability relationship between the characteristics of society and the properties of the waste produced. However, this is not yet a reality in the waste industry, which adopts sampling procedures that are expensive and slow. Furthermore, workers are subjected to the unpleasant odors emanating from the waste mass and are exposed to potential biological and chemical hazards (Adeleke *et al.*, 2021; Thomaz; Mahler; Calôba, 2023).

It is also necessary to reinforce that ANN can be valuable both in pandemic scenarios, in which it is imperative to avoid handling waste, and in post-pandemic reality, when it is necessary to fill in the information gaps caused by the application of restrictive measures, such as quarantines, which affected the normality of management. Furthermore, in a broader context, the simple and low-cost application can be advantageous for cities with deficiencies in the gravimetric characterization of waste caused by restrictions on technical and financial resources (Thomaz; Mahler; Calôba, 2023).

In the Brazilian scenario, models based on ANN have already been proposed to solve waste management challenges. It could be cited the model developed by Thomaz (2016), here identified as #POP.ELE.GDP.RSI-MRJ, which adopts a dataset from the study region itself, including population data, annual total electricity consumption, gross domestic product (GDP), and retail sales index (RSI), to predict the physical properties of MSW.

The context of the pandemic ended up being convenient for the development of waste management models based on ANN, as it is a procedure that does not expose workers to the hazards of field sampling. However, the adoption of the #POP.ELE.GDP.RSI-MRJ model, presented by Thomaz (2016), was not possible in such a context due to the timely unavailability of a dataset containing information from the RSI variable (IBGE, 2023b).

Faced with this last challenge of the unavailability of datasets, Thomaz, Mahler, and Calôba (2023) proposed a new model, here identified as #GDP.POP.PWS.SSY-MRJ, fed by a dataset from the study region itself, including population data, GDP, potable water supply, and sanitation system. The results of the #GDP.POP.PWS.SSY-MRJ model were adequate for predictions made up to the year 2020, even making it possible to fill the information gap relating to the pandemic period. However, at the time of preparing this study, there are no official data relating to the GDP of the Municipality of Rio de Janeiro available for years after 2020 (IBGE, 2023a; IBGE, 2023c).

It became evident that the #POP.ELE.GDP.RSI-MRJ model, presented by Thomaz (2016), and the #GDP.POP.PWS.SSY-MRJ model, presented by Thomaz, Mahler, and Calôba (2023), share a common issue: the unavailability of datasets at the time of preparing this study, which hinders the timely adoption of the models. Therefore, dataset interchangeability may be decisive for the long-term use of ANN.

Evolution is a continuous process, so it is natural that some datasets will become unavailable over time, while others will become available. In this sense, the present work proposes the interchangeability of datasets of ANN models developed to predict the gravimetric composition of MSW as an effective way to enable predictions later in the year 2020. To validate the proposal, the model proposed, here identified as #POP.EST.EDU.JBN-MRJ, was fed by an alternative dataset composed of population quantitative data, the number of establishments by economic activity, and the number of jobs by education degrees.

METHOD

Study area

The study area chosen to validate the model was the Municipality of Rio de Janeiro, the capital of the state of the same name, located in the southeast region of Brazil. Rio de Janeiro is internationally known for its cultural and scenic attractions, including the giant statue of Christ the Redeemer at the top of Corcovado Mountain and the Maracanã Stadium, one of the world's largest soccer stadiums. In addition, it is one of the main economic and financial centers of the country.

The Municipality of Rio de Janeiro is geographically remarkable and representative due to its diverse natural formations. It is bordered by the Atlantic

Ocean, Guanabara Bay, and Sepetiba Bay. By referring to the geospatial map (Appendix A) and the illustrated map (Appendix B), we can observe a contrast between the urban artificial landscape and the natural surroundings. These natural features include bays, sandbanks, beaches, lagoons, forests, valleys, and mountains. Notable locations include the Marapendi, Tijuca, Jacarepaguá, and Rodrigo de Freitas lagoons, as well as the Tijuca, Mendanha, and Pedra Branca massifs. Additionally, the beaches of Flamengo, Copacabana, Ipanema, São Conrado, and Barra da Tijuca contribute to the city's scenic beauty.

According to IBGE (2023d), in the last five decades, the population of the Municipality of Rio de Janeiro grew by more than 40%, reaching the mark of six million inhabitants in 2021. Table 1 shows the population quantity between the years 2006 and 2021. This period is marked by population decline between the years 2006 and 2007 and by small annual growth in the remainder of the period.

At the same time, according to MTE (2023b), the total number of establishments in the Municipality of Rio de Janeiro grew smoothly between 2006 and 2013, followed by annual declines throughout the remaining period until 2021. The number of establishments during the entire period, segregated by economic activity, can be seen in Table 2.

The total number of jobs in the Municipality of Rio de Janeiro grew by approximately 35.3% between 2006 and 2014 and declined by around 20.5% between 2014 and 2021, according to MTE (2023a). On the contrary, there was annual growth for practically the entire period in the number of positions held by professionals with master's and doctorate degrees. The number of jobs between 2006 and 2021 and their distribution by educational degrees can be observed in Table 3.

Waste management in the Municipality of Rio de Janeiro represents a collective obligation encompassing a multitude of actors and institutions, seeking to ensure adequate collection, processing, and disposal of waste (PMRJ, 2021). Furthermore, data related to the period from 2003 to 2021 indicate that the MSW collection coverage rate has consistently remained at 100% for a minimum period of two decades. At the same time, the accumulated amount of residential waste fluctuated between 0.65 and 0.97 kg per capita per day (IPP, 2023).

The MSW collection in Rio de Janeiro is carried out by the Municipal Urban Cleaning Company (COMLURB), which has been producing, processing, and supplying data on the collection and disposal of MSW for decades. The gravimetric composition provided by COMLURB (2023) was divided into standardized fractions: paper-cardboard; plastic; glass; metal; organic matter; and others. The variation in the gravimetric composition of MSW over the period between 2006 and 2021 can be observed in Table 4.

The potable water supply in Rio de Janeiro is characterized by extensive coverage, with a population service rate exceeding 90% since 2004 and reaching 100% in 2020. The supply network has grown approximately 16% between 2000 and 2021, extending to a length of 10,874 km. During the same period, the number of active water connections increased by over 80%, rising from 774,276 to 1,409,856 connections (SNIS, 2023a).

