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Statistical Modelling of Worldwide Share of Population with Cancer in the Aspect of Greenhouse Gas Emissions as Indicators of Climate Change by Generalized Linear Model Approach for Balanced Panel Data in Epidemiology

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Abstract – Greenhouse gas (GHG) emissions leading to global warming and climate change is an important topic in the world agenda for the United Nation's Sustainable Development Goal 13 as taking urgent action to combat climate change. Therefore, a rapidly increasing relationship between the GHG emissions that causes warming in the global climate and worldwide cancer risk has come to the fore. Starting from this point, in this study, the relationships between "worldwide share of population with cancer" and "annual total carbon dioxide (CO_2), nitrous oxide (N_2O), and methane (CH_4) greenhouse gas emissions" data are statistically investigated using generalized linear model (GLM) approach having "Gaussian", "inverse Gaussian", and "Gamma" distributions under "log" and "identity" link functions belonging to 187 countries' balanced panel data between 2000 and 2019. For this purpose, the response variable in this study is taken as "share of total population with any form of cancer", and also the explanatory variables are taken as "annual total CO_2, NO_2, and CH_4 greenhouse gas emissions measured in tonnes per person" belonging to these countries in the world from 2000 to 2019. The GLM approach for panel data having inverse Gaussian distribution under the log-link function is determined as the best fitted model according to goodness-of-fit test statistics (GOF) as the "quasi-likelihood under independence model criterion (QIC)" and the "corrected quasi-likelihood under independence model criterion (QICC)" with the minimum values 116.08 and 121.519, respectively. As the principle results and major conclusion of this study, share of total population with any form of cancer belonging to the 187 countries from 2000 to 2019 increases exp(0.079)=1.0822, exp(0.129)=1.1377, and exp(0.041)=1.0419 times by per capita increase in the CO_2, NO_2, and CH_4 greenhouse gas emissions measured in tonnes per person, respectively.

Keywords – Cancer, Greenhouse gas emissions, Climate change, Inverse Gaussian distribution, Gamma distribution, Gaussian distribution, Generalized linear model, panel data.

I. Introduction

Carbon dioxide (CO_2), nitrous oxide (N_2O), and methane (CH_4) mainly form greenhouse gases [1,2]. These gases are mainly responsible for the global warming in the atmosphere and climate change in the world [2,3]. Even small changes in the global warming and climate change cause hunger, famine, poverty, drought all over the world [4, 5]. Overcoming these vital problems is among the sustainable development goals of the United Nations by 2030 [6]. So dealing with the greenhouse gas (GHG) emissions mainly from CO_2, N_2O, and CH_4 is the major problem for the future of the world. From another perspective, the increase in the GHG emissions causing global warming and climate change negatively affects public health, worsen health conditions, and increases the incidence of cancer globally. Worldwide risk situations in terms of cancer, total GHG emissions, CO_2 emissions, N_2O emissions, and CH_4 emissions are given in Figure 1-Figure 5 for a visual better understanding.

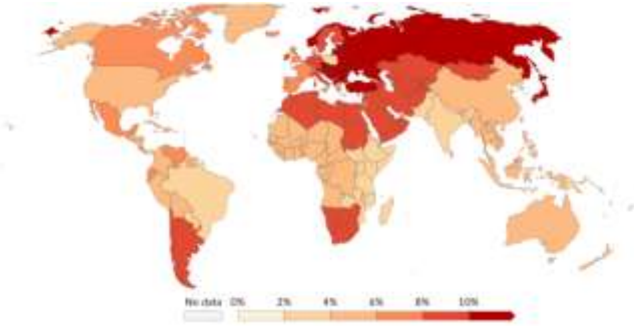

Figure 1. Share of population with cancer in 2019 [7,8,9]
Source: https://ourworldindata.org/grapher/share-of-population-with-cancer [7]

