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Meteorological variables and their Incidence in Infarcted Patients using the Objective Regressive Regression Methodology in the Hospital of Sagua la Grande, Villa Clara, Cuba

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Abstract

In this research, the number of infarction cases in the hospital of Sagua la Grande during the period, 2018-2021, was modelled by means of the methodology of the Regressive Objective Regression (ROR), taking into account the incidence of some meteorological variables. The data were analysed using mathematical modelling, by means of the ROR methodology, with the help of the SPSS statistical package, version 19. The municipality of Sagua la Grande was found to have the highest number of myocardial infarctions, followed by the municipalities of Cifuentes, Corralillo and Quemado de Güines. January and February were the months with the highest incidence, followed by May and November. Days 3 and 6 were those with the highest incidence, with more than 15 cases, while the lowest number of heart attacks occurred on days 2, 19 and 30, with an average of 9.4 cases attended. The highest number of cases attended occurred in the hours from 5am to 7.59am, from 8am to 11am, as well as at 6pm, 9pm and 11pm. The average number of cases attended was 11.2/hour. The highest number of infarction victims was in the 68-73 age group, with an average of 5.1 cases. The male sex was the most affected (63.92%), while the female sex was 36.08%. In the case of the climatic variables, the minimum temperature regressed in 4 cases, the mean relative humidity regressed in 2 steps, and rainfall one step back were significant. It is concluded that, the older the age, the greater the possibility of being infarcted, where the tendency of infarcts is to occur in the morning hours, so it is possible to predict acute myocardial infarction using the ROR methodology.

Keywords: Acute myocardial infarction, Modelling, Regressive Objective Regression, Sagua la Grande

1. Introduction

Nowadays, it is increasingly common to find young people diagnosed with acute myocardial infarction (AMI), which may be associated with an increase in risk factors such as work overload, work stress, poor dietary habits, sedentary lifestyle, obesity, smoking and addictions [1-3]. It is noteworthy that despite many studies addressing the relationship between infarcted patients and climatological variables [4-10], among many others; the opposite is true for addressing the relationship between climate variables with infarcted patients using mathematical modeling [11-14].

Studies related to the application of mathematical modeling in arboviral and parasitic entities, transmitted by vector organisms,

are much more numerous [15-19, 21-24], as well as recent research on the use of mathematical modeling as a function of COVID-19 [20, 25-28].
Internationally, research on the incidence of meteorological variables in infarcted patients using mathematical modeling is scarce [14,29-32], something similar happens in Cuba [33-37].
The objective of the research was to determine the level of incidence of some meteorological variables in infarcted patients by means of the Objective Regressive Regression methodology in the municipality of Sagua la Grande, Villa Clara, Cuba.

2. Material and methods

For the modeling and prognosis of acute myocardial infarction in the Hospital of Sagua La Grande, Villa Clara province, Cuba, it was modeled using the methodology of Objective Regressive Regression ROR [38], for which, in a first step, dichotomous variables DS, DI and NoC are created, where:

NoC: Number of cases of the base/trend of the series.
DS: Sawtooth
DI: Inverted Sawtooth
DS = 1, if NoC is odd; DI = 0, if NoC is even, when DI=1, DS=0 and vice versa.
Subsequently, the module corresponding to the Regression analysis of the statistical package SPSS, version 19.0 (IBM Company) was executed, specifically the ENTER method where the predicted variable and the ERROR are obtained.
Then the autocorrelations of the variable ERROR were obtained, paying attention to the maximum of the significant partial autocorrelations PACF. The new variables were then calculated taking into account the significant Lag of the PACF. Finally, these regressed variables were included in the new regression in a process of successive approximations until a white noise in the errors was obtained.
The data correspond to the years 2018 to 2021 belonging to the hospital " Martyrs of April 9" of Sagua la Grande municipality, Villa Clara province, Cuba. The meteorological variables of Sagua have an approximate location with the meteorological station of that municipality (Latitude: 22º13' N, Longitude: 80º02' W).