In terms of water volume, Rio de Janeiro produces or imports over 1 billion m^3 of drinking water annually. However, consumption varies, with recorded volumes ranging from 405 to 777 million m^3 in 2020 and 2018, respectively (SNIS, 2023b).

Regarding sanitation, there was a noticeable decline in service to the population from 2000 to 2009. During this period, the service rate dropped from 91.2% in 2000 to 68.7% in 2009. However, subsequent improvements raised the service rate to 80.9% in 2013 and eventually returned to 90% in 2021. Parallelly, the sewage network also expanded significantly, growing by approximately 73% from 2002 (4045 km) to 2021 (7009 km). Active connections nearly doubled, with 489,635 connections in 2009 and 965,444 connections in 2019. Additionally, the number of active autonomous units fluctuated by around 54%, reaching a low of 1,427,879 in 2009 and a high of 2,207,457 in 2021. The volume of sewage collected varied between 340 and 509 m^3 annually, while treatment volumes ranged from 244 to 355 million m^3 per year over the last two decades (SNIS, 2023c).

Modeling environment

The prediction method takes advantage of the fact that the properties of MSW are influenced by various indicators, including GDP, population, income, educational degree, family size, average age of family members, access to medical care insurance, availability of potable water supply, and sanitation systems (Vazquez *et al.*, 2020; Ghanbari; Kamalan; Sarraf, 2021; Noman *et al.*, 2023; Thomaz; Mahler; Calôba, 2023).

The crucial point of modeling is to choose variables based on relevance, frequency, and availability criteria (Thomaz; Mahler; Calôba, 2023). However, as mentioned previously, there are models based on ANN that use representative socioeconomic factors to address waste management challenges, but the adoption of these models may become unfeasible over time due to variations in the periodicity and availability of the factors that compose their datasets, evoking the necessary interchangeability.

The standard models #POP.ELE.GDP.RSI-MRJ (Thomaz, 2016) and #GDP.POP.PWS.SSY-MRJ (Thomaz; Mahler; Calôba, 2023) exemplify that the representativeness of socioeconomic factors is not the only important characteristic to be considered when conceptualizing datasets. In practice, the #POP.ELE.GDP.RSI-MRJ model is unavailable for use due to inconsistency in the periodicity of official RSI data from the study region since before the COVID-19 pandemic (IBGE, 2023b), while the applicability of the model #GDP.POP.PWS.SSY-MRJ is limited until the beginning of the pandemic due to the unavailability of official GDP data for the study region after 2020 (IBGE, 2023a; IBGE, 2023c).

To enable predictions for the period subsequent to the year 2020, it was proposed to build a model using alternative datasets, composed of

Table 1 – Estimated resident population of the Municipality of Rio de Janeiro, from 2006 to 2021.

INPUTS	2006	2007	2008	2009	2010	2011	2012	2013
Population	6,136,652	6,093,472	6,161,047	6,186,710	6,320,446	6,355,949	6,390,290	6,429,923
continuation	**2014**	**2015**	**2016**	**2017**	**2018**	**2019**	**2020**	**2021**
Population	6,453,682	6,476,631	6,498,837	6,520,266	6,688,927	6,718,903	6,747,815	6,775,561

Source: Compiled by the author based on IBGE (2023d).

Table 2 – Number of establishments by economic activity of the Municipality of Rio de Janeiro, from 2006 to 2021.

INPUTS		2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021
Number of establishments by economic activity	Mineral extractive	106	128	138	131	152	174	180	164	169	162	151	132	136	150	142	140
	Non-metallic minerals	236	224	209	221	271	229	217	227	240	233	228	215	218	202	184	183
	Metallurgical industry	708	715	701	705	650	716	738	715	714	688	643	580	541	490	473	473
	Mechanical industry	409	390	383	389	445	472	533	566	587	576	562	549	550	520	541	525
	Electrical and communications material industry	176	164	173	175	176	172	186	184	190	192	190	178	181	172	164	154
	Transport material industry	133	151	141	139	154	153	174	163	166	166	160	145	138	145	141	151
	Wood and furniture industry	254	254	261	263	284	293	290	304	308	287	265	248	240	221	201	197
	Paper, cardboard, publishing and graphic industry	1,129	1,123	1,162	1,135	1,128	1,155	1,182	1,179	1,166	1,128	1,050	971	890	783	729	674
	Rubber, tobacco, leather, fur, similar and miscellaneous industry	599	572	566	590	627	667	731	776	806	766	764	736	721	680	644	637
	Chemical industry of pharmaceuticals, veterinary products, perfumery...	754	723	689	671	678	685	696	664	663	609	597	573	531	486	481	445
	Textile industry of clothing and fabric artifacts	1,110	1,113	1,175	1,194	1,223	1,290	1,282	1,256	1,241	1,142	1,064	1,011	955	853	806	737
	shoe industry	33	34	30	29	26	24	23	19	19	18	13	13	11	11	11	10
	Industry of food products, beverages and ethyl alcohol	1,097	1,102	1,105	1,144	1,009	1,078	1,116	1,152	1,200	1,272	1,335	1,378	1,364	1,359	1,348	1,395
	Public utility industrial services	168	214	198	218	217	238	282	289	306	289	313	309	322	302	293	311
	Construction	2,745	2,877	3,026	3,191	3,500	4,003	4,305	4,662	4,994	4,872	4,430	3,996	3,752	3,765	3,704	3,958
	Retail business	32,267	32,919	33,384	33,949	34,893	36,079	37,251	37,388	37,622	36,870	36,397	35,444	34,706	33,238	32,126	31,816
	Wholesale	4,906	5,001	5,202	5,311	5,481	5,589	5,780	5,790	5,753	5,610	5,448	5,225	4,963	4,724	4,561	4,585
	Credit institutions, insurance and capitalization	2,605	2,782	2,878	2,923	3,073	3,045	3,041	2,985	3,019	3,000	3,049	3,015	2,999	2,996	2,686	2,974
	Commerce and administration of real estate, securities, technical services	32,230	32,539	33,053	33,690	34,544	35,492	36,433	36,832	37,127	37,149	36,992	36,761	36,515	36,278	36,016	36,289
	Transport and Communications	4,088	4,194	4,351	4,542	4,755	5,066	5,442	5,604	5,680	5,637	5,624	5,432	5,315	5,084	4,883	4,704
	Accommodation, food, repair, maintenance, writing services...	17,556	17,840	18,191	18,750	19,313	20,072	20,863	21,405	22,061	22,239	22,474	22,030	21,534	20,419	19,462	18,778
	Medical, dental and veterinary services	8,675	8,763	8,928	9,159	9,337	9,585	9,765	9,912	10,088	10,211	10,308	10,315	10,394	10,077	10,029	10,173
	Teaching	3,110	3,159	3,162	3,302	3,426	3,554	3,674	3,753	3,797	3,813	3,848	3,822	3,905	3,851	3,864	3,877
	Direct and autonomous public administration	303	294	284	297	293	313	310	319	299	296	302	300	297	288	284	286
	Agriculture, forestry, animal husbandry, plant extractivism	333	317	342	360	356	381	418	378	411	389	402	412	399	317	361	385