Figure 2. Greenhouse gas emissions in 2000 and 2019 [10,11,12]
Source: https://ourworldindata.org/greenhouse-gas-emissions [10]

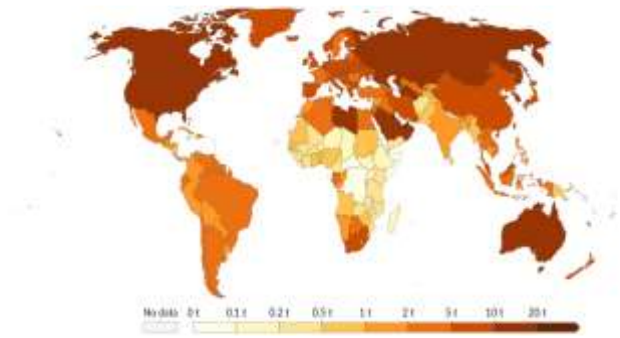

Figure 3. CO_2 emissions in 2019 [13,14,15]
Source: https://ourworldindata.org/grapher/annual-co2-emissions-per-country?tab=map&time=2019 [13]

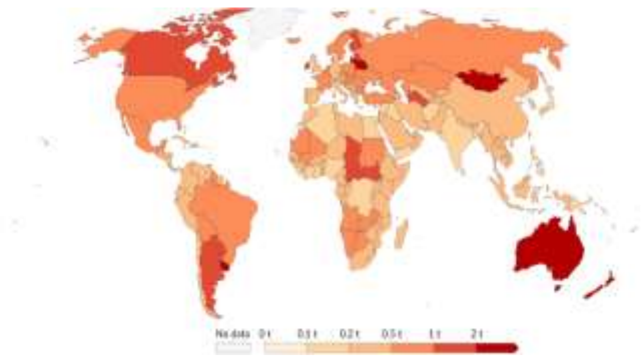

Figure 4. N_2O emissions in 2019 [16,17,18]
Source: https://ourworldindata.org/grapher/nitrous-oxide-emissions?time=2019 [16]

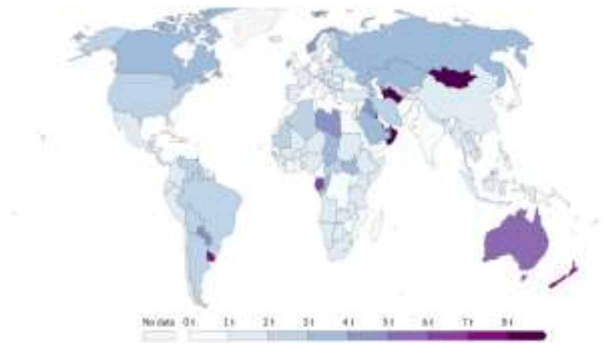

Figure 5. CH_4 emissions in 2019 [19,20,21]
Source: https://ourworldindata.org/grapher/per-capita-methane-emissions?time=2019 [19]

Nogueira et al. [22] investigated greenhouse gas emissions and cancer survival in the aspect of climate change. Aston et al. [23] studied the effects of greenhouse gas emissions on cancer by investigating nutrition in the UK. Smith et al. [24] determined the effects of greenhouse pollutants on the lung cancer in public health. Gao et al. [25] reviewed greenhouse gas emissions reduction on the public health globally. Erickson et al. [26] investigated greenhouse gas emissions and air quality in the aspect of the lung cancer. West et al. [27] studied extensively the relationships between greenhouse gas emissions, air quality and human health in lung cancer. Also Wilkinson et al. [28] developed strategies to prevent lung cancer in public health by reducing greenhouse-gas emissions. Interestingly, Gordon et al. [29] researched the effects of greenhouse-gas emissions on colorectal cancer. Haines et al. [30] also developed strategies to prevent cancer in public health by reducing greenhouse-gas emissions for low-income countries. Laine et al. [31] investigated European environmental health in the aspect of cancer in terms of greenhouse-gas emissions.