3. Results and discussion

First, the statistics of acute myocardial infarction (AMI) were calculated for the following variables:
1. Municipality, 2. Month, 3. Day, 4. Start time, 5. Age and 6. Sex
Subsequently, ROR modeling was applied according to the date of onset of infarction, taking into account patients from the four municipalities (Cifuentes, Sagua la Grande, Quemado de Güines and Corralillo) who are treated at the Sagua la Grande hospital (Table and Figure 1); in addition, the cross-correlations of the following meteorological variables were studied: Temperatures (Maximum, Minimum and Mean), Humidities (Maximum, Minimum and Mean), Rainfall, cloudiness, wind speed and Atmospheric pressure at station and sea level with the errors of the model without meteorological variables. The four largest cross-correlations were chosen and included in a new ROR model.

Table 1: ROR modeling for the municipalities of Cifuentes, Sagua la Grande, Quemado de Güines and Corralillo by date of entry

Descriptive statistics					
	N	**Minimum**	**Max.**	**Media**	**Standard deviation**
Date of entry_nu	4	44	145	72.75	48.286
N valid (by list)	4				

The following table shows the number of infarcted patients according to the four municipalities under study.

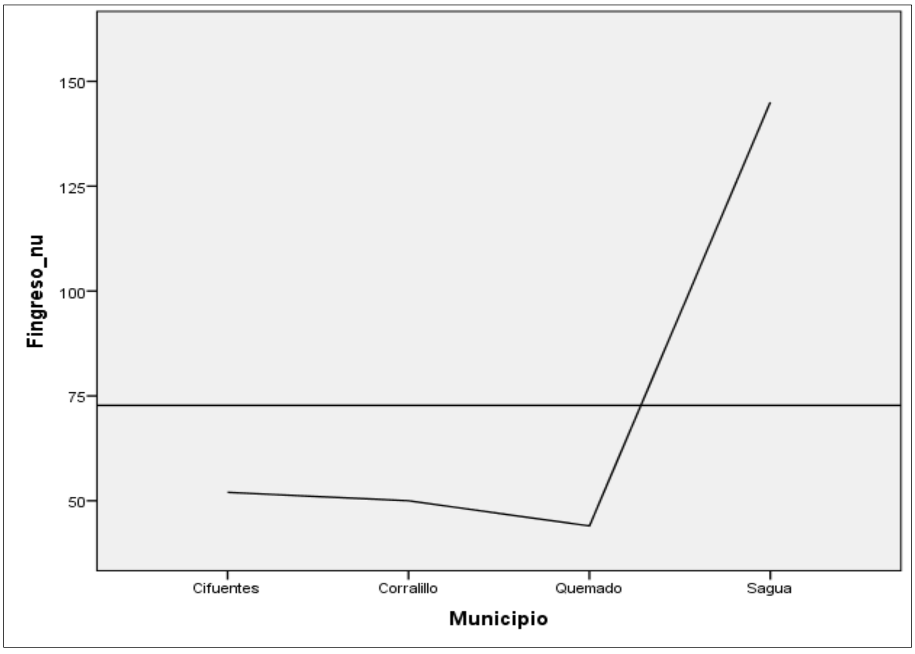

Fig 1: Number of infarcts by municipality

As shown in the figure, the municipality of Sagua la Grande had the highest number of myocardial infarctions, followed by Cifuentes, Corralillo and Quemado.
Regarding the statistics of acute myocardial infarction (AMI) by month, the results are shown in table and figure 2, where January and February were the months with the highest incidence, followed by May and November, while June and September were the months with the lowest number of infarctions. The mean was 24 cases per month. The minimum value was 14 cases and the maximum was 50; results that are largely consistent with those obtained by other authors [7, 39-42].