Source: Compiled by the author based on MTE (2023b).

variables from the study region itself, as in the standard models. For this model, available socioeconomic factors were taken into account, including at least complete annual data from a period of at least 15 years, covering the year 2021, as presented in Tables 1–3. These factors include the estimated resident population, establishments by economic activity, and jobs by education degrees.

The MATLAB software was adopted for ANN modeling, as adopted in the standard models, because it presented the best performance among the other programs tested, according to Thomaz, Mahler, and Calôba (2023). As the focus of this study is the interchangeability of datasets, the adoption of the same software for all models makes the comparison between results obtained by the standard and proposed models more efficient by eliminating any noise that could arise when adopting different software in the modeling.

The modeling stage of the proposed model followed the same rule adopted for standard models developed by Thomaz (2016) and Thomaz, Mahler, and Calôba (2023). At this stage, the chosen socioeconomic variables were filtered, processed, introduced into the MATLAB Workspace, and transformed into detailed datasets about the Municipality of Rio de Janeiro, which feed their respective models, as can be seen in Figure 2.

In technical terms, the MATLAB Deep Learning Toolbox accelerates the configuration process of the ANN as the Bayesian Regulation algorithm, adopted in the standard models #POP.ELE.GDP.RSI-MRJ (Thomaz, 2016) and #GDP.

Table 3 – Number of jobs by education degrees, from 2006 to 2021.

INPUTS		2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021
Number of jobs by education degrees	Illiterate	7,614	7,848	6,786	4,719	4,755	3,300	3,200	3,141	3,121	4,245	3,163	3,826	3,796	5,025	6,109	3,901
	4th Grade/5th Year Incomplete	61,094	60,279	66,561	56,066	62,389	64,747	68,695	64,819	65,687	58,018	47,413	42,217	40,805	44,956	40,803	38,556
	4th Grade/5th Year Complete	116,562	112,535	101,707	100,384	96,592	96,221	93,888	82,636	78,715	71,099	59,466	52,456	47,291	43,297	37,870	35,118
	8th Grade/9th Year Incomplete	155,861	157,670	150,818	164,014	158,009	158,395	150,261	145,467	143,866	132,410	112,296	97,967	91,716	87,358	78,024	74,552
	8th Grade/9th Year Complete	326,962	396,758	344,122	341,335	346,907	348,932	330,765	325,341	314,605	285,944	260,151	228,769	211,348	198,145	174,003	163,667
	High School Incomplete	156,637	160,499	162,137	163,202	169,546	170,445	162,950	165,000	165,048	152,058	133,118	118,470	116,273	115,094	100,335	99,121
	High School Complete	619,670	744,846	751,571	800,887	874,698	970,140	1,012,750	1,053,345	1,079,221	1,057,941	1,030,069	1,029,835	1,010,153	1,012,977	941,484	974,366
	Higher Education Incomplete	144,301	164,326	149,276	141,546	140,337	139,776	119,865	113,406	111,400	106,249	100,105	102,630	109,127	114,329	106,239	109,024
	Higher Education Complete	368,408	363,992	421,544	451,070	486,549	533,374	615,383	645,379	675,695	625,490	605,439	595,144	596,327	586,479	548,623	567,725
	Master's Degree	3,376	3,870	5,450	6,097	6,716	9,329	10,488	12,106	12,091	21,507	23,727	26,130	30,760	30,716	30,830	32,686
	Doctorate Degree	1,529	1,945	1,726	2,013	2,113	3,003	3,799	4,297	4,627	5,757	6,357	7,248	8,558	9,736	9,895	10,698

Source: Compiled by the author based on MTE (2023a).

Table 4 – Gravimetric composition of municipal solid waste in the Municipality of Rio de Janeiro from 2006 to 2021.

REFERENCE – MSW		2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021
Gravimetric composition	Paper – Cardboard (%)	14.83	14.56	15.96	16.08	16.46	16.84	15.99	16.83	15.62	15.14	14.82	14.70	14.31	14.63	11.17	15.44
	Plastic (%)	14.69	17.15	18.58	20.31	19.11	19.29	19.14	18.99	21.01	17.84	20.24	24.66	15.33	15.72	15.69	15.63
	Glass (%)	2.71	2.96	2.79	2.84	2.96	3.19	3.28	3.39	3.46	3.69	3.55	3.46	3.48	3.58	4.37	4.31
	Metal (%)	1.61	1.59	1.51	1.74	1.40	1.68	1.57	1.63	1.65	1.68	1.65	1.51	1.81	1.75	1.51	1.33
	Others (%)	4.82	5.51	4.95	5.40	5.04	6.33	6.75	6.35	6.26	8.05	6.51	6.46	14.56	16.99	20.48	17.90
	Organic matter (%)	61.35	58.23	56.21	53.63	55.02	52.68	53.28	52.81	52.00	53.60	53.23	49.21	50.51	47.33	46.78	45.39

Source: Compiled by the author based on COMLURB (2023).

POP.PWS.SSY-MRJ (Thomaz; Mahler; Calôba, 2023), is integrated into its functionalities. This algorithm recognizes the subsets of training, validation, and final tests indexed to the datasets, allowing the ANN to be evaluated in different scenarios of epochs or hidden layers.

The ANN in this study operates using multiple layers of output nodes, commonly called multilayer perceptron. These layers include hidden or intermediate layers. Within each layer, individual neurons maintain direct connections with neighboring neurons in the adjacent layer. During the training process, detected errors are fed back into the network to adjust weight values, ultimately minimizing the error function (Beale; Hagan; Demuth, 2022).