In the light of these studies in the literature, in this study, the relationships between “worldwide share of population with cancer” and “annual total carbon dioxide (CO_2), nitrous oxide (N_2O), and methane (CH_4) greenhouse gas emissions” data are statistically investigated using generalized linear model (GLM) approach having “Gaussian”, “inverse Gaussian”, and “Gamma” distributions under “log” and “identity” link functions belonging to 187 countries’ balanced panel data between 2000 and 2019.

II. Materials and Method

In the materials part of this study, the response variable is taken as “share of total population with any form of cancer”, and also the explanatory variables are taken as “annual total CO_2, NO_2, and CH_4 greenhouse gas emissions measured in tonnes per person” belonging to the187 countries in the world from 2000 to 2019.

The names and descriptions of the response and explanatory variables taken into the study to model the statistical relationships between them are given in Table 1.

Table 1. Descriptions of the variables for modelling worldwide share of population with cancer and greenhouse gas emissions data used in this study [32-35]

Response/Explanatory Variables	**Descriptions**
Share of population with cancer	Share of total population with any form of cancer, measured as the age-standardized percentage belonging to the 187 countries in the world from 2000 to 2019 [32]
CO_2 emissions	Annual total carbon dioxide (CO_2) emissions from fossil fuels and industry, measured in tonnes per person belonging to the 187 countries in the world from 2000 to 2019 [33].
N_2O emissions	Annual nitrous oxide (N_2O) emissions measured in tonnes of CO_2-equivalents belonging to the 187 countries in the world from 2000 to 2019 [34]
CH_4 emissions	Annual total methane (CH_4) emissions belonging to the 187 countries in the world from 2000 to 2019 [35]

Descriptive statistics of the response and explanatory variables taken in to the study belonging to the187 countries in the world from 2000 to 2019 are given in Table 2.

Table 2. Descriptive statistics of the response and explanatory variables taken into the study belonging to the187 countries in the world from 2000 to 2019