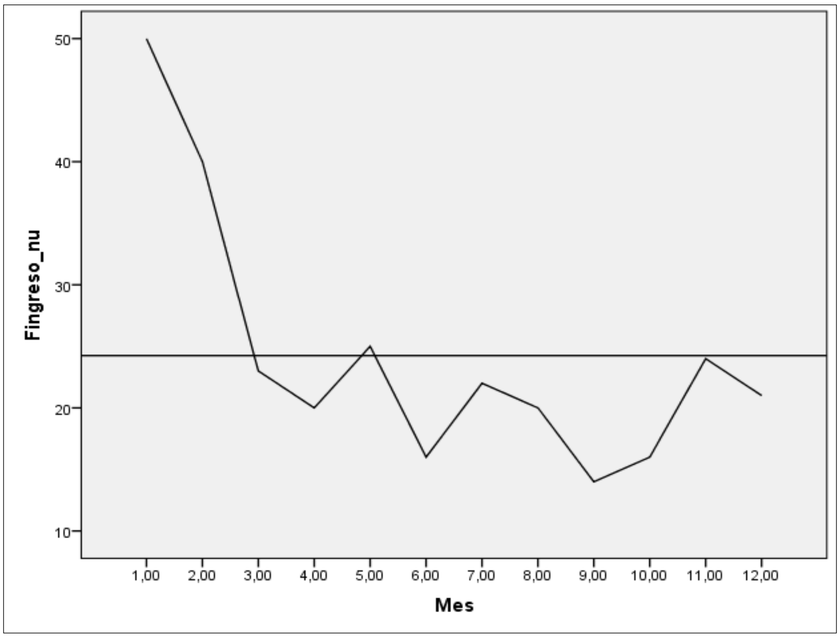

Fig 2: Number of infarcts per month

In relation to the number of infarcts per day (Table 2 and Figure 3) the results are shown, where days 3 and 6 were those with the highest incidence, with more than 15 cases, while those with the lowest number of infarcts were on days 2, 19 and day 30. The mean was 9.4 cases attended, results that coincide to some extent with those obtained by other authors in this regard [37,43,44].

Table 2: Number of infarction cases per day

Descriptive statistics					
	N	**Minimum**	**Max.**	**Media**	**Standard deviation**
Day	31	1.00	31.00	16.0000	9.09212
Date of entry_nu	31	4	16	9.39	3.116
N valid (by list)	31				

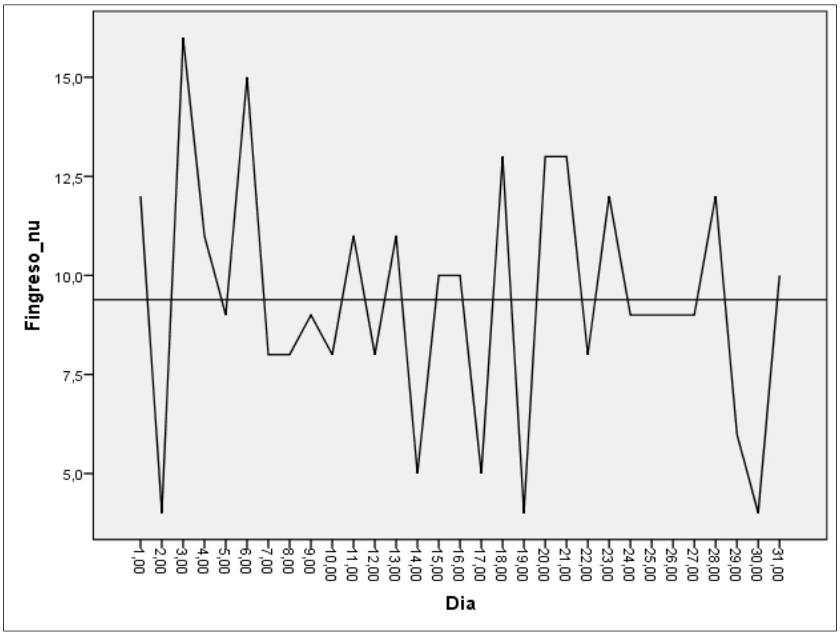

Fig 3: Number of infarcts per day

Regarding the number of infarcts per hour of onset (Figure 4), the study revealed the following results: the highest number of cases attended occurred from 5 to 7:59 am, from 8 to 11 am, at 6 pm, 9 pm, and 11 pm. The maximum is 31 infarcts and the minimum is 1, while the average number of cases attended is 11.2 per hour. Here the results achieved agree to some extent with several studies conducted, both in Cuba and in other countries [32, 36, 37, 42], of course, here are influenced by numerous factors/conditioners, both ecological, geographical, social and economic [4, 33, 45, 46, 47].