The hyperparameters and the arrangement of the ANN layers were performed using the empirical method proposed by Beale, Hagan, and Demuth (2022). The number of hidden layers was chosen based on the suitability of the results, avoiding excessive layers that could lead to overfitting and harm the generalization process. Initially, tests were conducted with ten epochs or hidden layers, and the number of epochs or layers was increased to nine hundred. However, simulations performed with more than 500 epochs or layers required a significant computational effort, but the performance of the results did not improve proportionally.

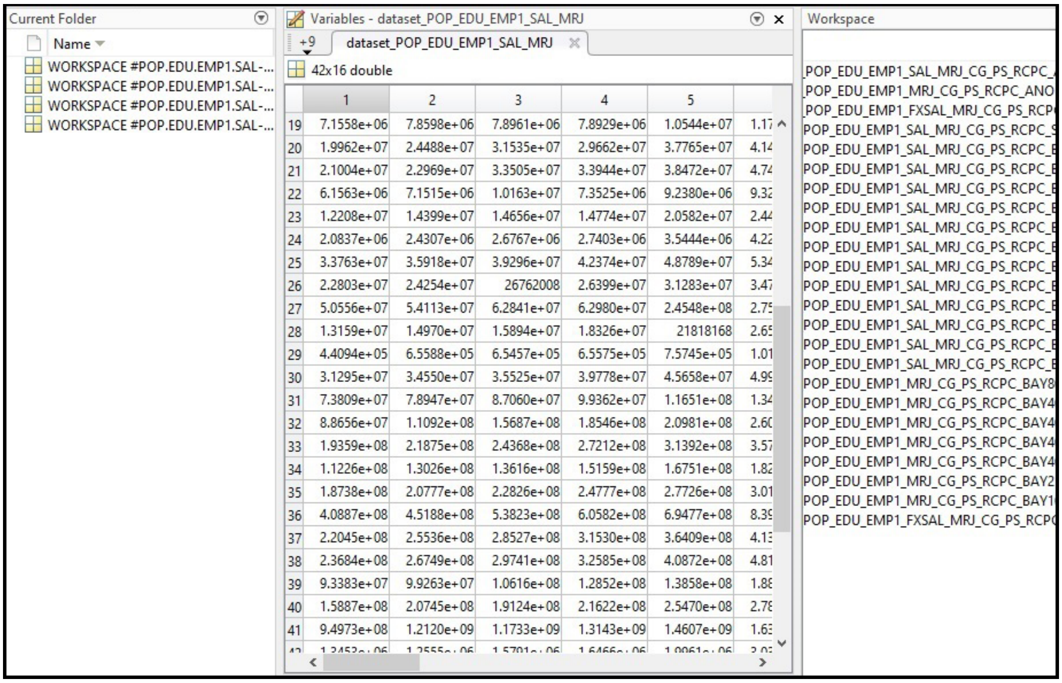
At the same time, real-time monitoring of network learning, as shown in Figure 3, makes it possible to cancel, reconfigure, and restart the process at any time. The evaluation of ANN training performance is carried out using the mean squared error (MSE) values in relation to the number of training epochs. The MSE metric emphasizes larger errors by squaring each individual error before averaging these squared errors, so the closer the MSE metric is to zero, the better the ANN performs.

Each simulation automatically generates one result matrix within the MATLAB Workspace, including the graphical representation of the obtained versus desired results. To check the robustness of the predictions, inspections corresponding to Equations 1 and 2 are additionally carried out:

$$\text{Absolut Error} = \text{Reference Value} - \text{Estimated Value} \quad \text{(Eq. 1)}$$

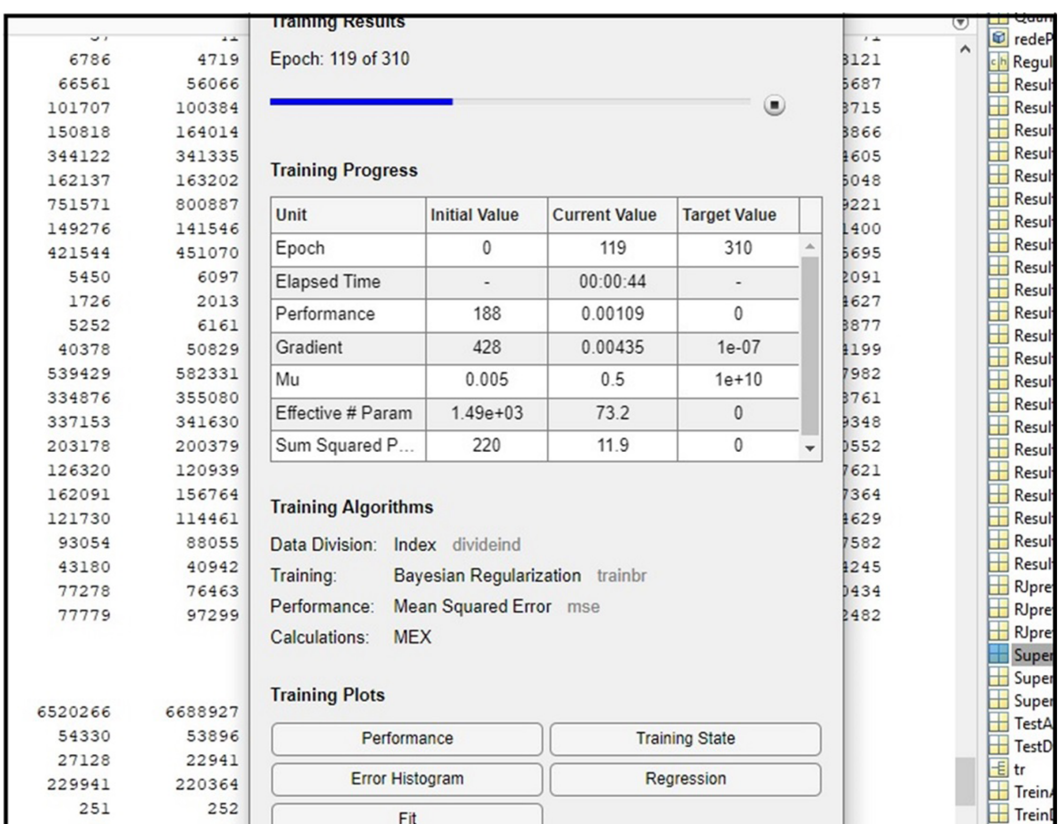
$$\text{Relative Error} = \frac{\text{Absolut Error}}{\text{Reference Value}} \quad \text{(Eq. 2)}$$

The validation of the proposed model was carried out by comparing the results achieved by the new model with the reference values (Table 4) and with the paradigm errors presented by the standard models #POP.ELE.GDP.