Years	Share of population with cancer				CO_2 emissions				N_2O emission				CH_4 emission			
	Min	Mean	Sd	Max	Min	Mean	Sd	Max	Min	Mean	Sd	Max	Min	Mean	Sd	Max
2000	1.6633	6.7882	3.4635	20.0739	0.0351	4.5263	6.9616	62.4115	0.0437	0.5400	0.6647	4.8478	0.2324	2.5453	5.3097	58.0343
2001	1.6434	6.8007	3.4752	20.0565	0.0317	4.5428	7.0512	67.4937	0.0455	0.5320	0.6538	5.2834	0.2313	2.4917	4.9039	49.9000
2002	1.6001	6.8206	3.4935	20.0151	0.0320	4.4891	6.7698	63.1899	0.0492	0.5289	0.6264	4.8909	0.2360	2.3995	4.6335	48.0917
2003	1.5492	6.8425	3.5159	19.9757	0.0235	4.6664	6.9381	62.1413	0.0505	0.5166	0.5509	3.6827	0.2336	2.4573	4.8558	51.4728
2004	1.5105	6.8602	3.5357	19.9460	0.0278	4.7382	6.9473	60.8270	0.0503	0.5199	0.5626	4.0287	0.2315	2.4466	4.7881	51.5031
2005	1.4982	6.8709	3.5476	19.9555	0.0208	4.7223	6.8187	56.0266	0.0495	0.5193	0.5401	3.4518	0.2313	2.4140	4.3937	45.3737
2006	1.5207	6.8740	3.5484	20.0128	0.0239	4.8030	6.9789	58.7451	0.0485	0.5219	0.5668	3.7831	0.2315	2.3864	4.1315	40.8050
2007	1.5617	6.8756	3.5496	20.1206	0.0254	4.7966	6.6476	48.2043	0.0481	0.5206	0.5570	3.5055	0.2324	2.3193	3.8815	37.8613
2008	1.6087	6.8753	3.5523	20.2401	0.0252	4.7721	6.4567	42.6764	0.0480	0.5157	0.5596	3.4763	0.2318	2.3306	3.8923	36.3820
2009	1.6488	6.8746	3.5570	20.3371	0.0194	4.5211	6.0881	40.4114	0.0477	0.4997	0.5286	3.4400	0.2316	2.2350	3.6262	34.8137
2010	1.6678	6.8738	3.5582	20.3852	0.0325	4.6824	6.3141	42.8486	0.0474	0.5077	0.5460	3.7138	0.2325	2.2495	3.7581	38.6662
2011	1.6736	6.8736	3.5520	20.3974	0.0360	4.6789	6.3245	45.1693	0.0482	0.5429	0.6816	4.6068	0.2373	2.2663	3.8660	40.3279
2012	1.6808	6.8714	3.5404	20.3932	0.0359	4.7063	6.4646	48.9702	0.0452	0.5373	0.6584	4.4635	0.2406	2.2695	3.8978	40.5424
2013	1.6882	6.8697	3.5292	20.3956	0.0244	4.5625	5.9850	40.6818	0.0424	0.5082	0.5372	3.4338	0.2411	2.2256	3.9416	41.7617
2014	1.6938	6.8693	3.5210	20.3992	0.0260	4.4879	5.8945	41.1735	0.0385	0.5016	0.5419	3.6652	0.2421	2.1768	3.6939	37.7185
2015	1.7032	6.8729	3.5190	20.3937	0.0331	4.4231	5.7411	37.7682	0.0351	0.5005	0.5410	3.8196	0.2459	2.1531	3.5311	35.5510
2016	1.7090	6.8779	3.5163	20.3939	0.0314	4.4029	5.5453	33.6722	0.0318	0.4976	0.5295	3.8769	0.2473	2.1144	3.3782	33.6788
2017	1.7167	6.8835	3.5129	20.3803	0.0368	4.4618	5.6357	36.9174	0.0308	0.5017	0.5540	3.9577	0.2478	2.1034	3.2672	31.9413
2018	1.8300	6.8839	3.4828	20.5149	0.0388	4.4279	5.5243	34.5041	0.0297	0.4904	0.5424	3.8629	0.2488	2.0777	3.2488	32.1103
2019	2.0310	6.8751	3.4336	20.8155	0.0399	4.4268	5.6184	35.9851	0.0303	0.4874	0.5366	3.9683	0.2447	2.0843	3.4954	35.9694

On the other hand, for an easier understanding, the line graphs of top 10 countries with the highest averages of the response and explanatory variables taken into the study from 2000 to 2019 are given in Figure 1.