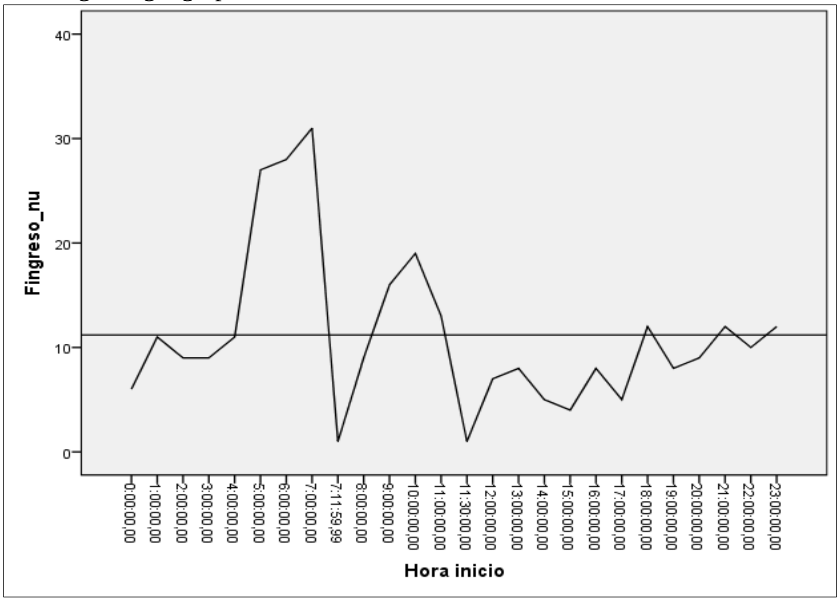

Fig 4: Number of infarcts per start time

In relation to the number of infarcted patients taking into account the variable age (Table 3, figure 5), the results showed that the greatest number of infarcted patients were between 68 and 73 years of age. The mean was 5.1 cases for given age. At a minimum, there is always an infarct from 31 to 97 years of age, which is largely associated with a whole series of comorbidities and underlying diseases that are exacerbated with age, results that coincide to some extent with those obtained by other authors in this regard [5, 37, 42, 44].

Table 3: Results of the number of infarction patients according to the variable age

Descriptive statistics					
	N	**Minimum**	**Max.**	**Media**	**Standard deviation**
Age	57	31	97	65.11	17.47
Date of entry_nu	57	1	17	5.11	3.72
N valid (by list)	57				