Source: Author.

Figure 2 – MATLAB Workspace.



Source: Author.

Figure 3 – Real-time monitoring of learning.

RSI-MRJ (Thomaz, 2016) and #GDP.POP.PWS.SSY-MRJ (Thomaz; Mahler; Calôba, 2023), less than 26% and 9%, respectively. The final test of the proposed model was conducted for the year 2021, symbolizing the evolution in relation to the previously established models. The results are available in the "Results and Discussion" section.

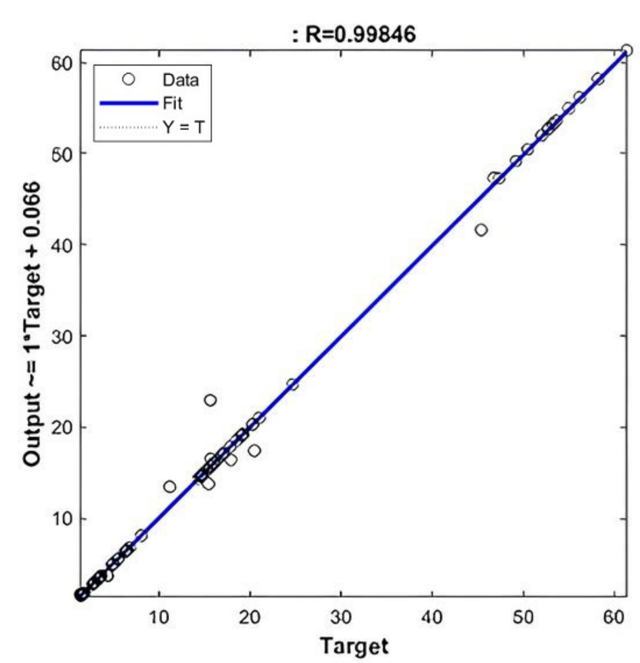
RESULTS AND DISCUSSION

Evaluating the #POP.EST.EDU.JBN-MRJ model

To evaluate the interchangeability of datasets, the new proposed model, here identified as #POP.EST.EDU.JBN-MRJ, repeated only one variable adopted in the standard models: the population quantity, as it is a representative variable with regular availability over the last five decades (IBGE, 2023d). At the same time, the economic variables, represented in standard models by the variables GDP (IBGE, 2023a; IBGE, 2023c) or RSI (IBGE, 2023b), were replaced by the variable number of establishments by economic activity (MTE, 2023b). Additionally, it incorporated the variable number of jobs by education degrees (MTE, 2023a), which simultaneously encompasses both economic and educational indicators.

Therefore, the socioeconomic dataset that feeds the ANN, corresponding to the years 2006–2021, is composed of data relating to the quantitative population, the number of establishments by economic activity, and the number of jobs by education degrees. Consolidated input data corresponding to socioeconomic factors (Tables 1–3) and targets related to the gravimetric composition of MSW (Table 4) were incorporated into MATLAB Workspace and subjected to the algorithm Bayesian Regulation through the Deep Learning Toolbox.

The graphical representation of the obtained versus desired results for the model #POP.EST.EDU.JBN-MRJ (Figure 4) makes it possible to observe the concentration of points close to the adjustment line, indicating, preliminarily, the adjustment between output and target for the entire period (2006–2021).



Source: Author.

Figure 4 – Model #POP.EST.EDU.JBN-MRJ regression plot.

To compare the results of the new model #POP.EST.EDU.JBN-MRJ with those from the models #POP.ELE.GDP.RSI-MRJ (Thomaz, 2016) and #POP.ELE.GDP.RSI-MRJ (Thomaz; Mahler; Calôba, 2023), the first targets selected were those corresponding to the year 2011, for which the two standard models were tested.

The prediction results for the year 2011 revealed errors of less than 10% for all fractions, as shown in Table 5.

While the maximum error in the standard model #POP.ELE.GDP.RSI-MRJ reached 26% and the maximum error in the standard model #POP.ELE.GDP.RSI-MRJ reached 9% (Thomaz, 2016; Thomaz; Mahler; Calôba, 2023), the maximum error evidenced for the new model #POP.EST.EDU.JBN-MRJ was 8.54 % in the module, therefore lower than errors paradigmatic associates to the standard models. Consequently, this scenario is favorable to the continuity of the validation procedures of the proposed model.

Then, to evaluate the performance of the model #POP.EST.EDU.JBN-MRJ in the pandemic context, the year 2020 was chosen, as it corresponds to the principle of disruption.

The prediction results for the year 2020 revealed errors smaller than 10% for most fractions, except for the fraction "Others", which presents an error of 18.21% in the module, according to Table 6.

The error of 18.21% for the "Others" fraction is expressive and, in a first analysis, would imply the invalidation of the new proposed model. However, it should be remembered that the predictions performed by artificial intelligence applications are based on logical patterns associated with expected behaviors.

Table 5 – Compliance check for the year 2011.

COMPLIANCE CHECK		Reference	Estimated	Error	
#POP.EST.EDU.JBN-MRJ		2011	2011	Absolute	Relative
Gravimetric composition	Paper - Cardboard	16.84%	16.37%	0.46126	2.74%
	Plastic	19.29%	19.87%	0.58103	−3.01%
	Glass	3.19%	3.46%	0.27229	−8.54%
	Metal	1.68%	1.73%	0.04733	−2.82%
	Others	6.33%	6.73%	0.39274	−6.20%
	Organic matter	52.68%	51.84%	0.83213	1.58%

Source: Author.

Table 6 – Compliance check for the year 2020.

COMPLIANCE CHECK		Reference	Estimated	Error	
#POP.EST.EDU.JBN–MRJ		2020	2020	Absolute	Relative
Gravimetric composition	Paper – Cardboard	11.17%	12.24%	1.06697	−9.55%
	Plastic	15.69%	14.50%	1.19306	7.60%
	Glass	4.37%	4.74%	0.37221	−8.52%
	Metal	1.51%	1.63%	0.12059	−7.99%
	Others	20.48%	16.75%	3.72900	18.21%
	Organic matter	46.78%	50.14%	3.36229	−7.19%

Source: Author.