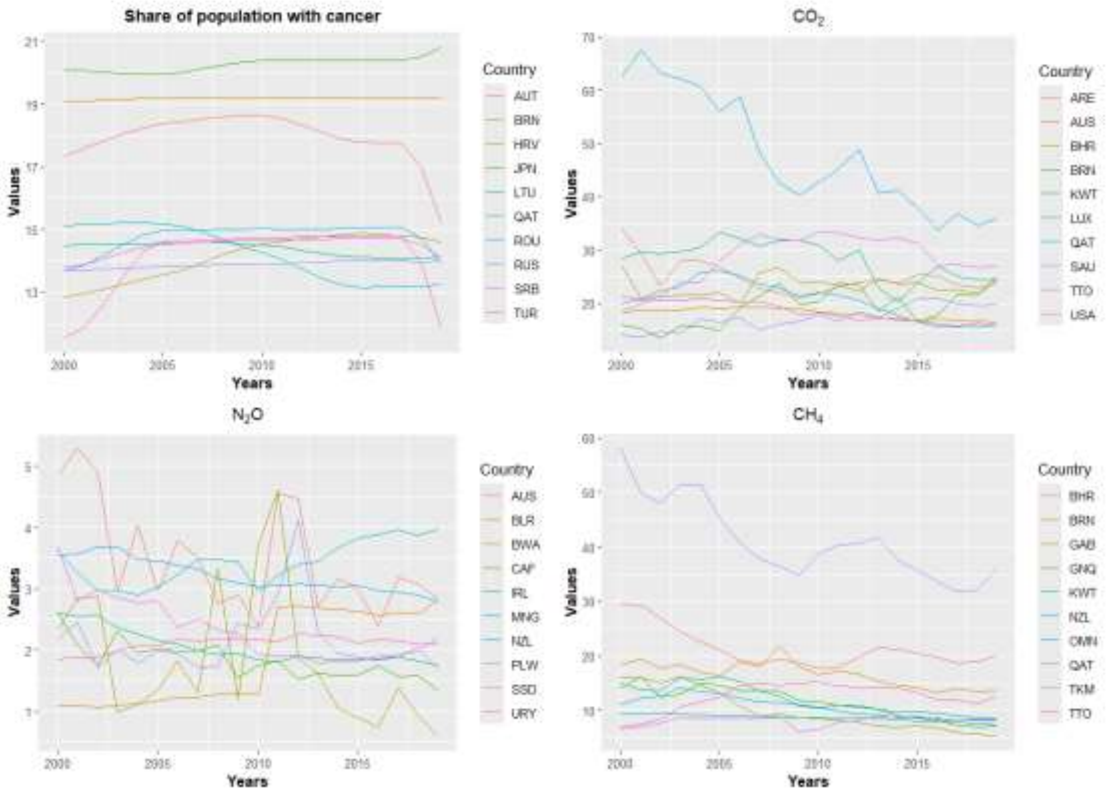

Figure 1. The line graphs of top ten countries with the highest averages of the response and explanatory variables taken into the study from 2000 to 2019

As can be seen from both Table 2 and Figure 1, top ten countries with the highest averages of response and explanatory variables taken into the study from 2000 to 2019 are Austria (AUT) with 17.9285, Brunei (BRN) with 19.1705, Croatia (HRV) with 14.1373, Japan (JPN) with 20.2601, Lithuania (LTU) with 14.3806, Qatar (QAT) with 14.2444, Romania (ROU) with 14.7498, Russia (RUS) with 13.8863, Serbia (SRB) with 14.477, and Turkey (TUR) with 14.0571 for “share of total population with any form of cancer”; Australia (AUS) with 18.0492, Bahrain (BHR) with 23.2118, Brunei (BRN) with 19.2095, Kuwait (KWT) with 28.2023, Luxembourg (LUX) with 20.5471, Qatar (QAT) with 47.9909, Saudi Arabia (SAU) with 17.2666, Trinidad and Tobago (TTO) with 28.2645, United Arab Emirates (ARE) with 24.875, and United States (USA) with 18.4866 for “CO_2 emissions”; Australia (AUS) with 3.4836, Belarus (BLR) with 1.8460, Botswana (BWA) with 1.8274, Central African Republic (CAF) with 1.8225, Ireland (IRL) with 2.0432, Mongolia (MNG) with 3.4267, New Zealand (NZL) with 3.2134, Palau (PLW) with 2.1711, South Sudan (SSD) with 2.3021, and Uruguay (URY) with 2.1050 for “N_2O emissions”, and also Bahrain (BHR) with 21.3280, Brunei (BRN) with 16.6857, Equatorial Guinea (GNQ) with 11.4452, Gabon (GAB) with 9.9472, Kuwait (KWT) with 12.039, New Zealand (NZL) with 8.6661, Oman (OMN) with 10.6524, Qatar (QAT) with 41.1253, Trinidad and Tobago (TTO) with 12.5317, and Turkmenistan (TKM) with 8.1206 for “CH_4 emissions”, respectively.