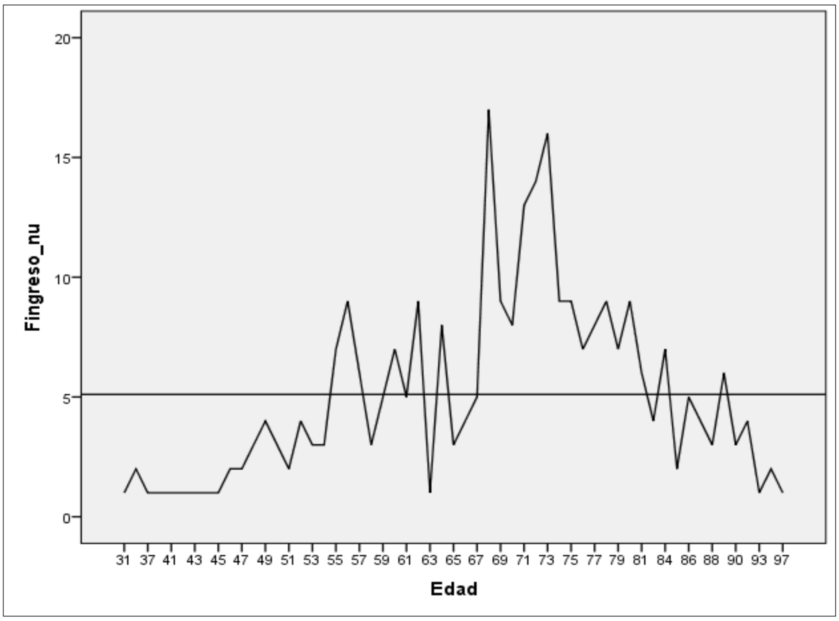

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Fig 5: Number of infarcted by age

As for the number of infarction victims by sex (Table 4, Figure 6), the highest number of infarction victims is in the male sex (63.92%), while in the female sex it was 36.08%, so men have a higher risk of suffering from this disease, whose results are largely consistent with those achieved by other researchers [14, 37, 42].

Table 4: Distribution of the number of patients with infarction according to sex

Case summaries[a]				
				Date of entry_nu
Sex	F	1		105
		Total	N	1
	M	1		186
		Total	N	1
	Total	N		2
a. Limited to the first 100 cases.				

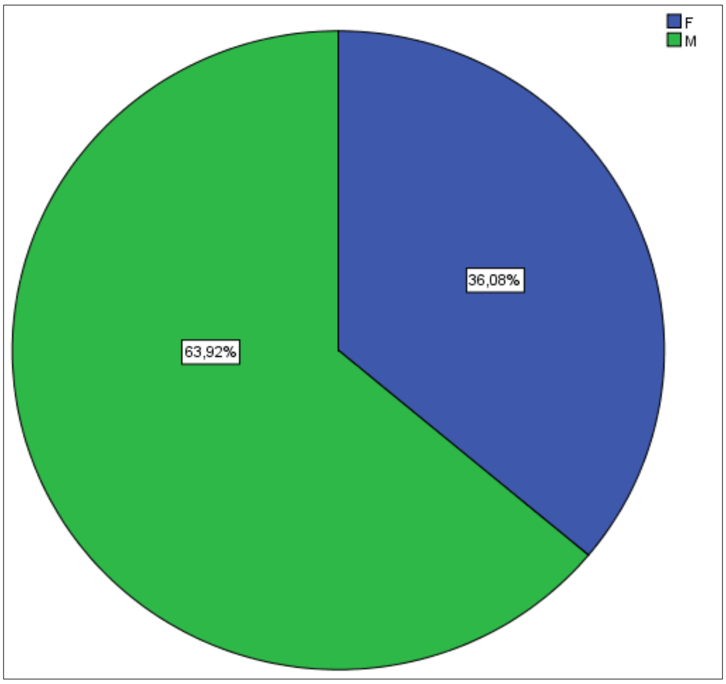

Fig 6: Number of infarcted by variable Sex (%)

3.1 ROR model of the date of onset of symptoms

Table 5 explains the 100 of the variability for the entry date, this date has an error calculated by the software.

Table 5: Results of variability by date of entry

Summary of model[c, d]					
Model	**R**	**R squared[b]**	**Adjusted R-squared**	**Standard error of estimation**	**Durbin-Watson**
1	1.000[a]	1.000	1.000	79 21:56:23.763	1.340

a. Predictors: Age, Step23, DI, NoC, SD
b. For regression through the origin (the model without intercept), R-squared measures the proportion of the variability in the dependent variable about the origin explained by the regression. This CANNOT be compared to R-squared for models that include intercept.
c. Dependent variable: F income
d. Linear regression through the origin

In table 6 Fisher's F is highly significant (100%), so the model is valid for prediction.