Consequently, this model was successful in revealing that the effective generation of "Others" waste is different from the expected pattern for the boundary conditions related to the proposed dataset.

As both the standard model and the proposed model have population quantitative variables and economic variables, it is possible to assume that the absence of the basic sanitation variable caused worsening in the proposed model. In this sense, to determine the reasons for such a discrepancy between the predicted value and the reference value, whose error represents twice the maximum paradigm, the first step corresponds to the appreciation of the historical behavior of the "Others" fraction to check if there is a change in the standard in any item related to sanitation.

According to COMLURB (2023), the "Others" fraction represented 14.56% of the waste gravimetric composition in 2018, 16.99% in 2019, and 20.48% in 2020. The "Others" fraction includes inert (stone, sand, earthenware, and ceramics), leaf/flowers, wood, rubber, cloth/rag, leather, bone, coconut, candle/paraffin, electro/electronic, textiles, and sanitary papers.

Analyzing the waste components of the "Others" fraction, it could be seen that the sudden increase was caused by the item "Textiles and Sanitary papers", which grew from 7.77% in 2019 to 11.55% in 2020, according to COMLURB (2023). This increase is consistent with the globally reported unusual consumer behavior of buying and hoarding toilet paper (Kirk; Rifkin, 2020; Laato *et al.*, 2020).

Consequently, the disruption in the pattern has negatively influenced the results of the proposed model, but not to a degree that hinders the ongoing evaluation, considering that the error of 18.21% is lower than the paradigm error of 26% associated with the standard model # POP.ELE.GDP.RSI-MRJ.

Afterward, the year 2021 was chosen for the final test because it represents the improvement proportioned by the proposed model #POP.EST.EDU.JBN-MRJ. The prediction results for the year 2021 revealed errors smaller than 10% for all fractions, but the fraction "Others" requires attention once again due to an error of 9.59% in modulus, slightly higher than the paradigm error attributed to the model # GDP.POP.PWS.SSY-MRJ, but less than half of the paradigm error attributed to the model #POP.ELE.GDP.RSI-MRJ (Thomaz, 2016; Thomaz; Mahler; Calôba, 2023). The results can be observed in Table 7.

The result shows that the generation of "Others" waste associated with the year 2021 remained different from the expected pattern for the boundary conditions linked to the dataset proposed, indicating that the phenomenon of unusual purchasing behavior that occurred in 2020 (Kirk; Rifkin, 2020; Laato *et al.*, 2020) was slightly maintained in 2021.

In general terms, the proposed model #POP.EST.EDU.JBN-MRJ performed better than the standard model #POP.ELE.GDP.RSI-MRJ (Thomaz, 2016), both for the validation subset and for the final test subset, indicating that the adoption of the new number variables of establishments by economic activity and number of jobs by education degrees provided greater accuracy in predictions.

Table 7 – Compliance check for the year 2021.

COMPLIANCE CHECK		Reference	Estimated	Error	
#POP.EST.EDU.JBN–MRJ		2021	2021	Absolut	Relative
Gravimetric composition	Paper – Cardboard	15.44%	16.66%	1.22358	-7.92%
	Plastic	15.63%	14.38%	1.25066	8.00%
	Glass	4.31%	4.51%	0.20485	-4.75%
	Metal	1.33%	1.27%	0.05636	4.24%
	Others	17.9%	16.18%	1.71729	9.59%
	Organic matter	45.39%	46.99%	1.59587	-3.52%

Source: Author.

On the contrary, although the proposed model achieved similar performance to the standard model for predictions related to the years 2011 and 2021, the standard model achieved better performance in predictions associated with the year 2020, indicating that the variables linked to basic sanitation adopted in the model #GDP.POP.PWS.SSY-MRJ (Thomaz; Mahler; Calôba, 2023) and absent in the #POP.EST.EDU.JBN-MRJ model may have been responsible for this greater assertiveness of the precursor model.

Potential accuracy improvement by combining interchangeable models

As previously stated, data on the GDP variable after 2020 were unavailable at the time of this study (IBGE, 2023a; IBGE, 2023c), making predictions using the #GDP.POP.PWS.SSY-MRJ model impossible, which is a noble reason for the interchangeability proposal. However, when GDP data is available for adoption of #GDP.POP.PWS.SSY-MRJ (Thomaz; Mahler; Calôba, 2023), it is advantageous to run predictions using the #POP.EST.EDU.JBN-MRJ model in parallel, even if its paradigm error is larger since the combined adoption of models can increase the effective accuracy of predictions. In fact, there are combinations in which the effective error may be lower than the smallest paradigm error of the models due to the reduction in the amplitude of the intersection set that includes the results obtained by the different models.

CONCLUSIONS

The selection of datasets based on relevance, frequency, and availability criteria is fundamental, but it essentially reflects the moment of conception, and it is not possible to control the future availability of the variables that structure the datasets. This may make the full adoption of the corresponding models unfeasible, as observed in the #POP.ELE.GDP.RSI-MRJ and #GDP.POP.PWS.SSY-MRJ models, which could not be adopted for predictions after the year 2020.

However, the advantages presented by ANN models, to the detriment of field sampling, such as speed, economy, and protection of workers against physical, chemical, and biological risks, require efforts to maintain updated, functional, and efficient models. In this sense, the present work proposes dataset interchangeability as an effective way to enable predictions of the gravimetric composition of MSW after the year 2020. To validate the proposal, the #POP.EST.EDU.JBN-MRJ model was fed by an alternative dataset composed of the variables quantitative population, number of establishments by economic activity, and number of jobs by education degrees.

The interchangeability proved to be consistent for the pre-pandemic period, with errors smaller than the paradigm limit. For predictions related to the years 2020 and 2021, errors of less than 10% were found for all fractions, but the "Others" fraction presented an error of 18.21% for the year 2020 and 9.59% for the year 2021. These errors are lower than the paradigm error attributed to the first standard model, #POP.ELE.GDP.RSI-MRJ, but higher than the 9% paradigm error attributed to the second standard model, #GDP.POP.PWS.SSY-MRJ, which required attention in the analysis stage. Consequently, interchangeability may be critical for the long-term use of ANN developed to achieve SDG.