In the method part of this study, “generalized linear model (GLM) approach for panel data” called “generalized estimating equations (GEE)” having “inverse Gaussian”, “Gamma”, and “Gaussian” distributions under “log” and “identity” link functions; “independent working correlation structure”; “hybrid” parameter estimation method combining Fisher scoring and Newton-Raphson methods; and also “maximum likelihood (ML)” scale parameter estimation method are performed, respectively. For more information, see [36-50].

III. RESULTS AND DISCUSSION

In this study, the relationships between "worldwide share of population with cancer" and "annual total CO_2, N_2O, and CH_4 greenhouse gas emissions belonging to 187 countries' balanced panel data between 2000 and 2019 are statistically investigated using the generalized linear model (GLM) approach having "Gaussian" distribution under "identity" link function and also "inverse Gaussian" and "Gamma" distributions under "log" link function. All models in this study are fitted by IBM SPSS Statistics 28 programme [51] under the assumption that panel data measurements belonging to the years are uncorrelated called "independent working correlation structure".

The results of the GLM approach having "Gaussian" distribution under "identity" link function belonging to 187 countries' balanced panel data between 2000 and 2019 are given in Table 3.

Table 3. The results of the GLM approach having "Gaussian" distribution under "identity" link function belonging to 187 countries' balanced panel data between 2000 and 2019

Explanatory Variables	$\hat{\beta}$	$s.e.(\hat{\beta})$	95% Wald Confidence Interval for β		Hypothesis Test for β		
			Lower	Upper	Wald Chi-Square	df	Sig.
(Intercept)	5.629	0.0286	5.573	5.685	38862.883	1	0.000
CO_2 emissions	0.312	0.0051	0.302	0.322	3772.420	1	0.000
N_2O emissions	0.296	0.0453	0.207	0.385	42.651	1	0.000
CH_4 emissions	0.153	0.0064	-0.166	-0.141	575.775	1	0.000
(Scale)	9.758						

The model equation of the GLM approach having "Gaussian" distribution under "identity" link function belonging to 187 countries' balanced panel data between 2000 and 2019 according to Table 3 is given as follows;

$$\log\left(\hat{\mu}_{ij}\right) = 5.629 + 0.312\left(CO_2\ Emis.\right)_{ij} + 0.296\left(N_2O\ Emis.\right)_{ij} + 0.153\left(CH_4\ Emis.\right)_{ij} \quad (1)$$

where $\boldsymbol{i} = 1, 2, ..., 187$ and $\boldsymbol{j} = 1, 2, ..., 20$ represent countries and years, respectively.

The results of the GLM approach having "gamma" distribution under "log" link function belonging to 187 countries' balanced panel data between 2000 and 2019 are given in Table 4.

Table 4. The results of the GLM approach having "gamma" distribution under "log" link function belonging to 187 countries' balanced panel data between 2000 and 2019

Explanatory Variables	$\hat{\beta}$	$s.e.(\hat{\beta})$	95% Wald Confidence Interval for β		Hypothesis Test for β			$\exp(\hat{\beta})$	95% Wald Confidence Interval for $\exp(\beta)$	
			Lower	Upper	Wald Chi-Square	df	Sig.		Lower	Upper
(Intercept)	1.694	0.0039	1.686	1.701	185401.891	1	0.000	5.439	5.398	5.482
CO_2 emissions	0.051	0.0009	0.050	0.053	3574.415	1	0.000	1.053	1.051	1.054
N_2O emissions	0.080	0.0061	0.068	0.092	167.581	1	0.000	1.083	1.070	1.096
CH_4 emissions	0.032	0.0015	0.029	0.035	467.852	1	0.000	1.033	1.029	1.036
(Scale)	0.203									

The model equation of the GLM approach having "gamma" distribution under "log" link function belonging to 187 countries' balanced panel data between 2000 and 2019 according to Table 4 is given as follows;

$$\log\left(\hat{\mu}_{ij}\right)=1.694+0.051\left(CO_2\ Emis.\right)_{ij}+0.080\left(N_2O\ Emis.\right)_{ij}+0.032\left(CH_4\ Emis.\right)_{ij} \quad (2)$$

where $\boldsymbol{i}=1,2,...,187$ and $\boldsymbol{j}=1,2,...,20$ represent countries and years, respectively.