Table 6: Results of the ANOVA test corroborating the validity of the model

ANOVA[a, b]						
Model		**Sum of Squares**	**GL**	**Quadratic mean**	**F**	**Sig.**
1	Regression	5473416673951823000000.000	5	1094683334790364500000.000	229622003.158	.000[c]
	Residue	13491537373037260.000	283	47673276936527.420		
	Total	5473418023105560000000.000[d]	288			

a. Dependent variable: F income

b. Linear regression through the origin
c. Predictors: Age, Step23, DI, NoC, SD
d. This total sum of squares is not corrected for the constant, because the constant is zero for regression through the origin.

Table 7 shows the model itself, which depends on SD and DI, which are variables in the model that measure the ups and downs of the series, where the trend is highly significant to increase, logical because time runs into the future and the date is increasing, age also entered into the model, although not significant, as it increases more cases may occur.

Table 7: Summary of the model by coefficients and standard error Coefficientsa, b

Model		Unstandardized coefficients		Standardized coefficients	t	Sig.
		B	Standard error	Beta		
1	DS	13727377252.586	2454714.236	.704	5592.251	.000
	DI	13727952449.410	2423150.126	.704	5665.333	.000
	Tendency	389364.988	4919.361	.005	79.149	.000
	Step23	4206511.163	6971848.278	.000	.603	.547
	Age	9912.557	32709.077	.000	.303	.762

a. Dependent variable: F income
b. Linear regression through the origin

Figure 7 shows the zero mean of the errors and the standard deviation very close to 1, which is very important in the Regression assumptions, where the graph does not differ from a normal distribution.

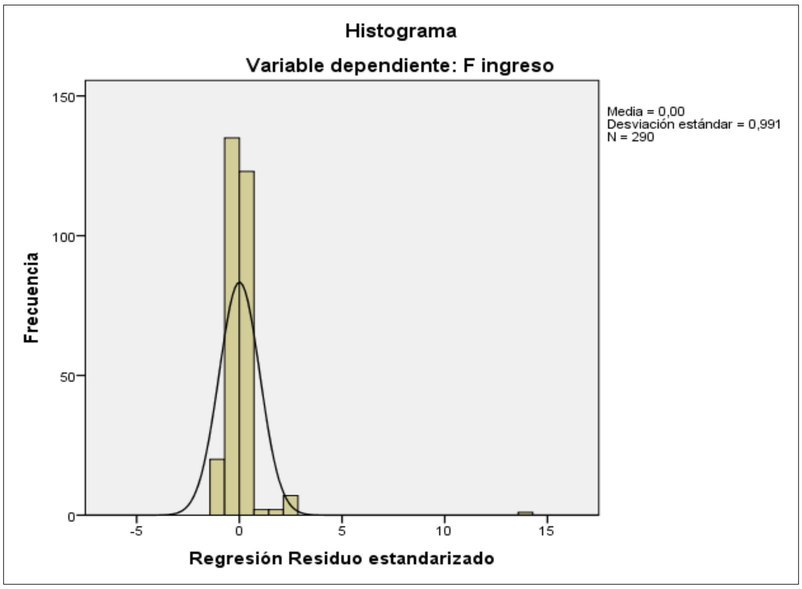

Fig 7: Histogram of entry date errors

3.2 ROR model of the time of symptom onset eight hours in advance

A model was made for the long-term start time eight hours in advance, which explains 84.9% of the variance, with six hours and 27 minutes of error. The Durbin Watson statistic is close to 2, so the introduction of new variables to the model is not necessary. Fisher's F was found to be highly significant (100%). The model depends on the hour 8 steps back (LAG8Hour), although not significantly, as well as age and trend, the latter telling us that it is in early hours where the presentation of acute myocardial infarction is more accentuated (Table 8).