Additionally, when revealing the error for the predictions of the "Others" fraction, the new proposed model also proved to be useful for detecting anomalous changes in the expected patterns. Therefore, the comparison between datasets resulted in the formulation of hypotheses about the variable that would have caused worsening in the proposed model. This resulted in a deeper analysis of the "Others" fraction, enabling the discovery that the abrupt change in the pattern was associated with the subfraction "Textiles and Sanitary Papers," related to an unusual consumer behavior of buying and hoarding toilet paper in the period observed.

Furthermore, the parallel application of different datasets proved to be more convenient than the unification of all available variables in a single dataset, because, while the absence of a single variable, such as GDP, can render a dataset unusable and consequently prevent the adoption of a model, the implementation of different models with alternative datasets makes it possible to reduce the effective error in predictions due to the reduction in the amplitude of the intersection set that includes the results obtained by the different models.

AUTHORS' CONTRIBUTIONS

Thomaz, I.P.L.: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Resources, Software, Validation, Visualization, Writing – original draft, Writing – review & editing. Mahler, C.F.: Project administration, Supervision.

REFERENCES

ADELEKE, Oluwatobi; AKINLABI, Stephen A.; JEN, Tien-Chien; DUNMADE Israel, Application of artificial neural networks for predicting the physical composition of municipal solid waste: An assessment of the impact of seasonal variation. *Waste Management & Research: The Journal for a Sustainable Circular Economy*, v. 39, n. 8, 2021. http://dx.doi.org/10.1177/0734242x21991642

ANDEOBU, Lynda; WIBOWO, Santoso; GRANDHI, Srimannarayana. Artificial intelligence applications for sustainable solid waste management practices in Australia: A systematic review. *Science of The Total Environment*, v. 834, 155389, 2022. https://doi.org/10.1016/j.scitotenv.2022.155389

BEALE, Mark Hudson; HAGAN, Martin; DEMUTH, Howard. *Deep Learning Toolbox™ User's Guide*. 14th ed. Massachusetts: MathWorks, 2022.

COMLURB - COMPANHIA MUNICIPAL DE LIMPEZA URBANA. *Tabela 1494* – Principais caracteristicas do lixo domicilar – composição gravimétrica percentual, peso específico e teor de umidade – Município do Rio de Janeiro – 1995-2023. 2023. Available at: www.arcgis.com/sharing/rest/content/items/ccdc3c0946ff430db6ef479befe8a5a5/data. Accessed on: 2023 Sep 11.

FAZRI, Muhammad Faizal; KUSUMA, Lintang Bayu; RAHMAWAN, Risa Burhani; FAUJI, Hardiana Nur; CAMILLE, Castarica. Implementing Artificial Intelligence to reduce marine ecosystem pollution. *IAIC Transactions on Sustainable Digital Innovation*, v. 4, n. 2, p. 101-108, 2023. https://doi.org/10.34306/itsdi.v4i2.579

GHANBARI, Forough; KAMALAN, Hamidreza; SARRAF, Amirpouya. An evolutionary machine learning approach for municipal solid waste generation estimation utilizing socioeconomic components. *Arabian Journal of Geosciences*, v. 14, n. 2, 2021. https://doi.org/10.1007/s12517-020-06348-w

IBGE - INSTITUTO BRASILEIRO DE GEOGRAFIA E ESTATÍSTICA. *Tabela 1517* – Produto Interno Bruto das capitais, segundo os setores econômicos – 2002-2012. 2023a. Available at: www.arcgis.com/sharing/rest/content/items/0fee074296c9473aa9752813c453d1c3/data. Accessed on: 2023 Sep 31.

IBGE - INSTITUTO BRASILEIRO DE GEOGRAFIA E ESTATÍSTICA. *Tabela 2261* – Índice do volume de vendas do comércio varejista por setor de atividade – Município do Rio de Janeiro – JAN 2000-DEZ 2011. 2023b. Available at: www.arcgis.com/sharing/rest/content/items/6abacfe6f53141d48c4b45ca0c314bf4/data. Accessed on: 2023 Jan 15.

IBGE - INSTITUTO BRASILEIRO DE GEOGRAFIA E ESTATÍSTICA. *Tabela 3438* – Produto Interno Bruto a preço de mercado corrente, segundo as Grandes Regiões, Unidades da Federação do Sudeste e suas capitais – 2010-2020. 2023c. Available at: www.arcgis.com/sharing/rest/content/items/fc0d70cdca5a44f39387db73b1110455/data. Accessed on: 2023 Sep 11.

IBGE - INSTITUTO BRASILEIRO DE GEOGRAFIA E ESTATÍSTICA. *Tabela 3704* – População residente estimada do Município do Rio de Janeiro – 1970 a 2022. 2023d. Available at: www.arcgis.com/sharing/rest/content/items/90106eb8874f4e8fbbc27678bbb1e772/data. Accessed on: 2023 Jul 7.

IPP - INSTITUTO PEREIRA PASSOS. *Tabela 2661* – Indicadores de resíduos sólidos urbanos – manejo de resíduos sólidos urbanos – Município do Rio de Janeiro – 2002-2022. 2023. Available at: www.arcgis.com/sharing/rest/content/items/3123338773b243509b2c1a91a4257f08/data. Accessed on: 2023 Jul 7.

KIRK, Colleen P.; RIFKIN, Laura S. I'll trade you diamonds for toilet paper: Consumer reacting, coping and adapting behaviors in the COVID-19 pandemic. *Journal of Business Research*, v. 117, p. 124-131, 2020. https://doi.org/10.1016/j.jbusres.2020.05.028

LAATO, Samuli; ISLAM, Najmul Mohammad; FAROOQ, Ali; DHIR, Amandeep. Unusual purchasing behavior during the early stages of the COVID-19 pandemic: The stimulus-organism-response approach. *Journal of Retailing and Consumer Services*, v. 57, 102224, 2020. https://doi.org/10.1016/j.jretconser.2020.102224

MOORE, Andrew. *AI-powered waste management system to revolutionize recycling*. College of Natural Resources News, 2023. Available at: https://cnr.ncsu.edu/news/2023/11/ai-waste-management/. Accessed on: 2024 Apr 7.

MTE - MINISTÉRIO DO TRABALHO E EMPREGO. *Tabela 746* – Número de empregos, por grau de instrução, segundo as faixas salariais – Município do Rio de Janeiro – 2019. 2023a. Available at: www.arcgis.com/sharing/rest/content/items/099aa2e990af474ca185d11f5f414b3c/data. Accessed on: 2023 Jul 7.