Finally, the results of the GLM approach having "inverse Gaussian" distribution under "log" link function belonging to 187 countries' balanced panel data between 2000 and 2019 are given in Table 5.

Table 5. The results of the GLM approach having "inverse Gaussian" distribution under "log" link function belonging to 187 countries' balanced panel data between 2000 and 2019

Explanatory Variables	$\hat{\beta}$	$s.e.\left(\hat{\beta}\right)$	**95% Wald Confidence Interval for β**		**Hypothesis Test for β**			$\exp\left(\hat{\beta}\right)$	**95% Wald Confidence Interval for $\exp(\beta)$**	
			Lower	**Upper**	**Wald Chi-Square**	**df**	**Sig.**		**Lower**	**Upper**
(Intercept)	1.588	0.0018	1.585	1.592	760642.796	1	0.000	4.895	4.877	4.912
CO_2 emissions	0.079	0.0008	0.077	0.080	9796.426	1	0.000	1.082	1.080	1.084
N_2O emissions	0.129	0.0082	0.113	0.145	245.413	1	0.000	1.137	1.119	1.156
CH_4 emissions	0.041	0.0035	0.034	0.048	139.640	1	0.000	1.042	1.035	1.049
(Scale)	0.029									

The model equation of the GLM approach having "inverse Gaussian" distribution under "log" link function belonging to 187 countries' balanced panel data between 2000 and 2019 according to Table 5 is given as follows;

$$\log\left(\hat{\mu}_{ij}\right)=1.588+0.079\left(CO_2\ Emis.\right)_{ij}+0.129\left(N_2O\ Emis.\right)_{ij}+0.041\left(CH_4\ Emis.\right)_{ij} \quad (3)$$

where $\boldsymbol{i}=1,2,...,187$ and $\boldsymbol{j}=1,2,...,20$ represent countries and years, respectively.

In order to determine the most appropriate statistical model among the GLMs having "Gaussian", "inverse Gaussian", and "Gamma" distributions under "log" and "identity" link functions, values of the goodness-of-fit (GOF) test statistics as QIC and QICC information criteria are given in Table 6.

Table 6. GOF test statistics belonging to the GLMs having "Gaussian", "inverse Gaussian", and "Gamma" distributions under "log" and "identity" link functions belonging to 187 countries' balanced panel data between 2000 and 2019

Model/IC	**QIC**	**QICC**
Gaussian	36458.338	36465.27
Gamma	720.488	727.158
Inverse Gaussian	116.008*	121.519*

*the smallest value indicates the most appropriate model

IV. CONCLUSION

In this study, GLM approach having “Gaussian” distribution under “identity” link function and GLM approaches having “inverse Gaussian” and “Gamma” distributions under “log” link function are used for modelling worldwide share of population with cancer and greenhouse gases emissions data. As a result of these modellings, statistically, best performing model is the GLM approach having “inverse Gaussian” distribution under “log” link function according to the GOF test statistics as QIC with 116.008 and QICC with 121.519.

The following main statistical inferences can be obtained according to the GLM approach having “inverse Gaussian” distribution under “log” link function, as the best performing model from Eq.(3) as follows;

Share of total population with any form of cancer belonging to the 187 countries increases $\exp(0.079)=1.082$, $\exp(0.129)=1.137$, and $\exp(0.041)=1.042$ percentages by one tonnes change per person for annual total CO_2, NO_2, and CH_4 greenhouse gas emissions, respectively.

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Conflict of interest: The author states no conflict of interest.

Ethical approval: The conducted research is not related to either human or animal use.

Data availability statement: All the data used in this study are public available in Our World in Data [32-35].

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