Table 8: Summary of the template for the eight-hour advance AIM filing time

Coefficients $^{a, b}$						
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Standard Error	Beta		
1	DS	33627.071	8900.226	.546	3.778	.000
	DI	31108.139	8698.768	.503	3.576	.000
	Tendency	-17.946	16.989	-.070	-1.056	.292
	LAG8Hour	.087	.059	.088	1.477	.141
	Age	58.396	111.258	.094	.525	.600

a. Dependent variable: Start time
b. Linear regression through the origin

3.3 One-hour advance start time ROR model

Because the short time is important, this model was performed one hour in advance (Table 9), which explains 85.1% of variability, with an error of six hours and 26 minutes. Fisher's F was highly significant (100%), with a value of 121.2. It depends on the symptoms eight hours ago (Lag8Hour) and one hour ago (Lag1Hour); the coefficient of the latter is similar in absolute value, although of different sign, as well as age, these three variables are not statistically significant, but they contribute variance explained in the model, only the predicted value of the date of admission, was highly significant, where the trend also tells us that the onset time is tending to the morning hours, which is consistent with what is shown in Figure 4, therefore, these results are largely consistent with the results obtained by other authors in this regard [32,36,37,42].

Table 9: Summary of the template for the one-hour advance AIM filing time

Coeficientes[a, b]						
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Standard Error	Beta		
1	DI	-2268.546	2772.747	-.037	-.818	.414
	Tendency	-21.084	17.075	-.082	-1.235	.218
	Edad	30.564	112.247	.049	.272	.786
	LAG8Hour	.091	.059	.092	1.551	.122
	LAG1Hour	-.098	.060	-.098	-1.626	.105
	Predicted Date of entry	2.855E-6	.000	.901	4.121	.000

a. Dependent variable: Start time
b. Linear regression through the origin

Subsequently, a study was carried out with the meteorological variables that had the greatest influence on the errors of the previous model, according to the cross-correlation coefficient, selecting the four highest values of all the variables (Table 10).

Table 10: Meteorological variables with the highest incidence in the study

Variables	Delay	Correlation coefficient
Mean Temperature	4	-0.151
Mean Relative Humidity	2	0.081
Rain	1	0.123
Sea level pressure	7	-0.031

This new model explains 86.1% with an equal error of six hours and 16 minutes (Table 11). Fisher's F was 87, significant at 100%. Now, the previous variables were not significant, only the minimum temperature regressed in 4 cases (Lag4Tn), the average relative humidity regressed in 2 steps (Lag2Hrm), and the rainfall one step back (Lag1Lluv), results that coincide with those achieved by other authors in relation to these variables [4,5,11,41,43,47], while atmospheric pressure regressed 7 cases back, was also not significant; with the inclusion of the meteorological variables, 1% more explained variance is explained, and since we are dealing with human lives, one life matters, so identifying the time of onset of infarction a little more precisely is really very important [8,10,35,37].

Table 11: Summary of the model for the presentation of the AIM taking into account some meteorological variables

Coefficients[a, b]						
Model		Unstandardized coefficients		Standardized coefficients	t	Sig.
		B	Standard error	Beta		
1	DI	-2115.356	2716.743	-.034	-.779	.437
	Tendency	-15.841	16.620	-.062	-.953	.341
	Age	21.959	109.539	.035	.200	.841
	LAG8Hour	.076	.057	.077	1.319	.188
	LAG1Hour	-.081	.059	-.081	-1.371	.172
	LAG4Tn	-1510.527	440.367	-.710	-3.430	.001
	LAG2Hrm	510.802	237.032	.908	2.155	.032
	LAG1Lluv	437.437	185.261	.080	2.361	.019
	LAG7Patmm	28.469	19.541	.663	1.457	.146

a. Dependent variable: Start time
b. Linear regression through the origin

3.4 Comparison with other world regions

Meteorological phenomena and acute coronary syndromes have a longstanding association. 2500 years ago, Hippocrates already recognized the effect of weather and climate on man [39, 40, 43, 45, 48]. Since then, many studies demonstrated a variety of weather variables which are related to hospital admissions, acute coronary syndrome, acute myocardial infarction, and mortality [11, 42, 44, 46].