MTE - MINISTÉRIO DO TRABALHO E EMPREGO. *Tabela 2632* – Número de estabelecimentos por atividade econômica segundo as Áreas de Planejamento (AP), Regiões Administrativas (RA) e Bairros – Município do Rio de Janeiro – 2021. 2023b. Available at: www.arcgis.com/sharing/rest/content/items/26dabff74b114564bb5a0d4f9e73586b/data. Accessed on: 2023 Jul 7.

NOMAN, Abdullah All; RAFIZUL, Islam; MONIRUZZAMAN, Monir; KRAFT, Eckhard; BERNER, Senta. Assessment of municipal solid waste from households in Khulna city of Bangladesh. *Heliyon*, v. 9, n. 12, e22446, 2023. https://doi.org/10.1016/j.heliyon.2023.e22446

ONYEAKA, Helen; TAMASIGA, Phemelo; NWAUZOMA, Uju Mary; MIRI, Taghi; JULIET, Uche Chioma; NWAIWU, Ogueri; AKINSEMOLU, Adenike A. Using artificial intelligence to tackle food waste and enhance the circular economy: Maximising resource efficiency and minimising environmental impact: A review. *Sustainability*, v. 15, n. 13, p. 10482, 2023. https://doi.org/10.3390/su151310482

PMRJ - PREFEITURA DA CIDADE DO RIO DE JANEIRO. *Plano Municipal de Gestão Integrada de Resíduos Sólidos – PMGIRS da Cidade do Rio de Janeiro*. 2021. Available at: www.rio.rj.gov.br/dlstatic/10112/13305794/4334422/PMGIRSVERSAO12_08_21.pdf. Accessed on: 2023 Jun 7.

SAID, Zafar; SHARMA, Prabhakar; THI BICH NHUONG, Quach; BORA, Bhaskor J; LICHTFOUSE, Eric; KHALID, Haris M.; LUQUE, Rafael; NGUYEN, Xuan Phuong; HOANG, Anh Tuan. Intelligent approaches for sustainable management and valorisation of food waste. *Bioresource Technology*, v. 377, 128952, 2023. https://doi.org/10.1016/j.biortech.2023.128952

SÁNCHEZ, Antoni. Special Issue Titled "10th Anniversary of Processes: Recent Advances in Environmental and Green Processes". *Processes*, v. 12, n. 3, p. 552, 2024. https://doi.org/10.3390/pr12030552

SEYYEDI, Seyed Reza; KOWSARI, Elaheh; RAMAKRISHNA, Seeram; GHEIBI, Mohammad; CHINNAPPAN, Amutha. Marine plastics, circular economy, and artificial intelligence: A comprehensive review of challenges, solutions, and policies. *Journal of Environmental Management*, v. 345, 118591, 2023. https://doi.org/10.1016/j.jenvman.2023.118591

SHEKOOHIYAN, Sakine; HADADIAN, Mobina; HEIDARI, Mohsen; HOSSEINZADEH-BANDBAFHA, Homa. Life cycle assessment of Tehran Municipal solid waste during the COVID-19 pandemic and environmental impacts prediction using machine learning. *Case Studies in Chemical and Environmental Engineering*, v. 7, 10331, 2023. https://doi.org/10.1016/j.cscee.2023.100331

SNIS - SISTEMA NACIONAL DE INFORMAÇÕES SOBRE SANEAMENTO. *Tabela 1477* – População total, população atendida, quantidade de ligações, quantidade de economias e extensão de rede de abastecimento de água – Município do Rio de Janeiro – 1996-2022. 2023a. Avalilable at: https://www.arcgis.com/sharing/rest/content/items/0e0c2674837242b18d78f9a66f638433/data. Accessed on: 2023 Jul 7.

SNIS - SISTEMA NACIONAL DE INFORMAÇÕES SOBRE SANEAMENTO. *Tabela 1479* – Volumes de produção e distribuição pela rede de abastecimento de água – Município do Rio de Janeiro – 1996-2022. 2023b. Available at: https://www.arcgis.com/sharing/rest/content/items/17823cc5cc994c9588cd38ba890fb1cd/data. Accessed on: 2023 Jul 7.

SNIS - SISTEMA NACIONAL DE INFORMAÇÕES SOBRE SANEAMENTO. *Tabela 1485* – População atendida, quantidade de ligações, quantidade de economias ativas, volumes e extensão da rede do sistema de esgotamento sanitário – Município do Rio de Janeiro – 1996-2022. 2023c. Available at: https://www.arcgis.com/sharing/rest/content/items/ad48cb6eea134cecb5586a7f3efead14/data. Accessed on: 2023 Jul 10.

THOMAZ, Igor Pinhal Luqueci. *Use of Artificial Neural Networks (ANN) to predict the gravimetric composition and specific weight of Municipal Solid Waste (MSW)*. Rio de Janeiro: COPPE/Federal University of Rio de Janeiro, 2016.

THOMAZ, Igor Pinhal Luqueci; MAHLER, Claudio Fernando; CALÔBA, Luiz Pereira. Artificial Intelligence (AI) applied to waste management: a contingency measure to fill out the lack of information resulting from restrictions on field sampling. *Waste Management Bulletin*, v. 1, n. 3, p. 11-17, 2023. https://doi.org/10.1016/j.wmb.2023.06.002

UNEP - UNITED NATIONS ENVIRONMENT PROGRAMME; ISWA - INTERNATIONAL SOLID WASTE ASSOCIATION. *Global Waste Management Outlook 2024 - Beyond an age of waste: Turning rubbish into a resource*. 2024. http://dx.doi.org/10.59117/20.500.11822/44939

VALIZADEH, Jaber; HAFEZALKOTOB, Ashkan; ALIZADEH, Seyed Mehdi Seyed; MOZAFARI, Peyman. Hazardous infectious waste collection and government aid distribution during COVID-19: A robust mathematical leader-follower model approach. *Sustainable Cities and Society*, v. 69, 102814, 2021. https://doi.org/10.1016/j.scs.2021.102814

VAZQUEZ, Yamila V.; BARRAGÁN, Federico; CASTILLO, Luciana A.; BARBOSA, Silvia E. Analysis of the relationship between the amount and type of MSW and population socioeconomic level: Bahía Blanca case study, Argentina. *Heliyon*, v. 6, n. 6, e04343, 2020. https://doi.org/10.1016/j.heliyon.2020.e04343