Air temperature, air pressure, dew point temperature, relative humidity, wind speed, precipitation, old and hot weather episodes, daylight as well as daily weather extremes are thought to have an association with coronary thrombosis, and this is true for various regions all over the world [7, 11, 42, 49].

Analyzed fifteen Northeast Asian cities and observed cold and heat effects having a significant impact on cardiorespiratory mortality [49]. Aylin observed a significant association in Great Britain between mortality and temperature with 1.5 higher odds of dying for every 1^{0}C reduction in winter temperature [50] and Marchant *et al.* (1993) [51] noted an excess of infarctions on colder days in both winter and summer. For Canada e.g., Bayentin *et al*. (2010) [52] observed an up to 12% increase in the daily hospital admission rate for coronary heart disease from cold temperature during wither and hot episodes during summer. Continuous exposure to weather extremes was more important than an isolated day of extreme. In Iran, the daily minimum temperature correlated well with acute coronary events, and this was statistically highly significant [14].

The EXHAUSTION project, a European Union funded study, found an unfavorable link between extreme temperatures and heart health. Cold and hot weather, both contributed to additional deaths from heart disease and stroke in people suffering from heart problems which brings potential consequences of climate change into focus. In the summer of 2003, over 70,000 additional deaths were documented in Europe due to extreme heat waves. Temperature drops of 10 °C - from 5 °C to -5 °C - increased the risk of dying from cardiovascular disease by 19 % and the risk of dying from coronary heart disease by 22%. With a drop in temperature of 11 °C, from 2 °C to -9 °C, the risk of developing coronary heart disease increased by 4 %. And this mainly affected people who were already suffering from heart problems before the temperature fluctuations [7, 41, 53].

Overall, the highest risk of acute coronary events usually occurs during winter months or extremely hot summer weather. Although low air temperature, low atmospheric air pressure, high wind velocity and shorter sunshine duration were associated with a higher risk for acute myocardial infarction, the most important association was observed for air temperature [6, 43, 54]. Interestingly, most extreme weather conditions such as tornado outbreaks have not found to increase the prevalence of cardiovascular events and did not lead to increased hospital admissions for acute cardiovascular events [5, 45, 55, 59].

Sun daylight seems to influence the incidence of acute coronary events. The daily rhythm of acute myocardial infarction is a proven fact, which has also been demonstrated in the current study. The highest incidence of acute myocardial infarction occurs in the morning hours between 5:00 a.m. – 12:00 a.m. comprising 35% to 40% of all acute coronary events; a second peak, lower than the morning has been found late in the afternoon [56-58].

The influence of meteorological phenomena on human health and particularly on cardiorespiratory physiology has been observed in various countries over all continents, e.g., in the United States, Spain, Greece, Brazil, Chile, Canada, China, Italy, Japan, Taiwan, Thailand and others [4, 10, 14, 39, 41].

Still, many questions about the effects of weather phenomena on the human body, the pathophysiology and the overall health are still open for discussion. The association between cold temperatures and deaths was more pronounced in men and in people living in areas of low socioeconomic status, hence the meteorological effects, and even the circadian cycle itself on the human body are complex and multifactorial [51, 55, 58]. Further research is necessary, as climate change may lead to an increase in the average global temperature, but also to extreme cold in some regions. Hence, further knowledge is urgently necessary to offer personalized advice to people at greatest risk of negative health effects from heat and cold as well as from other weather phenomena.

4. Conclusion

In conclusion, climatological variables have a high incidence in the appearance of acute myocardial infarction, especially in people over 65 years of age, where this variable entered the models in a positive way; that is, the older the person is, the greater the possibility of being infarcted, and preferably male individuals, with the winter months being those with the highest incidence, and where the early hours of the day play a fundamental role. Therefore, it is of great value to have mathematical models, both in the short and long term, to be able to predict in a timely and accurate manner the time of onset of infarction, which is really very important, since human lives are at stake.

Compliance with ethical standards

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Disclosure of conflict of interest

No conflict of interest exists among the Authors.

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